Capturing complex processes of human performance

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Chapter 1: Introduction

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The processes involved in human performance seem inherently *complex* and *dynamic*. For example, in order to “read the game”, a soccer player must integrate all the information from the ongoing movements and positions of team members, the opponents, the relative positions between them, where the ball is located, etc. Furthermore, an individual’s motor performance, which is particularly crucial in sports, depends on various simultaneous processes at different levels of the motor system: Cells, muscles, limbs, the brain, and so forth. In addition, individuals and teams do not perform in a void, but in achievement contexts, in which they strive for their goals, and their psychological states and performance may fluctuate as a function of many personal and environmental factors. For example, an athlete may enter a positive or negative spiral when perceiving that he or she is progressing or regressing in relation to the preferred goal or outcome (e.g., the victory). This perception of progress and regress, and the positive and negative psychological and behavioral (performance) changes accompanying this perception, are called positive and negative *psychological momentum* (PM; e.g., Gernigon, Briki, & Eykens, 2010). Positive and negative PM can emerge from one’s (or the opponent’s) mistakes, referee decisions, crowd behaviors, one’s psychological and physical state at a certain moment, and the interactions between these factors (Taylor & Demick, 1994). In addition, switching from performance on a relatively short time frame to a long-term process, individuals develop their abilities over multiple years, and hence over many practice or competition occasions. Ultimately, very few individuals develop world-class performance (e.g., winning Olympic medals), and their excellent abilities develop out of a combination of a variety of personal and environmental factors in interaction (e.g., motivation, coaching, family support, practice; Simonton, 1999).

The current dissertation aims to capture complex dynamic performance-related processes, including the topics illustrated above. This means that we examine complexity at different levels and time scales (from motor processes during one task, up to ability development during a career; see Table 1).

Table 1. Overview of the dissertation. Each chapter has a different focus on complex processes and time scales.

Chapter	Focus (complex processes)	Time scale(s)
2	Level of complexity of cognitive skills, measured while watching soccer game plays	Single game plays (video clips)
3	Complexity of motor organization, measured during ergometer rowing	Single rowing ergometer session consisting of 550 rowing strokes
4	Dynamics of psychological momentum in teams, measured during ergometer races	Single ergometer race
5	Connection between short and long-term psychological momentum, measured during and across ergometer races	Single ergometer race, as well as a sequence of ergometer races
6	Development of excellence out of complexity, modeled over the course of a career	Life span of ability development

The studies have been conducted in a sports context, in which ongoing psychological and performance processes take place. These processes (e.g., PM, talent development) are, however, also relevant to other achievement contexts such as education and business (Day, Gordon, & Fink, 2012), in which individuals or teams are typically considered as goal-oriented, performance-driven agents (e.g., Katz, 2001). That said, the sports context provides particularly well-defined performance criteria (e.g., winning or losing), the actions needed to meet those criteria are clear (e.g., scoring goals in soccer), and performers can often be studied on a relatively small surface (e.g., a soccer field) within a relatively short time frame (e.g., a match).

1.1 Why Would Performance Processes Be Complex?

The word *complex* is mentioned several times in this chapter. Importantly, complexity is not just reflected in the number of components that are involved in psychological and performance processes (e.g., the number and kinds of cells or muscles that are active during performance, the number of personal and environmental variables that shape the development of excellence). Instead, a complex phenomenon or system is characterized by emergence and adaptation. More specifically, with regard to human performance this is the emergence and adaptation of psychological and performance states from the ongoing *interaction* between various intrapersonal (psychological and physical) and situational components (e.g., Kello et al., 2010; Kelso, 1995; Van Geert & Fischer, 2009). This conceptualization is different from the notion of *complicatedness*. In a complicated system many components are involved, which can be studied in isolation, and the resulting psychological and performance states can be understood when knowing the contributions of the individual components (Ottino, 2004). In other words, a resulting state, such as world-class sport performance, can be understood from the addition of a number of causal components (e.g., motivation, physical skills, personality), that can therefore be studied in isolation in order to understand why some individuals develop world-class performance. The complexity perspective, however, assumes that the underlying mechanism of a certain state is multi-causal and dynamic, making it virtually impossible to reduce the explanation to one or a few directly-identifiable components.

However, researchers in the domain of social sciences have primarily attempted to untangle the *complicatedness* underlying human behavior. That is, by isolating one or a few independent variables researchers aimed to find an explanation for the occurrence of a psychological or performance state within a sample of participants (see also Van Geert, 2009a for a related discussion on static versus dynamic models of explanation). This entails that not the process itself (e.g., talent *development*) is studied, but how the results of those processes (e.g., world-class performance) are distributed over the population, and relate to other measurable components within the population (e.g., physical characteristics, motivation). The principal question that follows from this aim is whether the variance in some potential (performance) predictor *x* explains a significant portion of variance in performance outcome *y* (Atkinson & Nevill, 2001).

To give an illustration, with regard to talent or excellence development, typical questions would be what the contributions are of, for example, genes, amount of practice, environmental support, or cognitive commitment to become an excellent performer. Studies focusing on such questions have provided important insights into the kinds of factors contributing to excellent performance. For example, Van Yperen (2009) assessed—amongst other things—the goal commitment (independent variable) of youth AJAX players of the same cohort with a questionnaire. Fifteen years later he determined the career success (dependent variable) of the players (i.e., who had been playing in the Premier league in The Netherlands or another European country for at least 10 years, and who eventually did not end up playing in a professional league). When analyzing the results, Van Yperen (2009) controlled for potential confounds such as the soccer level of the players at the time of data collection (i.e., 15 years earlier). He found that players having a successful career also had a higher goal commitment at the time they were assessed in the youth academy, thereby marking goal commitment as a potential causal component of ultimate excellent performance, and demonstrating that psychological variables may play a pivotal role in talent development. More specifically, Van Yperen (2009) found that goal commitment explained 14% of the variance in soccer players' career success.

Continuing with the example of the study of Van Yperen (2009), while 14% explained variance is a large portion according to the guidelines in social sciences (Cohen, 1988), 86% was not accounted for by the variable goal commitment. It is obvious that various other factors play a role, yet it remains highly probable that we will never come close to explaining 100% of the variance, even if all substantial factors are included. Although the prevailing interpretation for this would be that measurements always involve random error variance (Van Geert & Van Dijk, 2002), an alternative perspective could be that the underlying components of human performance are in an *ongoing interaction*, which provides the principal explanation for the development of career success. For example, support from parents and friends, recent successes and investments of the coach may influence the goal commitment of a player, which in turn positively influences the supporting environment again, and so on (cf. Phillips, Davids, Renshaw, & Portus, 2010). Note that the dynamic interactions we refer to here are different from the interaction effects studied in the social sciences. These are generally limited to 2 or 3 interacting factors, often with a limited number of levels. Hence, the conventional method is to refine models using an additive strategy (adding factors and interaction effects to causal models). Using this method, a newly added variable or interaction term will often lead to only a minor gain in explained variance of the resultant psychological or performance state (Van Geert, 2009a). Therefore, this dissertation explores new models (rather than new potential determinants) to capture the complex processes of human performance.

Note that this dissertation is not intended to falsify or criticize the approach that is based on studying the (isolated) components that contribute to human performance (i.e. complicated models). This approach does provide important information, particularly if the research aim is to explain the distribution of human performance in the population, based on the distribution of specific causal underlying components. However, the current dissertation aims to capture the complex *processes* underlying human performance states, that is, how psychological and performance states emerge out of the *ongoing interaction* between various intrapersonal (psychological and physiological) and situational components. In order to do so, an important step is to find and apply the tools to measure the emergence and adaptation of complex psychological and performance patterns.

Although the complexity approach is not mainstream in the domain of social sciences, it has rapidly grown across different scientific domains (e.g., Gleick, 2008; Kauffman, 1995; Strogatz, 2003). Furthermore, its merits are increasingly recognized in the study of social dynamics (Castellano, Fortunato, & Loreto, 2009), developmental psychology (e.g., Van Geert, 2000), and sport sciences (e.g., Davids et al., 2014; Gernigon et al., 2010). The methods we apply here are thus inspired by applications and propositions from several scientific domains, including nonlinear dynamical systems in learning and development (e.g., Newell, Liu, & Mayer-Kress, 2001; Thelen & Smith, 1994; Van Geert, 1991; 1994; 2000), dynamical social psychology (Nowak & Vallacher, 1998; Vallacher, Read, & Nowak, 2002), synergetics (e.g., Haken, 1977; 1983; Haken, Kelso, & Bunz, 1985), self-organized critical dynamical systems in physics, biology, and cognitive psychology (e.g., Bak, Tang, & Wiesenfeld, 1987; Glass, 2001; Van Orden, Holden, & Turvey, 2003), network science (Newman, Barabási, & Watts, 2006), and mathematical modeling (e.g., Van Geert, 1991; Van der Maas et al., 2006).

1.2 How Can We Capture Complex Processes of Human Performance?

In order to provide insights into the complex processes involved in human performance, the research focus should be on obtaining an understanding of higher-order psychological and performance patterns, and the underlying system of dynamically interacting components (Nowak & Vallacher, 1998). Throughout this dissertation we propose different methods and techniques to capture complexity in various performance-related processes. Chapter 2 starts with an approach based on Skill Theory (Fischer, 1980). Skill theory lends itself particularly well to extract a measure of *complexity in cognitive skills*, which corresponds to a higher order measure reflecting the way individuals (continuously) structure the components in the world they perceive or interact with (Fischer & Bidell, 2006). Using Skill Theory, complexity can be extracted from actions and verbalizations while individuals are exposed to, or interact with, task material (Van Der Steen, Steenbeek, & Van Geert, 2012). Chapter 3 demonstrates how we can extract a measure of complexity that is assumed to reflect the *underlying complex dynamic organization* from which actual performance emerges. In this chapter complexity thus refers to the underlying system that generates human performance, which can be captured with nonlinear time series techniques applied to real-time performance data.

For the Chapters 4 and 5 we identified some important (collective) psychological and behavioral variables, whose changes would provide insights into the dynamics of a specific complex, performance related phenomenon: Psychological momentum (PM). We specifically study how these collective variables change under the influence of experimentally applied perturbations (i.e., progressing or regressing in relation to one's goal in competitive sport situations). In Chapter 6, we use mathematical modeling techniques in order to capture performance patterns on the long term, during the development of excellence. Here, the complexity is reflected in the ongoing interactions between the components, and the fact that the developmental trajectories towards excellent performance are a function of these interacting (changing) components.

The methods we employ in the different studies should of course stem from solid theoretical considerations that warrant their applications to the study of (complex) human performance processes. The methods and their theoretical underpinnings for each subsequent chapter are therefore elaborated on below.

1.3 Capturing Complexity of Athletes' Cognitive Skills (Chapter 2)

Expert athletes have been found to outperform non-experts in terms of their perceptual-cognitive skills (Mann, Williams, Ward, & Janelle, 2007). For instance, experts are able to anticipate events faster and more accurately (e.g., predicting the direction of a cross), and make better decisions than non-expert players (e.g., deciding where to move to receive the ball from a team member; for a demonstration of such skills in a famous expert—Christiano Ronaldo—, see https://www.youtube.com/watch?v=vSL-gPMPVXI). These skills would emerge from the continuous information pick-up of the athletes, which makes an athlete able to "read the game" (Bjurwill, 1993; Williams, 2000). Examples of relevant information in soccer, for instance, are the ball, opponents, team members, and their movements or changing positions. In addition, experts would pay attention to postural and bodily orientation information, mostly the shooting side of the player including the hip, leg, and foot (Williams, 2000). A soccer player thus constructs his (dynamic) representation of the actions taking place on the soccer field, which is based on the integration of multiple elements in continuous interaction (e.g., the players, opponents, ball, etc.). Capturing the complexity (i.e., the integration of the interacting components) of these representations has remained a challenge for researchers (e.g., McPherson, 2000; Roca, Ford, McRobert, & Williams, 2011).

In the domain of developmental psychology, Fischer (1980) has developed a cognitive-developmental theory, proposing that development (or improvement) of cognitive skills can be expressed in terms of increasing complexity (Fischer, 1980; Fischer & Bidell, 2006). Related to this, Fischer proposed a complexity scale along which cognitive skills could be classified according to the way task- or object-related components are integrated to construct a (dynamic) representation. The scale ranges from a representation of one single observable characteristic of the task or object under study—single sensorimotor level—onto a representation of the relations between characteristics that constitute high (complexity) level properties of the task or object—abstraction level. Although this theory has never been applied to the achievement domain of sports, its applicability has been proven in other domains, science education in particular. For instance, in a recent study conducted by my favorite colleague, Van Der Steen (2014), the complexity of children's representations of gravity and air pressure was examined. The complexity level of a child with regard to gravity, for instance, was reflected in the verbalizations of the child while working on a gravity task. If the researcher would release a ball, and would ask the child to explain what happened, the child could answer at different levels. An answer at the sensorimotor level would be “The ball falls down”, which is simple and directly observable. If the child would have given the (unlikely) answer that “gravity caused the ball to fall down when you released it”, it would reflect an abstract level, because the explanation is more than a simple observation of what happens and includes a general understanding of the law that explains the ball falling down from the moment it is released.

Because of (a) the challenge to capture the complexity of (dynamic) representations that athletes such as soccer players construct during game plays, (b) the potential of Skill Theory to measure the complexity of representations that are constructed, and (c) the previous successful applications of Skill Theory in educational contexts, Chapter 2 attempts to measure the complexity of soccer players’ representations. More specifically, we designed a soccer-specific coding scheme and we coded the complexity of soccer players’ verbalizations of the actions that took place in video clips they were exposed to. Our method, based on Skill Theory, thus allowed us to extract the complexity, regardless of the specific components that were verbalized (e.g., a player, the ball, the kind of action). For example, when a player in the clip gives a cross from the left, the soccer player may describe the action as “the player shoots”, which reflects a representation of a low complexity level, including the connection between two directly observable components (i.e., the player and the ball). However, the soccer player could also integrate several components of the action, such as the ball, goal, and players, as well as relative positions between these components, by stating: “The *left wingback* gives a cross to the *striker* at the *second post*”. In addition to the general interest to capture the complexity of cognitive skills of athletes, we specifically address whether the complexity level of the soccer game play representations, is related to the level of expertise of soccer players.

1.4 Capturing Complexity in Motor Performance (Chapter 3)

Whereas Chapter 2 is focused on complexity at the level of cognitive skills, assessed while athletes watched sports video clips, Chapter 3 examines the complexity of the motor system that generates actual sport performances. When performing bodily movements, various processes take place that contribute to how the movements are executed, including neuronal activity, muscle contractions, limb movements, and so forth. The processes involved in movement execution are not only numerous, but also coupled, and take place at different levels and time scales. This entails that motor performance emerges from continuously interacting component processes (i.e., interaction-dominant dynamics), which is opposed to the perspective that human performance is determined by localized functions or modules that command our movement sequence to be carried out, such as a central pattern generator or motor program (i.e., component dominant dynamics; see Wijnants, 2014).

Our assumption that sport performance—here motor performance in particular—emerges from interaction dominant dynamics (i.e., complexity) rather than component dominance, is based on two lines of reasoning that have been proposed in the literature. The first is that elite athletes' performance is, and should be, coordinated, yet flexible (Chow, Davids, Hristovski, Araújo, & Passos, 2011; Phillips, Portus, Davids, & Renshaw, 2012; Seifert, Button, & Davids, 2013). That is, even if movement patterns show regularities (e.g., in repeated rowing strokes), they are also adaptive (e.g., a rower can easily adjust his movements to speed up or react to a branch in the water). One principle hypothesis according to the interaction dominant perspective, is that the human motor system organizes itself around metastable states, meaning that it is placed in between order (regularity) and disorder (flexibility) (e.g., Kello, Beltz, Holden, & Van Orden, 2007; for a general theoretical model, see Bak, Tang, & Wiesenfeld, 1988). The second line of reasoning is of a statistical nature. If our motor performance is generated by separate components performing specific functions to generate our movements, we would expect that repeated movement measures (e.g., of movement duration) reveal random variations from measure-to-measure, called *white noise*. In other words, if each measure (e.g., the duration of a single rowing stroke) is the sum of independent component effects, and each subsequent movement is independent from the former, we should observe a normal distribution of measures with error variance on either side (cf. central limit theorem, see Kello et al., 2010). In reality, however, white noise in time series of human processes is the exception rather than the rule (Kello et al., 2007).

In the domain of physiology and motor control, white noise patterns are only observed in people who suffer from a (physiological or motor) disease (e.g., Goldberger et al., 2002; Hausdorff et al., 1997; 2001). Measuring healthy physical processes in real-time, researchers virtually always find that the pattern of variation is characterized by many high-frequency and low-amplitude fluctuations that are nested in low-frequency and high-amplitude fluctuations, which is called *pink noise* (or 1/*f* noise). This pink noise pattern would be a typical expression of complexity, as it would reflect that motor processes at faster time scales are nested in processes at slower time scales, and that all these processes interact cooperatively to generate our performance (e.g., Van Orden et al., 2003). In line with this reasoning, the time series of heart beat intervals of healthy adults reveal prominent patterns of pink noise, whereas a clear deviation from pink noise (e.g., random variation in intervals) signals heart failure (e.g., Goldberger et al., 2002). In addition, stride interval time series of healthy young adults reveal patterns of pink noise, whereas stride intervals of people with Huntington or Parkinson disease demonstrate white noise patterns (e.g., Hausdorff, 2009; Hausdorff et al., 1997).

Assuming that human physiology and motor control is characterized by complexity—physiological and motor processes take place across multiple time scales in interaction—, which is expressed in a pink noise time series, it is likely that time series of sport performance also reveal this pattern. In line with the fact that cyclical (i.e., repetitive) movements lend themselves best for the analysis of temporal structures (e.g., Glass, 2001; Wijnants, Bosman, Hasselman, Cox, & Van Orden, 2009; Wijnants, Cox, Hasselman, Bosman, & Van Orden, 2012), Chapter 3 aims to examine the noise patterns in rowers' rowing strokes at ergometers. Furthermore, given the proposition that elite athletes' performance is characterized by movement patterns that are both regular and flexible (e.g., Chow et al., 2011; Phillips et al., 2012; Seifert et al., 2013), we test whether elite athletes' time series of ergometer performance reveal more prominent patterns of pink noise compared to the performance of sub-elite athletes.

1.5 Emergence of Positive and Negative Psychological Momentum in Teams (Chapter 4)

In the Chapters discussed above, we aim to capture complexity during tasks in which participants are not “perturbed”. In reality, however, individuals or teams often perform their actions to achieve specific goals, and along the way they encounter positive or negative events (i.e., the perturbations) that bring them closer to, or further away from, a desired goal. The psychological and behavioral performance changes, that occur while progressing or regressing in relation to a goal, can be studied within the dynamical framework of psychological momentum (PM; Gernigon et al., 2010).

In general, positive and negative PM have been considered as dynamic states that may emerge and disappear (Adler, 1981; Adler & Aldler, 1981; Gernigon et al., 2010). More specifically, according to the most recent definition, PM is “a positive or negative dynamics of cognitive, affective, motivational, physiological, and behavioral responses (and their couplings) to the perception of movement toward or away from either an appetitive or aversive outcome” (Gernigon et al., 2010, p. 397). The complex nature of PM is reflected in the various interacting cognitive, affective, behavioral, and situational components from which positive and negative PM emerge (Briki, Den Hartigh, Hauw, & Gernigon, 2012; Gernigon et al., 2010). In team performance, athletes are also involved in continuous interactions with their team members. During a competition, positive and negative PM thus emerge out of complexity (i.e., the interacting components).

A major challenge with regard to research on PM is to study its dynamical nature, that is, *how* positive and negative PM states actually emerge. To date, research on PM has mainly focused on the antecedents of PM (i.e., specific personal and situational components that may cause PM) and its consequences (i.e., performance changes) (e.g., Tayor & Demick, 1994; Vallerand, Colavecchio, & Pelletier, 1988), thereby limiting the understanding of the *emergence* of this complex phenomenon. Our suggestion that the emergence of PM is difficult to capture based on this conventional approach has been indirectly supported by a reviewer, who noted that “there are more factors that influence PM than researchers can count”. This also contributes to the idea that deeper insights into the PM process are unlikely to come from attempts to search for the additional influence of specific factors. To obtain a better understanding of PM dynamics, we should thus apply an alternative method, which allows us to examine the process, that is, *how* PM moves to its two forms (i.e., positive and negative PM).

About three decades ago, Haken et al. (1985) proposed a method to study how different coordination patterns form in biological systems, which I will briefly explain given its applicability to PM research. The HKB method was established based on an experimental research program to understand the emergence of different states of coordination in humans, as well as the conditions that give rise to the different states (for a review, see Kelso, 1995). The main purpose of Kelso and colleagues' research program was to come to an understanding of changes in coordination patterns with a parsimonious framework based on the following theoretical concepts and recommendations. First, many components can be experimentally studied (e.g., activations of different muscles or muscle groups), but according to the HKB method one should determine the essential variables (i.e., collective variables or order parameters) in order to characterize the coordination dynamics. The second methodological recommendation is that one should determine the variable (i.e., the control parameter) that induces a change from one coordinative state to another (Beek, Verschoor, & Kelso, 1997).

The first major insight based on the HKB method was that anti-phase (abduction-adduction) finger movements change to an in-phase pattern at some critical movement frequency (e.g., Haken et al., 1985; Schöner & Kelso, 1988). When the movement frequency decreased again, people remained in the in-phase pattern for some time, that is, a shift back to the anti-phase pattern was delayed, which is called hysteresis. In these studies the relative phase (i.e., the relative timing difference between the two fingers) was the collective variable, which captures the pattern emergence from the interactions among various neuronal, muscular, and metabolic components. The movement frequency was the control parameter that changes (but does not prescribe) the coordination pattern. By showing that an in-phase pattern is more stable (i.e., more easily maintained) than an anti-phase pattern, Kelso and colleagues concluded that the in-phase coordination pattern is a stronger 'attractor'—a state or pattern toward which the behavior tends to evolve—than the anti-phase pattern (Schöner & Kelso, 1988).

Recently, Gernigon et al. (2010) proposed that an adaptation of the HKB method is very well suited to study PM dynamics. In line with Gernigon et al.'s proposition, Chapter 4 specifically examines the dynamics of team PM by applying the principles of the HKB method. In line with these principles, the first question to be answered is which variables are essential to characterize team PM dynamics. First, because (team) PM involves both psychological and behavioral variables, we focus on collective variables in both spheres. At the psychological level, we take collective efficacy into consideration, which is considered one of the most powerful team attributes. Collective efficacy is not an aggregate of individual self-efficacies, but rather an emergent phenomenon on the group level that is related to PM, thereby qualifying as a suitable collective variable (Bandura, 1997; Tasa, Tagger, & Seijts, 2007). According to the literature on team performance, another essential and emergent team-variable related to PM is task-cohesion (Carron & Hausenblas, 1998; Eisler & Spink, 1998), which we therefore also take into account. At the behavioral level, the coordination between the team members' actions and the team efforts are typical team level variables that are critical for team performance (Kozlowski & Ilgen, 2006), and likely undergo changes when moving from positive to negative team PM and vice versa (Adler, 1981).

The second question is what variable induces a change from positive to negative team PM, that is, what could be the control parameter? According to earlier literature, PM would be triggered when perceiving progress or regress in relation to the outcome or goal one wants to reach (e.g., winning a match in sports; Gernigon et al., 2010; Vallerand et al., 1988). In line with the guidelines of the HKB method, the position in relation to a desired outcome or goal would qualify as a control parameter that can be varied (thereby manipulating progress and regress). Thus, taken together, Chapter 4 is inspired by the original HKB method and its proposed adaptation to study PM (Gernigon et al., 2010). In this chapter, we specifically examine team PM dynamics by studying *how* collective efficacy, task-cohesion, efforts, and interpersonal coordination change when rowing teams progress or regress in relation to the victory in an ergometer race.

1.6 The Interconnection Between PM Within and Across Task Performance (Chapter 5)

Although the previous literature focused on PM within a task or match (see Chapter 4), theorists have proposed that complex dynamical processes take place at several interacting levels and time scales (e.g., Newell et al., 2001). With regard to PM, this would mean that the PM dynamics within a task are probably embedded in a PM process that takes place over a longer time scale (i.e., over multiple tasks). In turn, the PM process that takes place on the longer term time scale, is influenced by the single tasks.

While empirical evidence is repeatedly found for the proposition that human physiological and motor processes emerge from interacting processes across multiple time scales (Chapter 2), interacting time scales with regard to social phenomena are mostly hypothesized in theoretical works (e.g., Granic & Patterson, 2006; Lichtwarck-Aschoff, Van Geert, Bosma, & Kunnen, 2008; Van Geert & Steenbeek, 2005). However, some empirical indications have been found in the domain of learning based on observations of natural student – teacher interactions. For instance, Steenbeek, Janssen, and Van Geert (2012) studied student – teacher arithmetic sessions and students' learning trajectories over a school year. They found that ineffective sessions (e.g., due to initiations of the student that are followed by (repeated) ineffective feedback or responses of the teacher) influence the quality of the student – teacher communication in the next session, and hence results in a suboptimal learning trajectory of the student over the course of the school year. In other words, the short term dynamics shape the long term learning trajectory, and the learning trajectory influences the student – teacher dynamics within (next) sessions.

In the domain of motor learning, Zanone and Kelso (1992) conducted an experiment in which they exposed individuals to a coordination task they had to learn (i.e., moving fingers in a 90° relative phase, which is a relatively difficult coordination pattern, see Haken et al., 1985; Kelso, 1995; Schöner & Kelso, 1988). The authors found that it was difficult for most participants to produce the pattern at the baseline session, before learning the coordination task. However, learning the task in single sessions (short-term) seemed to change the pre-existing preferred coordination patterns (i.e., the attractor landscape), which became visible when examining the coordination dynamics across sessions (longer-term). More specifically, Zanone and Kelso (1992) found that the participants learned to execute a 90° relative phase coordination in a fairly stable manner over the course of the experiment (i.e., five days). This suggests that the short term learning sessions altered the attractor landscape of possible coordination patterns that extended over the longer term (i.e., across sessions), which in turn constrained the performance of the coordination task within the next session (short-term).

Chapter 5 is based on the propositions that (a) processes involved in human performance take place across multiple time scales that are interconnected (e.g., Steenbeek et al., 2012), (b) pre-existing dynamics can be altered by performances in successive sessions (Zanone & Kelso, 1992), and (c) PM dynamics can be studied based on an adapted HKB method (see Chapter 4). In the first conceptualization of PM in the literature, Adler (1981) proposed that PM takes place within a task (e.g., a sports match), but also across tasks, such as during a sports tournament or season. Given that PM is considered a complex dynamical phenomenon (Gernigon et al., 2010), long- and short-term PM processes should be interconnected (cf. Steenbeek et al., 2012). Furthermore, because successive sessions may influence pre-existing dynamics, repeated successful or unsuccessful sessions should affect the PM dynamics within a subsequent session (cf. Zanone & Kelso, 1992).

Recent research on PM dynamics in individuals has shown that, within a competition, negative PM is entered more rapidly and is more stable than positive PM (i.e., negative PM is a stronger “attractor state”; Briki, Den Hartigh, Markman, Micallef, & Gernigon, 2013). Because dynamics can be altered by previous sessions or experiences (Zanone & Kelso, 1992), we propose that previous successful competitions leading to long-term positive PM could weaken the negative PM attractor within a subsequent competition. In Chapter 5 we experimentally test this question during an ergometer-rowing tournament, by (a) manipulating athletes’ successive races, which they could either win or lose, respectively, and (b) letting athletes gradually regress from an almost-victory to a defeat in the last session in order to study the PM dynamics within that race. The collective variables we take into account are the perceptions of momentum, self-efficacy, and the effort exertion of the athletes.

1.7 Emergence of Excellent Performance Out of Complexity (Chapter 6)

In the chapters outlined above, we aim to study complex dynamic processes on relatively short time scales (i.e., during task performance and across a few tasks). Such processes can often be examined within the specific context in which they take place. Processes developing over a long period of time are more difficult to capture based on observational and experimental research designs. However, researchers have shown that such processes can be investigated using computer simulations (e.g., Nowak, Szamrej, & Latané, 1990; Nowak, Vallacher, Tesser, & Borkowski, 2000; Schuhmacher, Ballato, & Van Geert, 2014; Van Geert, 1991). To date, one of the most challenging long-term processes to capture in relation to human performance is the development of excellence (Detterman, 2014; Kaufman, 2013). Since the 19th century, researchers and philosophers have attempted to find the components that underlie excellence development (Simonton, 1999). Currently, about 150 years later, the debate on the underlying components continues to exist (e.g., Detterman, 2014; Kaufman, 2013). In addition, major components that have been proposed previously, such as deliberate practice (Ericsson, Krampe, & Tesch-Römer, 1993), turn out to be not as important as previously assumed (Hambrick et al., 2014; Macnamara, Hambrick, & Oswald, 2014). In line with our complexity perspective on human performance processes, Chapter 6 proposes that excellence emerges out of mutual interactions between several performance-related components, such as one’s ability, practice, family support, coach or teacher support, that form a dynamic network.

The central focus in Chapter 6 is to study the topology from which excellence develops. In general, a network topology can be envisioned as a graph characterized by several nodes, which correspond to the components (e.g., ability level, amount of practice) that are connected via a number of links. In the past decades, different kinds of network topologies have been proposed, and the ones that are applied most frequently are the random network (Erdös & Renyi, 1960), which formed the basis for more “real-world” network topologies, such as the small-world network (Watts & Strogatz, 1998) and the scale-free network (Barabási, 2009; Barabási & Albert, 1999). In a random network (Erdös & Renyi, 1960), couples of randomly selected nodes are connected, and each node has the same probability of being connected to any other node within the network. In a small-world network (Watts & Strogatz, 1998), most nodes are connected to their nearest neighbor nodes, whereas some nodes are randomly connected to more distant nodes in the network. Hence, this kind of network is characterized by a high clustering of components with some shortcuts to other (clusters of) components. Many real-world phenomena exhibit small world properties, such as the spread of rumors, epidemic diseases, or computer viruses (see Strogatz, 2003). In a scale free network (Barabási, 2009; Barabási & Albert, 1999), few nodes are connected to many other nodes, and a large number of nodes are poorly connected (hence generating a scale-free power law relationship between the number of links and the amount of components having that number of links). Scale free networks properties are found in, amongst others, the world-wide-web, protein interactions, and traffic dynamics (see Barabási, 2009).

Research on talent and excellence development has shown that an individual's ability is influenced by several components, including practice, parental support, coach and teacher support, and it is likely that such components in turn influence the individual's ability, either directly or indirectly (cf. Küpers, Van Dijk, & Van Geert, 2014; Van Geert & Steenbeek, 2005). In Chapter 6 we therefore simulate ability-networks including *directed* links between the nodes, which means that the connections run from one node to another. These connections are sparse and randomly assigned (cf. Erdös & Renyi, 1960), and each node has few direct links, but could be indirectly connected to a large portion of the other nodes (cf. Watts & Strogatz, 1998). Moreover, nodes (e.g., developing an interest in activities outside one's ability domain) may appear or disappear over an individual's (career) development and establish connections with other nodes (cf. Barabási, 2009). Although this network topology thus has similarities with existing network models that have been used to examine complex processes, it is tailored to the characteristics of human ability development.

In short, the network model we propose in Chapter 6 explains excellence as a developmental and emergent property. In a particular individual's ability network, a node could have a supportive effect on other nodes (e.g., a coach who stimulates the motivation and interest of a child), but it could also inhibit the development of another node (e.g., a tough coach who negatively affects the motivation and interest of the child). Thus, the network constantly develops through changes in the levels (i.e., values) of the nodes, among others as a consequence of the interactions with other changing nodes. In addition, the directed links between the components could be symmetric, asymmetric, direct, and indirect. We aim to demonstrate that this model, characterized as a network with dynamic properties, provides a basis to understand the process of excellence development. We will do so by showing the correspondence between the network model predictions and the existing literature on talent and excellence development.