COGNITIVE AND CONATIVE UNDERPINNINGS OF SPORT EXPERTISE

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COGNITIVE AND CONATIVE UNDERPINNINGS OF SPORT EXPERTISE

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Abstract

The study of expertise helps us not only understand outstanding expert feats, but also processes and mechanisms leading to and underlying expert performance. In this thesis topic of expertise is approached through multiple perspectives, utilizing both experimental and correlational designs. In order to provide more precise, sensitive and robust data analyses, multilevel, structural equation and Bayesian modelling has been used throughout all of the studies conducted for this thesis. In Study 1 (Chapter 2) the importance of kinetic, domain-specific knowledge, for experts ability of anticipation has been demonstrated by comparing anticipatory ability of expert (N=10) versus non-expert handball goalkeepers (N=10). This study emphasizes necessity of utilization of movement analysis for choosing parts of movement sequences relevant for anticipation; as well as necessity of combining outcome measures (accuracy and reaction time) for deepening our interpretation and understanding of underpinning cognitive processes. In addition to that, two studies (Studies 2 and 3 in Chapters 3 and 4, respectively) underline the role conative factors play in expert performance, practice and development of expertise. Analyses conducted on performance, practice and grit data (Study 2, Chapter 3), collected on a sample of elite youth Australian soccer athletes (N=388), showed that grit has a sizeable positive influence on performance (β=.44), and its influence is both direct and indirect (through practice). Furthermore, in Study 3 (Chapter 4) grit has been shown to influence acquisition of practice during early development, differentiating among the players of different skill and leading to snowballing effects of the amount of accumulated practice hours. Finally, in Study 4 (Chapter 5), an analysis was conducted of real-life performance data of NBA players (N=400), and age-related changes in the performance, over the span of players' careers, showing that greater pre-peak increase (up to the age of 27) in performance was followed by shallower and slower post-peak decline, regardless of the position players' played. These findings not only help better understanding of expert performance, its development and retainment throughout lifespan, but also have the potential to extend beyond the laboratory by adding to the creation of training regimes and talent identification/development programs.

Keywords: Sport expertise, Anticipation, Grit, Practice, Aging, Multilevel analysis, SEM Mediation, Bayesian Modelling

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Declaration

I declare that the work contained in this thesis has not been submitted for any other award and that it is all my own work. I also confirm that this work fully acknowledges opinions, ideas and contributions from the work of others.

Any ethical clearance for the research presented in this commentary has been approved. Approval has been sought and granted through the Researcher's submission to NorthumbriaUniversity's Ethics Online System on 10th of September, 2019.

I declare that the Word Count of this Thesis is 62,518 words.

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Chapter 1: Introduction

Almost everyone has witnessed, at some point in their lives, in person or through a device, acts that are seemingly impossible and completely out of scope human capabilities. Usain Bolt, again and again, breaking word records in sprinting (that he previously set himself!) in multiple running categories (100 meters, 200 meters and 4 x 100 meters relay). Not only that, but the new running time records he has set have been deemed physically impossible to achieve prior to him setting them – alike numerous other broken records (Ericsson & Lehmann, 1996). World class tennis players regularly serving the ball at speeds at or over 230 km/h (men) or 200 km/h (women) and their opponents being able to not only return that but also do it strategically. Basketball players are scoring points from the half-court line (or even at greater distances), without breaking a sweat, or seemingly staying in the air forever once they jump off for a dunk. Chess grandmasters playing multiple opponents at once and beating them all in remarkably short time span. Radiologists that can just briefly glance at x-rays and immediately know what the correct diagnosis is. Given these feats, and the complexity of the environments they are achieved in, it is no wonder that they defy our logic and make us believe that those experts must possess some superhuman abilities that make them special. Research on expertise investigates a wide variety of topics, such as (but not limited to): how exactly these seemingly impossible feats come together, what cognitive processes (for example attention, perception, memory etc.) underpin experts' outstanding performances, how is expertise implemented in the brain, what individual characteristics and activities are necessary for the highest levels of performance, how do experts develop and maintain those abilities over their lifespans and so on.

Expertise and categorization of expertise

Even though it might seem a bit trivial, because most of experts can be clearly recognized at a first glance, a definition of experts is in order. The easiest understanding for comprehending what makes an expert is the one based upon (expert) performance. Experts are people who, on a regular basis, produce clearly outstanding performances (Ericsson, 2007). Their performances speak for themselves and they are not a one-off occurrence. However, there are domains where experts, instead of based upon their performance, are decided by general consensus - politics or stock trading for example. The main difference between these "colloquial experts" and "performance based experts" is the nature of the environment they perform in (Bilalić, 2017). General rules in sport and games are

constant (the changes in specific rules that occasionally happen do not change the whole activity in general), pathological elements in radiology rarely change as well. In other words, the environment, in which they operate, is consistent thus allowing experts to acquire knowledge of regularities, be it consciously or unconsciously, and use that acquired knowledge to deal with new situation they find themselves in. When it comes to domains such as politics or stoke trading, they are regulated by numerous (unknown) factors thus making the attempt to pick up regularities (and using that for prediction) extremely hard if not completely impossible. Knowing what stocks are doing well at the moment does not help us know what will happen in the future and how that will impact stock performance (a good example of this in fairly recent history, were stocks of GameStop which were predicted by experts to flop, but, driven by a handful internet enthusiasts buying them for nostalgia sake, received greatest growth than they've seen ever before[1]). This lack of consistency prevents practitioners of these domains to acquire knowledge and expend upon it thus making them unable to, on regular basis, keep producing outstanding performances. The knowledge of particular features of (constantly repeating) patterns in a domain enables experts to see the problems they come across (within the domain) differently from novices. It is not the case of them having superhuman abilities (such as super speed or ability to fly) that enables their magnificent performances, but rather that they employ their knowledge of the domain to utilize completely different kinds of strategies. Given that novices lack this knowledge, when coming across the same problems as domain experts, they have to rely on basic/general cognitive processes and strategies and are thus unable to produce anything similar to expert level performance (Broadbent et al., 2019).

In this thesis, my main focus is sport expertise, as well as its cognitive and conative underpinnings.

As mentioned above, where expert performance can be measure objectively and where there is a normal distribution of the performance in the population, all performance that is two standard deviations above the mean performance (so around top 5%) can be considered expert performance. However, more often than not, there are either no objective measures of the performance (like in the case of creative domains such as arts) or where the performance of an individual is tied together with the performance of the entire group the person belongs to (in team sports for example) making it much harder to distinguish between different levels of expertise (and experts versus non-experts). This is

[1] https://www.economist.com/finance-and-economics/2021/01/30/the-frenzied-rise-of-gamestop

especially problematic when it comes to scientific research, as the lack of clarity regarding the definitions used for categorisation in research has serious implications for the validity, reliability and generalizability of the findings from the studies in these scientific areas. Multitude of researcher have noted struggles when defining precisely what constitutes expert performance in sport domains (Charness & Schultetus, 1999; Salthouse, 2004; Swann et al., 2015)

Studies investigating topics related to sport expertise generally utilize two distinct approaches to this problem:

1. Usage of *distribution based criteria* (such as individual differences) to identify experts based on where they fall relative to the remaining of their relevant population (Ericsson & Charness, 1994). This approach stems from the definition of experts based on their exceptionality, but is more specific in its deliver as requires the comparisons to be made only versus the target population relevant to the expertise (in other words expert basketball players ought to be compared to other basketball players of differing levels of expertise, rather than any other sport person or expert in general). It is the most commonly utilized approach in research (Baker et al., 2015), with participants belonging at the top and bottom of the distribution being compared (on their performance on different tasks/criteria) against each other.
2. Usage of specific *standards of performance* one needs to demonstrate to be classified a certain level of expertise. This approach, instead of classifying people based on their individual differences in performance, takes into consideration if the person can meet a predefined criterion level of performance for a specific skill. Even though some researchers argue that this approach more fully encompasses all levels and domains of expertise (Baker and Farrow, 2015) it is not as widely used as comparison based paradigms.

However, both of these approaches come in hand with a wide variety of practical and theoretical concerns (Baker et al., 2015). Defining characteristics of expertise are very variable (while in some sports the quantity of correct decisions/movements is of importance, while in others, such as figure skating, it is the quality of the movement that is the key) not only across different sports but also between different positions within the same sport (for example, libero in volleyball has drastically different role and expertise than the setter does), therefore predefining the universal required criteria of performance to be categorized as an expert, or finding the universal measures of performance for comparison paradigm, becomes, at instances, unfeasible. This is particularly problematic in team

sports where although the end objective is the same (to win), the individual goal and roles of the players on the team are not only different based on the position they play, but can also change numerous times throughout the game and entire season (Araújo et al., 2015).

Swann and colleagues (2015) have conducted a systematic review to better understand the breadth of definitions utilized in the study of sport expertise and found eight different ways of defining sport expertise (by using three different types of rationale), which vary on the continuum of validity, thus proposing their own taxonomy based on the study's findings. Their taxonomy, as well as the taxonomy provided by Baker and colleagues (Baker et al., 2015) will be briefly discussed, to provide a better illustration of more robust ways of defining and categorizing different levels of expertise, in the following paragraph. However, for clarity sake, it should be noted that different experts whose performance data was used in this thesis (Chapter 2 and Chapter 5), belong to the highest categories of both of the taxonomies.

In their systematic review, as mentioned beforehand, Swann and colleagues (2015) identified common themes used as criteria in majority of studies to define experts: competing at international and/or national level; the amount of experience they have (with different studies pointing out different types of experience as most important, such as competitive experience, experience of elite training, etc.); professionalism (being a professional athlete and playing in professional leagues); the amount and frequency of their training time; participation in elite talent development programmes; competing at regional level; competing at university level; and objective sport/country specific measure (such as possessing a black belt in martial arts or the number of handicaps on has in golf). They have also pointed out low-validity of definitions used in almost third of the studies that either did not include performance standards when recruiting their experts (and have, rather, focused exclusively on the amount of engagement with sport-related activities and athlete has had) or did not include standards of competitive experience they used for identifying athletes (for example, not specifying what is the ranking of the league, that athletes competed in, on national/international level). Due to this, they proposed that to judge athletes' performance, within the sport, one should take into account athletes' highest standard of performance, success they achieved at that level of performance and the amount of experience they gained at that level of performance. Additionally, to compare athletes between different sports, Swann and the colleagues (2015) propose that one needs to take into account the level of competitiveness of the specific sports within a specific country and within the sport itself. To capture those ideas, they proposed a formula to assign adequate ponders to each of the relevant (previously mentioned) criteria and calculate a total score of one's expertise:

Eliteness/expertise of athletic sample = [(Highest level of performance + Success at highest level + Experience at the highest level/2)/3] x [(Competitiveness of the sport in the country + Global competitiveness of the sport)/2]

The total score is then used to classify athletes into one of the 4 categories: 1) *semi-elite* athletes, whose highest level of participation is below the top standards of their sport; 2) *competitive-elite* athletes, who compete at the highest standards of their sport but do not achieve any success in it; 3) *successful-elite* athletes, who not only compete at the highest standards of their sport but have also had some success in it, albeit infrequent; and 4) *world-class elite* athletes, who had achieved sustained success at the highest levels of competition for a prolonged time (for more detailed breakdown, as well as explanation of how each of the criteria is scored, please see Swann et al., 2015).

Although not utilizing mathematical formulas, Baker and colleagues (2015) provide a more granular breakdown of different levels of expertise to incorporate of skill acquisition from naïveté to expertise/eminence, please see Figure 1.1 below.

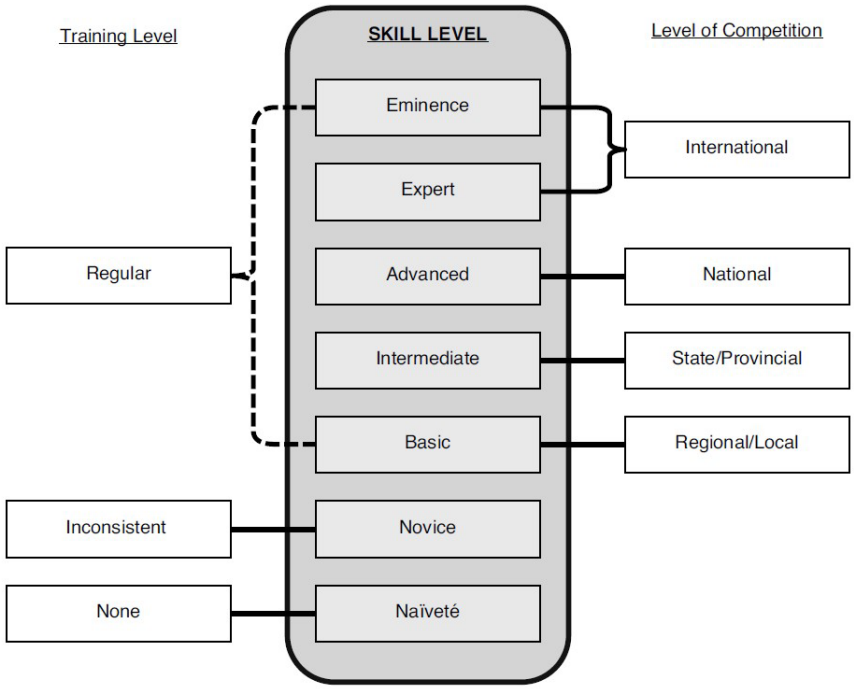

Figure 1.1. Taxonomy categories of expertise (acquired from Baker & Farrow, 2015).

For their taxonomy, training frequency and level of competition are important for distinguishing between the levels of expertise. The first two stages represent the early stages of skill

development, with no competitive engagement in sport, but differing amounts of training engagement. *Naïveté* represents people who are completely unfamiliar with the sport of interest and had no (training) engagement with it prior. *Novice,* on the other hand, is a newly initiated person with a limited knowledge of the domain of the specific sport. Novices are most commonly utilized in studies that compare performance of best and worst performance; though an argument could be made that using naïveté would provide a superior design (Baker et al., 2015).

In this taxonomy, once engagement in sport practice becomes regularity, athletes move into transitional stages of skill development. Even though number of hours spent engaged in practice will differ between different stages, the regularity of the said practice is what sets advanced stages apart from the early ones. Once novices acquire required fundamental knowledge and skills to begin competing at the sport (usually at local or regional levels) they progress to *basic* level. To differentiate between *intermediate* and *advanced* level, Baker and colleagues (2015) propose utilizing levels of the competition the athletes participate in. According to that idea, players who are skilled enough to compete at state or provincial level, but not higher, belong in the intermediate level of expertise, whilst players who compete at national level are categorized as advanced.

Finally, athletes that compete at international level are considered to be at the peak level of skill development and are categorized as *experts*. Baker and colleagues (2015), however, argue that a distinction ought to be made between exceptional athletes performing at the peak of the skill level and those who manage to transcend that even further. Those athletes, whose performance can grant them a seat in "the hall of fame" (between 1-4% of all experts, depending on the sport, according to the authors), are to be categorized in the *eminence* category. However, most of the studies in this domain, when discussing experts, do not make the distinction between the two (and more commonly refer to the players who are not necessarily of "hall of fame" caliber).

As mentioned earlier, experts, and their performance, that are discussed in this thesis (specifically in Chapters 2 and 5) would be categorized in expert level in Baker and colleagues' (2015) taxonomy or, alternatively, in world-class elite athlete category in Swann and colleagues' (2015) taxonomy.

Nature versus Nurture debate in expertise

Discussions about varying factors that underlay and impact human performance and abilities (within any field) can be traced all the way back to philosophers of ancient Greece. Plato, in *The*

Republic (ca. 380 B. C. E.), claims that "no two persons are born alike but each differs from the other in individual endowments". However, it was not until Francis Galton's work on heritability of intelligence (1869) that the phrase "nature vs. nurture" was coined. This phrase, to this day, represents the idea of existence of two different groups of sources of variance in performance (and individual differences): 1) innate factors everyone is born with (such as genetics, some biological characteristics, and similar) and 2) environmental factors - both in terms of geographical environment as well as social one (for example: country someone is born in or live in, familial bonds, social economic status, friend groups they belong to). Since then, arguments of importance of either of those factors have constantly been had, and continue to be, with greater importance being put on either one of them, in line with widely accepted scientific stances of the time. Even though philosophical and scientific in nature, those arguments had some important social and political implications (for more in depth overview of scientific impact on non-scientific spheres of life, see Pinker, 2002).

Darwin's *Origin of Species* (1859), as well as Galton's *Hereditary Genius* (1869), were one of the first publications that popularized the idea that biology was the main determinant of expertise and achievement. Both of these publications caused a widespread stir within many scientific communities resulting in a slew of influential studies that further confirmed the idea of innate abilities. One of such influential findings was a statistic that Fisher (1918) developed and introduced, labelled "heritability". It quantified the amount of individual difference a person exhibit that stemmed from their genetic heritage further emphasizing the role nature plays in human development and for human accomplishment. However, in the first half of 1900s, as a reaction to this view of experts being "born", a new movement gained prominence advocating for the view that experts are, in fact, "made". The so called environmentalist camp proposed that every individual starts as "tabula rasa" (with no innate traits) and forms and develops all of their characteristics and abilities through interactions with the environment. This viewpoint is best demonstrated by famous Watson's claim (1924):

> "Give me a dozen healthy infants and my own specified world to bring them up in, and I'll guarantee to take anyone at random and train him to become any kind of specialist I might select – doctor, lawyer, artist… regardless of his talents, penchants, tendencies, abilities, vocations and race of his ancestors."

Like mentioned above, ever since Galton's first usage (1869) of "nature vs. nurture" the debate of their importance has been ongoing and has been marked by radical shifts in opinion – going from one extreme to the other. Often, these radical shifts were driven by social and cultural factors (Pinker, 2002) - for example, many of misdeeds committed during WWII were rationalized by ideas rooted in

biological determinism. These shifts in understanding of human abilities can also be noted within the field of sport expertise as well.

Nature versus nurture in sport expertise

In parallel with Spearman's (1904) idea of general intelligence, *g*, underlying human mental abilities, a search for similar generalized motor ability begun. Concept of generalized motor ability is built on the ideas that: 1) all motor skills are related to one another; 2) because a single global ability underpins them all; 3) therefore people are capable of performing *all* motor skills similarly. In addition to that, a concept of motor educability was also important for this line of thinking, as it represents the idea that all people have general ability to learn motor skills (Baker & Farrow, 2015). Almost all research done during this period was in search of support for global motor ability, however correlational studies found very little association between seemingly related forms of motor ability. On top of that, very little support was provided for the idea of motor educability as well. As a matter of fact, majority of findings seemed to indicate that motor abilities are not only independent, but also very specific to types of practice individuals undergo (in other words an expert in tennis will not perform in badminton as well as an expert in badminton does, and vice versa, despite the seeming similarity of sports they both play). This has led to researchers focusing on specific characteristics and skills that vary between groups who differ in levels of skill, and has started, what is today known as, research of expertise.[2] Two groups of studies that shaped the future of research of expertise in general were studies done by de Groot (1965) and Simon & Chase (1973; Chase & Simon, 1973) on chess players. Heavily relying on paradigms from newly emerged cognitive psychology, they enquired about difference in mental processes in experts and non-experts when encountering problem from specific expertise fields. In the 1980s two groups of studies were the first to apply this approach and open the door to research in the field of sport expertise.

[2] It should be noted that the notion of generalized motor ability has not been completely abandoned and has, in last decade, seen some increase in interest with search for generalized motor tests to help inform talent detection and identification (for more see Faber et al., 2014)

Nowadays, there is a growing dissent in the literature. Simonton (1999) points out that even though environmental factors, such as practice, account for more variance in expert performance than innate abilities do, for complete understanding of expertise it is necessary to look into and investigate every single factor that contributes to and impacts expert performance, rather than keeping sole focus of research on whatever factor accounts for the most of variance. Therefore Hambrick and colleagues (Hambrick et al., 2018) propose a multifactorial model that takes into account all relevant factors when researching expertise. Figure 1.2 displays their general framework for multifactorial perspective on expertise (and see more in depth description of it further below).

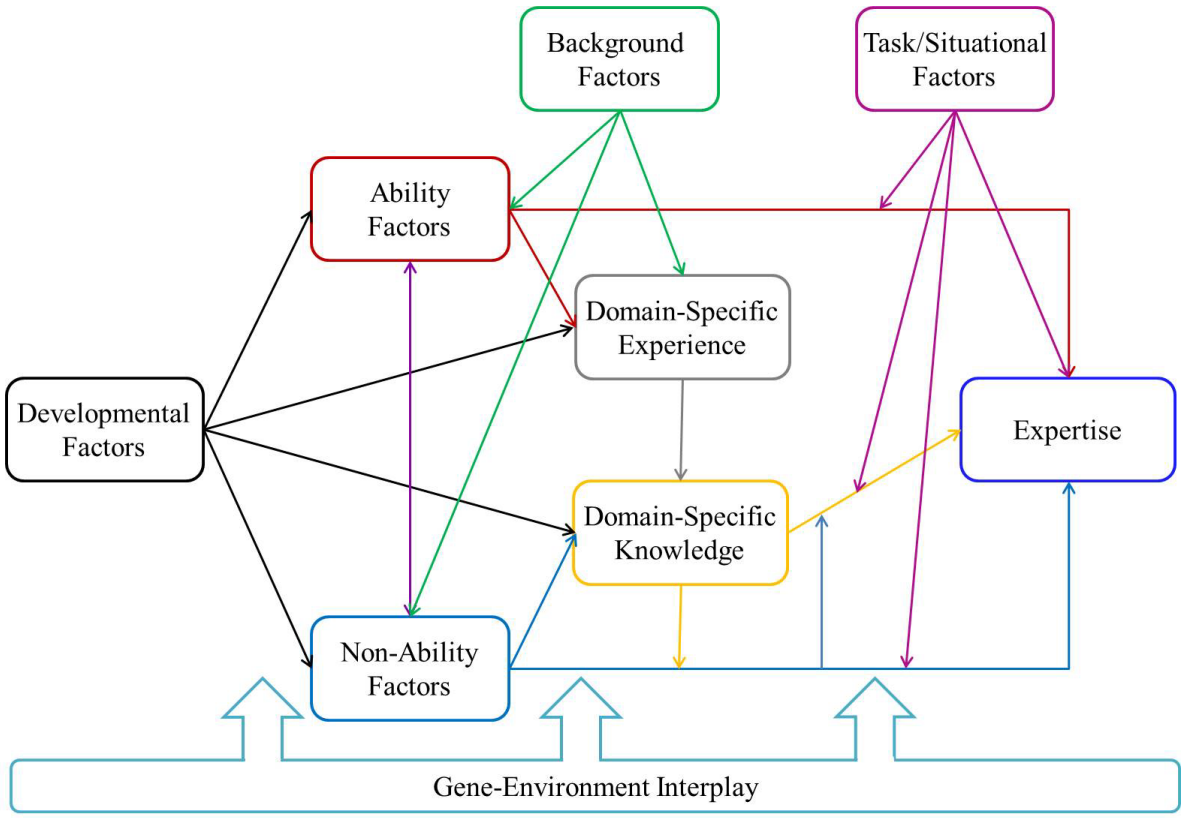

Figure 1.2. General framework for multifactorial perspective on expertise (adapted from Hambrick et al., 2018).

Janet Starkes and colleagues (Allard & Starkes, 1980; Starkes, 1987) investigated different cognitive advantages in sports like basketball and volleyball. Soon following their pioneering research, Bruce Abernathy and colleagues (Abernethy & Russell, 1984; 1987) examined underpinnings of expert anticipation in racket sports. Even though both of these groups of studies investigated different topics, their findings further established the notion that differences between experts and their less-skilled peers

were not due to their innate abilities (they were born with) but rather, seemed to have been developed through significant time and effort devoted to practicing and playing their sport. This has further been cemented with influential Ericsson's study (Ericsson et al., 1993), conducted on musicians, on deliberate practice, in which Ericsson and colleagues demonstrated that only consistent and prolonged engagement in highly effortful activities, with a goal of improvement and followed by an immediate feedback, leads to development of expertise and expert performance (more on this later in this chapter). However, as previously mentioned, it is believed that for the complete understanding of expertise one needs to investigate all factors contributing to and impacting expert performance, regardless of the amount of contribution/impacts those factor make, instead of centring focus on the most impactful factor only.

According to Hambrick and colleagues (2018), as it can be seen on the Figure 1.2, there are 7 main predictors of expertise, with gene-environment interplay having a possible impact on all the levels of the model: (1) *Developmental factors* (such as age and starting age); (2) *Background factors* (such as socioeconomic status, country of origin and parental involvement); (3) *Ability factors* (basic cognitive, perceptual and physiological traits); (4) *Non-ability factors* (personality, motivation and temperament); (5) *Domain-specific experience* (including training and other forms of experience); (6) *Domain-specific knowledge* (including specialized knowledge, skills and strategies); and (7) *Task/Situational factors* (such as task complexity, time pressure, the presence of external evaluation and the predictability of the task environment). These factors are believed to have both direct and indirect effect on expertise (see Hambrick et al., 2016, for an expanded version of this model). Given that factors themselves, relationships between them (and expertise), as well as methodological approaches, their benefits and setbacks can be investigated, there is a plethora of research topics within the field of expertise, such as anticipation, pattern perception, gaze behaviours, attentional control, decision making, skill acquisition, deliberate practice, physical and anthropometric factors, role of genetic factors, family and social support, developmental experiences, self-regulatory skill, personality traits, maintenance of performance, aging, and similar (for more in depth reviews see Baker & Farrow, 2015; Hambrick et al., 2018; Ericsson et al., 2018).

In this thesis I focused on some of developmental, ability and non-ability factors and their relationship to expertise and each other.

Cognitive mechanisms underpinning expert performance

Now that expertise has been defined and histories of scientific and philosophical approaches to expertise have been discussed, the question that logically follows is how *do* experts achieve their incredible performances? What cognitive processes underlay their coups? Through years of exposure to their field of specialization, experts acquire knowledge of regularities that occur in the domain (Chase & Simon, 1973a; Gobet et al., 2001; Gobet & Simon, 1996). As previously mentioned, in order for experts to be able to recognise and learn about the regularities in their domain, it is necessary for the domain to have consistent rules and re-emerging situations. These regularities are stored in experts' long term memory[3] and represent knowledge structures (Richman et al., 1995). Knowledge structures are typically in form of chunks (referred to as templates and schemes as well), which are meaningful units of individual objects. They are acquired and formed through experiencing common occurrences in the environment (Bilalić, 2017). Bryan and Harter (1897), while researching skills and strategies utilized by experts and novices in the Morse language (in form of both receiving and sending messages via telegrams), showcased the importance and utilization of these knowledge structures. In their study, experts, with prolonged practice, were able to not only send and receive longer messages, but have also changed their strategic approach to the whole situation completely. In initial stages of expertise development, the changes in strategy were only quantitative: focus, when receiving and typing out messages, changed from processing individual letters to processing whole words, or even multiple words at a time. However, at later stages of development, the shift in experts' strategies is of qualitative nature: their focus switches from individual letters/words to waiting to get an idea about the meaning of the content (as a whole) first, before initiating the required motor response[4]. In other words, when encountering a problem situation in their own field, experts do not focus on individual features of it, but rather on specific chunks of information that are meaningful for finding and implementing the solution. Experts' performance looks impressive not because they are able to employ the same processing strategies everyone else uses much faster, but because it requires development of qualitatively different, knowledge based, cognitive strategies. The more practice and experience experts have, the more refined, complex and elaborate these knowledge structures become (Bilalić et al., 2010, 2011; Broadbent, 2015; Broadbent et al., 2015, 2019).

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[3] Long term memory is storage of acquired knowledge that keeps the information (stored in there) available for retrieval for months, years, decades, after acquiring it (Atkinson & Shiffrin, 1968).

[4] This study, its approach and findings, had left its mark in all domains of expertise, including motor, earning the authors the title of founders of skill acquisition approach (Bilalić, 2017).

When experts face a new situation (for them) within the domain (of expertise), their domain specific knowledge, acquired through practice and experience in the domain and stored in long term memory, becomes automatically activated. The newly encountered situation is then compared to all other regular occurrences the experts have learned and stored previously (Feigenbaum & Simon, 1984). During this automatic process of comparisons between the new situations and previously encountered ones, experts' attention is being guided by their knowledge structures (Lohse, 2015) allowing them to quickly grasp the essence of new situation, focus on important aspects of it and ignore the irrelevant ones. Furthermore, knowledge structures in experts' long term memory, on top of information about occurring situations and rules, are made of common action plans and response sequences suitable for the particular situation (Chase & Simon, 1973b). These actions, made in response to the encountered situation, are also automatically accessed and executed once the observed situation has been recognized and matched to adequate knowledge structure. In motor domain, and therefore in sport expertise as well, these actions consist of various motor sequences, that can differ in complexity (Bilalić, 2017). Often referred to as motor programs, this well-rehearsed sequences of movements, stored in memory[5], are sent to all parts of the body for execution. On top of kinetic information about how certain joints and muscles come together to enable specific movements, motor programs also code common aspects of movement such as the timing and synchronization of different components (Broadbent et al., 2015; Schmidt, 1975). In other words, the universal cognitive mechanisms, that underlay sport expertise, consist of automatic engagement of (domain specific) *knowledge*, stored in long term memory, which is, in turn, utilized to guide *attention* and *perception* to the important aspects of the environment, to process gathered information and to trigger execution of appropriate *motor programs*.

The nature of these knowledge structures, however, is not universal and will differ between different domains of expertise. One of the main debates within motor, and therefore sport, expertise was whether the expert knowledge was visual or kinetic in nature (Baker & Farrow, 2015). One of the approaches to answering this question was utilization of stimuli that contain only kinetic information about movement and disregard any visual and contextual information, otherwise known as point-light stimuli. For point-light manipulation, researchers replace all major joint centres with point light sources thus, when presenting the videos of movements to participant, there is nothing on the display but constellations of dots moving together (as actual players would be moving). Therefore, any information about texture, colour, shape, contour, surroundings, and so on (typically found in actual

[5] The specific type of memory that contains motor programs, is called *procedural* (or *non-declarative*) *memory* as it encompasses (often complex) procedures for dealing with encountered situations – execution of which is usually automated, hard to verbalize and seemingly effortless (Milner et al., 1998).

sport or presented game sequences) is missing in point light display – they only contain kinetic information about sequences of movements. The idea behind this approach is that if, indeed, it is the actual movements that are the most informative cues for performance, removing all of the contextual cues should not have any impact on experts' performance. Several research groups demonstrated that this was the case (Abernethy et al., 2001; Ward et al., 2002; Hodges et al., 2006; Farrow & Abernethy, 2015). These studies, once again, reinforce the point that stored information is not about particular body parts and their perception, but rather, it is about how these body parts behave as a unit and how they are employed in motions. Since the information is kinetic in nature, chunks stored in long term memory are more like motion sequences, rather than static patterns typically found in different domains of expertise (Bilalić, 2017). It is this kinetic information, stored in procedural memory, that allows for experts' outstanding performances.

Anticipation in sport

Skilled sportspeople, through years of engagement with (their own) sport, have stored, in long term memory, a plethora of constellations from their domain of expertise. When they encounter a new situation, for example a tennis player about to receive a serve from their opponent, experts automatically look for similar patterns in their memory. This process of pattern recognitions enables them to perceive the situation as it unfolds, focusing only on important aspects of it and disregarding the rest, and to choose the most adequate motor program as a response. As previously shown, this is what underpins their superhuman-like performance. However, the question remains how exactly does this superior applied memory, combined with efficient interplay of perception and attention, help experts in their motor performance? When receiving and trying to return a serve in tennis, even though knowing where to look and what to expect from certain type of serve helps immensely, experts still have just mere fractions of a second to not only make a correct guess about where the serve will land, but also to find a way to return it back in a strategic way (that gives them the advantage). The most informed and accurate decision about landing location of the serve (including the amount of spin there is on the ball and similar information) is made once the ball has left the racket and the opponent cannot influence its trajectory anymore; yet waiting until that moment does not leave one enough time to process the serve, chose the correct motor program and execute it. This characteristic of ball sports Abernathy (1991) named *time paradox*. Experts constantly have to balance between waiting for enough information about what is going to happen next and having enough time for timely and

strategic motor responses. Yet, when watching the very best players perform, one cannot help but get the feeling that they have all the time in the world to achieve their marvellous coups.

Due to the temporal restrictions experts are forced to make their decision, and act upon it, based on information that precedes release of the ball (without seeing the ball trajectory). This ability, to seemingly "predict the future", is called *anticipation* (Broadbent, 2015; Farrow & Abernethy, 2015; Williams et al., 2019). Experimental studies, conducted in multitude of sports, have shown, time and time again, experts' ability to "pick up" early cues from kinetic information available in order to anticipate the outcome of the situation and execute adequate motor programs in response (for historical review of research done on anticipation, please see Farrow & Abernethy, 2015; Loffing & Cañal-Bruland, 2017; Williams et al., 2019; Williams & Jackson, 2019a).

A typical experiment in this line of research involves presenting videos containing movement (or game) sequences and asking participants, that differ in their levels of skill, to make a decision on what is to happen next (Bilalić, 2017). For example, in their series of pioneering studies, Abernathy and colleagues (Abernethy & Russell, 1984; 1987; Abernethy, 1991; Abernethy et al., 1993), had players, different in skill levels, of racket sports (such as tennis, badminton, squash) watch a short video sequence of a gameplay, just preceding the moment when the ball leaves the racket. Participants would then be asked to predict where on the court the ball would land and their accuracy, as well as time required to provide an answer, was recorded. Abernethy and colleagues found that more skilled players were much more accurate and faster in answering than their less skilled counterparts.

Even when conducted in more realistic settings (for example 11 versus 11 situations in soccer or whole game sequences (instead of just a small cut out of it) in basketball and tennis) experts were shown to make a call on what is going to happen next more accurate and faster than novice players (for a review, see Hodges et al., 2006). Research on anticipation has consistently demonstrated experts' vastly superior anticipatory ability across a wide range of sports (Abernethy et al., 2001; Aglioti et al., 2008; Alsharji, 2014; Broadbent, 2015; Broadbent et al., 2019; Jones & Miles, 1978; Loffing et al., 2014; Mann et al., 2007; Müller et al., 2006; Ward et al., 2002; Williams et al., 1999, 2019; Williams & Jackson, 2019b).

The ability to anticipate opponents' movements is vital for success in sport, especially for high-speed sports, such as ball-sports for example (Hagemann et al., 2007). Given that this ability relies upon knowledge-based cognitive strategies, some believe that experts' superior anticipation skills (and, thus, their performance) are not transferable between different sport domains (Vicente & Wang, 1998). Studies that support that idea have shown that once misplaced out of their domain of

expertise, the anticipatory advantage experts have is lost and their performance in experimental tasks drops to the level of novice performance (Calvo-Merino et al., 2006; Aglioti et al., 2008; Abreu et al., 2012; Farrow & Abernethy, 2015; Bilalić, 2017; Loffing & Cañal-Bruland, 2017; Williams & Jackson, 2019b). That being said, it should also be pointed out that there are studies contradicting this idea and demonstrating that expertise is not only transferrable across sport domains, but it also facilities transfer of anticipation skills (G. Moore & Müller, 2014; Rosalie & Müller, 2014).

So far, sport experts' ability to reliably predict what will happen next, based on the information preceding ball release, has been demonstrated. However, the question of strategies experts utilize for anticipation still remains. Eye movement tracking is one of the techniques that can be employed to provide more insight into that. Eye movements, in cognitivist paradigm, are understood to be indication of attention – the longer they are fixated on something, the more attention is believed to be awarded to that fixation point. Areas where experts fixate their gaze, be it for a fraction of a second or longer, are deemed to be the most informative in the environment (Bilalić, 2017).

Based on everything discussed prior, it should not come as a surprise that experts and novices have very different strategies when scanning their environment (Broadbent, 2015; Broadbent et al., 2015, 2019; Kredel et al., 2017). Experts tend to scan only the areas with the most relevant information about the situation they are encountering, while disregarding the rest of redundant information. Novices, on the other hand, due to the lack of domain specific knowledge, tend to pay attention to all of the elements in the environment, regardless of how informative or redundant they are. Studies conducted on tennis players of varying skill levels, showed that experts, when trying to predict where a serve will land, pay attention to rotation of the trunk and shoulders of the opponent during the execution of the serve, whilst novices pay attention to the rotation of the servers' head (Goulet et al., 1989; Singer et al., 1996).

However, in order to confirm that the areas experts look at really are the most informative ones, and that those areas, indeed, do have a hand in their anticipation and decision making – on need to manipulate those areas and see if that manipulation impacts expert performance. This is precisely what *occlusion paradigm,* popularized by Abernethy's work (Abernethy, 1991; Abernethy et al., 2001; Abernethy & Russell, 1984, 1987; Farrow & Abernethy, 2015), is about – chosen parts of movement sequences are obstructed from perception and, both expert and novice, performance on the tasks is measured and compared to how it was prior to the obstruction. Using as an example the previously mentioned findings of importance of trunk rotation for anticipating tennis serve – to confirm that finding, one would need to edit trunk area out of the video stimuli and then present it (together with

non-edited version) to participants and measure their performance. This type of occlusion, when one area in space if being occluded, is called *spatial occlusion*.

Another, commonly used occlusion technique is called *temporal occlusion* where, instead of obstructing certain body parts that perform movement sequences, whole segments of movement sequences are being obstructed. This is achieved by stopping/cutting the videos at certain time points, prior to ball release, and asking participants to make a prediction of the outcome at that specific moment of movement execution. A very influential study, done by Algioti and colleagues (Aglioti et al., 2008), utilized temporal occlusion when researching anticipation in expert basketball players (please see more details on this study in the following section on neural underpinnings of sport expertise). That helped them understand not only which parts of the movement sequence were the most informative for outcome prediction in experts, but also the way in which experts' AON (differently) process kinetic information available in earlier and later stages of movement sequence. Figure 1.3 shows an example, from their study, of temporal occlusion in basketball. It should be noted that combinations of both occlusion techniques are also possible and have been utilized in number of studies (for example Abernethy & Russell, 1987; Causer et al., 2017; Mann et al., 2007).

Figure 1.3. Example of temporal occlusion used for researching anticipation in basketball. The video was stopped at the various times (the numbers at the top indicating how many milliseconds in the cut was made), and the participants were asked to say whether the free throw would be successful (IN) or unsuccessful (OUT). Example provided shows a shot that was successful. Accuracy of answers, as well as how early into the video successful predictions are made, are of relevancy when comparing expert and novice performance (adapted from Aglioti et al., 2008).

Despite the (demonstrated) importance of occlusion techniques (especially temporal occlusion) for understanding anticipation, and expert performance in general, there is a surprising lack of consensus in the literature regarding the best strategies for choosing the most meaningful time points within the movement sequences, as well as the appropriate duration of chosen time segments. Both of these impact the relevance and the amount of information the cut carries and, therefore, impact the outcome (and conclusions being made). Furthermore, studies analyse and interpret the typical behavioural outcomes that are measured, accuracy and reaction time, independent from each other.

In Chapter 2: Anticipation in handball, I try to tackle these problems, within the context of anticipatory ability of handball goalkeepers, by answering following questions:

1.	What is the best strategy for choosing occlusion point?
2.	When the cuts ought to be made – how long video segments should last?
3.	What is the importance of meaningful occlusion points?
4.	How to better utilize outcome measures to further our understanding of expert abilities and their performance?

At this point, I would like to point out that my original plans for this thesis were to, on top of conative underpinnings of expertise that will be discussed below, do further research within the field of anticipation, specifically subfield of deception. However, the research was stalled for a year due to the unavailability of the facilities required for creating the stimuli and, once those were able to be made, it was rendered completely impossible by the start of currently ongoing pandemic (not to mention that those stimuli are now gone as well as a result of the cyber-attack that the university underwent – wiping out the memory of all university computer systems). If this part of thesis gives the impression of being abruptly abandoned, I wanted to assure you that it was not due to my will, but as a result of series of unfortunate circumstances, and that I hope to get back to planned studies in the near future.

Neural underpinnings of sport expertise

Now that the cognitive mechanisms enabling experts' astounding performances have been discussed and established, the question remains how does the brain accommodate them, if at all?

Measuring neural basis of expert athlete performance might seemingly be impossible given that there is almost no equipment capable of moving around with experts while their perform on the court/field, not to mention that most of the equipment used for neural science nowadays still requires participants to lay down and be still. However, investigating cognitive component of expert skills, as demonstrated with research done on anticipation, does not necessarily require for experts to execute the motor programs – one can simply show them a video of movement/game sequences and have them reply by pressing a button.

One of the most influential studies in sport expertise, that used this exact approach, was study done by Aglioti and their colleagues (2008), who looked into basketball experts and their anticipation skills. This study is unique, not only because of how it integrates behavioural and neural measurements, but also because of the participant groups it was conducted upon. Unlike the regular approach within expertise paradigm (Bilalić et al., 2010, 2012), where participants are typically in a group of experts or less experienced peers (novices), Aglioti and colleagues incorporated expert watchers as well (coaches and basketball journalist) to separate and measure importance of visual and kinetic information (providing another approach to answering the question regarding nature of sport expert knowledge). As usual, they had participants watch videos of basketball free-throws and predict whether the shot will be in or out.

On top of typical behavioural measures, they also measured excitability of the muscles in the hands and arms of participants (as those body parts are responsible for the final part of execution of motor program – shooting the ball). They also included videos of motion in soccer (kicking a ball) to make sure that any potential difference in muscle excitability caught stems from expertise and not just because of watching any movement on the screen. Their results upheld the previous findings of superior anticipatory skills of experts, as well as their reliance on kinetic information, as both novices and expert watchers underperformed when compared to experts. In other words their findings indicate that there is no substitute for learning by doing, as merely perceiving, that expert watchers utilize in similar amounts as expert players, was not enough to compensate for the lack of (actual) regular execution of motor sequences.

Furthermore, their physiological measures indicated greater excitability of hands and arm muscles among expert players (that differed during earlier and later stages of (observing) free throw execution) than non-player participants. However, the excitability dropped to the same level of non-players participants when observing soccer movements (muscle excitability was the same in non-player participants regardless of the observed domain). Results of their studies seemed to insinuate that

brain areas responsible for execution of physical movements could also be in charge of observation and understanding of the movement of others. In other words, their results seemed to indicate the importance of mirror neurons[6] for expert performances. Areas typically containing mirror neurons in human brains are called *action observation network (AON)* – see components of AON on Figure 1.4:

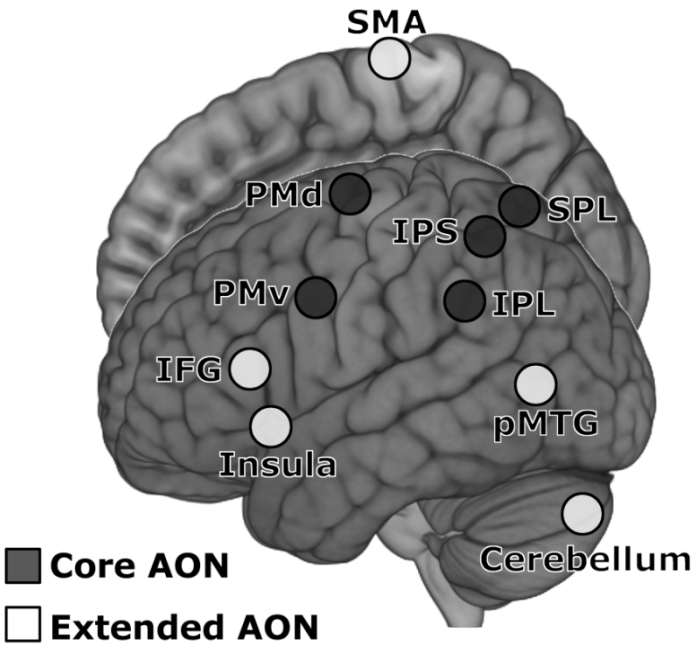

Figure 1.4 Action observation network (AON) in sports – areas that experts typically engage more when observing videos from their domain. Core AON areas: PM = premotor ventral, PMd = premotor dorsal, IPS = intraparietal sulcus, SPL = superiror parietal lobe, IPL = inferior parietal lobe. Extended AON areas: IFG = inferior frontal gyrus, Insula, pMTG = posterior middle temporal gyrus, Cerebellum, SMA (acquired from Bilalić, 2017).

Neural mechanism behind their influence is believed to be following (Bilalić, 2017; Hambrick et al., 2018):

[6] Mirror neurons are a subset of neurons responsible for execution of movements, but are also active when observing movements made by others. They are often found in the premotor and parietal brain areas. Mirror neurons are believed to play a part in a wide range of phenomena, from learning and movement to empathy (Rizzolatti, 2005).

Observation of actions performed by others activates mirror neurons, which are typically found in premotor and parietal areas. They send information to primary motor areas (in motor cortex), where motor programs (acquired through practice) are stored. This seems to simulate the execution of the observed action. If the observed action is similar to learned motor programs, that in turn triggers primary motor area to send impulses for the execution of appropriate movements to limbs through the corticospinal tract. Inadequate motor sequences, in contrast, do not elicit activation of motor programs (hence why there was no difference in muscle excitability for non-players in Aglioti's study (2008) , but was for expert players).

Beatriz Calvo-Merino and her colleagues (Calvo-Merino et al., 2005; 2006) , demonstrated just that when analysing brain activation in the mirror neuron regions among dancers and non-dancers. Not only different amounts of activation, but also different neural patterns, where observed in experts and non-experts when perceiving dance moves. Furthermore, the different neural activation was observed within the experts themselves when observing dance moves they expert in and those they do not (for example when ballet dancers watch breakdance moves and vice versa). This, once again, indicates that AON cannot simulate observed movements with which it had no previous experience physically executing them. In addition to that, studies were conducted on neural basis of anticipation in sport specifically, demonstrating different levels of activation, in different parts of AON, when experts and non-experts observe video stimuli and try to predict the outcome. These findings undeniably identify AON as the neural basis of anticipation and main engine of motor expertise. Expert athletes, when observing actions, employ AON to simulate the same action in order to gain insight into what is going to happen next. This simulation is an essential part of anticipation, which is supported by all main components of AON, prefrontal, motor and parietal cortex (Bilalić, 2017). This neural implementation is not a random occurrence – it is a direct consequence of the cognitive strategies that expert athletes regularly employ.

Genetic underpinnings of sport expertise

It is worth noting here, while talking about biological underpinnings of expertise, expert performance and expert characteristics, that in the last two decades there had been an influx in studies trying to understand genetic underpinnings of sport expertise as well (Ahmetov & Fedotovskaya, 2012; Bray et al., 2009; Pérusse et al., 2013). Sport performance, as any performance in general, is considered to be a complex phenotype, impacted by a coaction of physiological, psychological, social

and other environmental factors, and is, therefore, expected to be impacted by a multitude of genes. However majority of the candidate genes were not resulting in variants responsible for phenotypes of interest (Pitsiladis & Wang, 2015).

Currently, there has been a switch in approach to researching this topic – so called genomic approach is being utilized. This approach, instead of focusing on single genes, and their resulting phenotype variants, does genetic studies at genome-wide level – large numbers of genetic variants are being simultaneously tested across entire human genome without specifying hypothesis prior to start of testing (alike exploratory approach). This is in order to gather larger samples to increase the statistical power. At the moment, there are several cohorts on which genome wide association studies (GWASs) are being conducted (Pitsiladis et al., 2013). Findings so far have been mixed, with different groups being able to identify some single nucleotide polymorphisms associated with some of skills of interest, however, overall, current genetic tests cannot (yet) help talent identification or help in designing individual training regimes to maximize performance (for more in depth review, please see Pitsiladis & Wang, 2015).

Deliberate practice

Thus far, the importance of domain specific knowledge for experts' abilities and performance has been emphasized numerous times. Along with that, a method of acquiring that knowledge has been pointed out as well – through exposure to and engagement with the domain, typically in different forms of practice. However, not all forms of engagement within the domain will result in equivalent amount of impact on expertise (Bilalić, 2017). Ericsson and colleagues (1993), in their pioneering research, introduced the concept of *deliberate practice* and demonstrated its importance on expertise. Their findings were the basis for creation of *Deliberate practice framework (DPF)*, which provides the details on how (very specific type of) practice leads to skill improvement and expertise attainment (Ford et al., 2015).

Ericsson and colleagues (1993) conducted a series of studies on musicians which differed in level of skill, but were matched on age and other relevant variables, measuring the amount and type of engagement they had with music, both in formal and non-formal context, and everyday activities, throughout their lives. Furthermore, they enquired about enjoyability of measured activities, effortfulness, as well as their perceived relevance for skill acquisition (and thus expertise development). When analysing differences in engagement between more and less skilled musicians,

highly effortful, solitary practice, solely focused on improving ones performance, conducted under supervision and with constant feedback proved to be the best discriminator between the two groups. The highly skilled musicians spent significantly more time in this type of practice activity (10000+ hours) than their less skilled peers did (those who still pursued musicianship, but were less successful, spent around 8000 hours, while those who switched to the route of becoming music teachers spent only 5000 hours in this type of activity).[7] Ericsson and colleagues therefore named this activity deliberate practice, as it is performed with (deliberate) intention to improve own skills.

To further consolidate importance of deliberate practice for expertise development, studies have been conducted, in domains where expert levels are easier to quantify (for example, there are individual rankings of experts), using deliberate practice hours to try and predict skill level of participants. Findings demonstrated that deliberate practice was not only a good differentiator between differently skilled experts, but is also able to explain a large part of performance variance among experts (Charness et al., 2005; Ward et al., 2004, 2007).

Ericsson (Ericsson et al., 2018), in process of operationalizing deliberate practice and developing deliberate practice theory, emphasized several key characteristics of this type of practice: 1) it is conducted in a solitary manner; 2) it is conducted with the intention of improving own performance; 3) it is conducted under supervision and with regular feedback (for performance improvement); 4) it is perceived to be highly relevant for skill development by (developing) experts themselves; 5) it is highly effortful; 6) it is *not* inherently enjoyable[8]; and 7) a key part of it is monotonic benefits assumption[9] – the idea that "the amount of time an individual spends engaging in deliberate practice activities is monotonically related to that individual's acquired performance level" (Ericsson et al., 1993, p. 368).

Furthermore, Ericsson pointed out the major constraints in long-term engagement in deliberate practice: motivational, effort and resource constraint. Motivational constrain refers to the high levels of motivation needed to engage with deliberate practice (long term) given the amount of effort it requires,

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[7] Even though there were some other differences between the groups deliberate practice was deemed the most important for expertise attainment.

[8] However, this specific characteristic has brought upon numerous discussions, especially in the field of sport (Baker et al., 2020) – it seems likely that Ericsson (1993), in the original study, overextended the findings on enjoyably, as ratings for enjoyability of deliberate practice were still fairly high, just lower when compared to other measured activities. In other words, it would seem that the participants did not rate deliberate practice as non-enjoyable, but rather, as less enjoyable than (some) other activities.

[9] Monotonic stands for two or more variables moving together in the same direction, both either increase or decrease together – applied to the example at hand: when the amount of deliberate practice increases, so does performance (Everitt & Skrondal, 2010).

as well as the lack of enjoyment that doing the activity brings. Effort constrain specify that engaging in deliberate practice requires ones' full attention to be maintained at all times during the engagement activity. This is considered to be constrain as maintaining full attention for prolonged periods of time is very taxing and hard to achieve (Ford et al., 2015). Finally, resource constrain refers to necessity of support provided to (future) experts by their social circles (families, friends, significant others) as well as by other professionals that work within the domain of expertise (coaches, teachers). Furthermore, it refers to physical resources as well, such as: facilities for practice, equipment, transport from and to the place of practice and so on.

More recent updates to DPF, also included "arrested development", the plateau in performance many experts experience, as another constrain to the framework (Ericsson, 2003, 2007, 2014). Ericsson proposes that people who are satisfied with level of their own performance, once they hit the plateau in development, will not engage in deliberate (effortful) practice to try overcoming it and further improving. Experts, on the other hand, will not be content with being merely competent and will, as a consequence of that, plan and engage in further deliberate practice to try and overcome the plateau. Experts' constant engagement in deliberate practice (and motivation to do so) continues to improve their performance beyond their current levels – illustrating how differences in quantity and quality of deliberate practice impact performance across time (Ford et al., 2015).

Deliberate practice in sport

The link between (deliberate) practice and (expert) performance has been well established in the literature by now, in multitude of domains, including sports (Baker et al., 2020; Baker & Young, 2014; Campitelli & Gobet, 2011; Ericsson, 2020; Macnamara & Hambrick, 2020). Furthermore, DPF has made such an impact on understanding performance, that its relevance has been documented and, sometimes wrongly, interpreted in numerous non-scientific pieces of literature and entertainment such as *Outliers* (Gladwell, 2008), *Talent Code* (Coyle, 2009), *Talent is Overrated* (Colvin, 2010). All of them popularizing idea that expertise is result of practice, and practice alone, and that by abiding by the *10000-hour rule*[10] anyone can become an expert.

[10] Gladwell (2008) popularized the idea that one needs 10000 hours of (deliberate) practice to attain expertise, which, according to Gladwell came from Ericsson's original study done on musicians (1993). However, Ericsson later stated that this was a misinterpretation of the studies' findings (Ericsson, 2013) – even though elite musician did, indeed, reached 10000+ hours of deliberate practice in the specific studies, the number of hours (of practice) is not set to 10000 and will differ from domain to domain.

In sports, deliberate practice refers to, both, the theory as well the activity engaged in by athletes with the intention of improving certain aspects of their performance in competition (Ford et al., 2015). Athletes, typically, first analyse their performance to identify key weaknesses, which can be psychological, physical, tactical and skill based (Jones, 2012), upon which they develop appropriate training regimes. These training programs consist of different types of activities which, depending on specific aspects of performance players want to improve on, can be very sport specific (for example shooting technique when executing free throws in basketball) or general (i. e. working on own fitness, strength, mental endurance, et cetera).

The first formal test of deliberate practice theory in domain of sport was conducted by Hodges (1995), employing the same methods used in Ericsson's study (1993), on adult male Canadian international and club-level (Olympic-style) wrestlers. Hodges found the same positive monotonic relationship between deliberate practice and level of expertise as Ericsson and colleagues. However, unlike in Ercisson's case, the type of practice activity that differentiated the best between skill levels was *group practice*. Furthermore, out of all practice activities that athletes' deemed relevant for their performance, 50% of them were rated as highly enjoyable (those including sport specific activities such as practice with teammates, working on a specific skill, and so on). The only activities, that were both relevant to performance and deemed unenjoyable, were general sporting activities (such as flexibility, endurance, weight training, and so on), thus, according to DPF, these were the only

Following this study, Ericsson's methods of counting hours of activity engagement have been employed, time and time again, in studies looking into relationship between (deliberate) practice and skill level (and performance) in sport, following the similar pattern of results as Hodges found (1995). In general, more skilled athletes have accumulated more practice hours than their less skilled peers (Baker et al., 2020; Baker & Young, 2014; Ward et al., 2004) and, out of highly relevant activities for expertise attainment, fitness activities were rated low for enjoyment, while sport-specific activities were rated high (Law et al., 2007; Young & Salmela, 2002). This started an ongoing debate on what constitutes deliberate practice in sport, given that in many sports, especially the fast-paced, team based, ball sports, key component of performance is the ability to perform together, in unison, with the rest of one's team, thus making practice of that type of behaviour more relevant for overall performance than practice activities focused solely on improving ones' physical conditions (Abernethy et al., 2003; Baker et al., 2020).

Furthermore, competition, which Ericsson (1993) labelled as not-deliberate practice due to the lack of repetition of movement sequences and lack of feedback when doing so, has been found to be

perceived highly relevant for expertise attainment by both practitioners and researchers (Abernethy et al., 2003; Campitelli & Gobet, 2011; Gobet & Campitelli, 2007; Singer & Janelle, 1999). There is still no consensus on best route to defining, and thus measuring, deliberate practice in sport – with some advocating to measure only the practice activities that match the original conceptualization as much as possible (Ericsson, 2020; Ericsson & Harwell, 2019), while others advocate for a change of defining characteristics of deliberate practice in sport (Baker et al., 2020; Ford et al., 2015).

Choosing either of the routes will result in different amounts of hours attributed to deliberate practice (alone), thus in different interpretations and implications of the findings. Most of the research, nowadays, takes into account the amount of time spent engaging in *all* sport-related activities, be it in form of practice or non-practice activities[11], categorizes them into groups, and then analyses and interprets results per a group of activity (however, there is no clear cut guidance on how to categorize activities into groups). In Chapter 3: Grit - Deliberate practice mediation on performance and Chapter 4: Snowball effect of grit on (deliberate) practice, I will elaborate more on how activities were grouped and measured in this thesis.

Engagement in sporting activities during early expertise development

Due to the monotonic benefits assumption of DPF, a popular belief is that the start of engagement with sporting activities should happen early in the childhood for expertise to be attained. However, in their own studies Ericsson and colleagues (1993) actually explicitly describe pre-deliberate practice phase of sport participation, during which athletes interact with sporting activities due to pure interest and enjoyment (on its own) and develop the motivation to improve their own performance, but do not state specifically for how long, prior to engaging with deliberate practice, this phase is to last and, therefore, when it is expected to start (in order to achieve the optimal expertise development). There are three pathways to expertise, which are most commonly debated about in the science of sport expertise: *Early Specialisation* versus *Early Diversification* versus *Early Engagement*.

The early specialisation route stems directly from the postulates of DPF (Ericsson et al., 1993), and the strong positive correlation found between amounts of (deliberate) practice and expert

[11] Ford and colleagues (2013) introduced the concept of *deliberate environment* that represents combination of all of the activities athletes might engage in to improve their performance, but that are not practice – such as: diet and nutrition, sleep, recovery, watching and analyzing performances of others or one's own previous performances, team meeting and debriefs to work on strategies, et cetera. In deliberate environment, majority of made decisions, and displayed behaviors, are in servitude of improving athletes' performances in the competitions, even if they are not conducted on the court/field (Ford et al., 2015).

performance (Newell & Rosenbloom, 1981). In this pathway it is postulated that, in order to gain the most benefits out of their (deliberate) practice, children ought to limit participation to a single sport, with a deliberate focus on training and development in that sport, all year round (Wiersma, 2000). Baker and colleagues (2009) suggest 4 parameters of early specialization: 1) Early start age in sport – to become experts, athletes need to begin engaging in activities relevant for skill development as early (in life) as possible; 2) Early involvement in one sport (as opposed to participation in multiple sports) – the involvement with sport-related activities needs to be focused on a specific sport (one wishes to become and expert in) instead of diversifying focus on multiple different sports; 3) Early involvement in focused, high intensity practice – sport specific activities need to constitute deliberate practice for one to be able to develop into an expert (focus on enjoyable activities that are not conducted with the intent to improve one's skill and performance will not lead to the development of expertise, regardless of the amount of hours one spends engaging); and 4) Early involvement in competitive sports – the earlier athletes start engaging in competitive sports, the more experience they will accumulate and be able to utilize to improve their performance.

However, there were numerous studies that casted doubt on this pathway by demonstrating harmful outcomes of early specialization such: as physical injuries (Baxter-Jones & Helms, 1996; Baxter-Jones et al., 1993, Law et al., 2007; Maffulli et al., 2005); as well as negative psychosocial outcomes – for example: decrease in sport enjoyment, fear of failure, low self-confidence, low self-esteem, compromised social development, dropout, burnout, eating disorders and so on (Davison et al., 2002; Harlick & McKenzie, 2000; Hill, 1988; Law et al., 2007; Maffulli et al., 2005; Wankel & Kreisel, 1985). Despite that, in their recent review of the current state of knowledge on this topic, Baker and colleagues (2021) stated that more research needs to be done on early specialization, in order to better understand mechanism behind the maladaptive outcomes as well as the benefits it leads to, before condemning it and abandoning it.

As an alternative to this pathway, early diversification approach was proposed, pointing out the reports given by the expert athletes themselves about the importance of engagement in enjoyable, play-like activities, though multitude of sports, during the early years of their development. Côté (1999), in an effort to better understand how engagement with sporting activities changes throughout an expert athlete's development, as well as what other factors impact engagement, ran a series of interviews with expert youth athletes (competing at the highest levels of competition available to them at that age) and all of their family members (parents and siblings). As a result of those interviews Côté formed a model explaining (and predicting) engagement in sporting activities throughout expert athlete's career called *Developmental Model of Sport Participation (DMSP)*.

This model postulates 3 stages of development, during which different types of engagement are important, the sampling years, the specializing years and the investment years; followed by a post-stage focused on maintenance of skills and performance, the perfection/performance years. The key characteristic of the first stage, the sampling years (typically happening between ages 6-13) [12], is exploration of different sports (and sporting activities) with main goal of having fun and enjoying. These activities, termed *deliberate play* (Côté & Hay, 2022), are believed to stimulate one's interest and intrinsic motivation due to the fun and enjoyment associated with the participation alone. The second stage, the sampling years (typically between ages 13-15), is more characteristic of what Ericsson (1993) refers to as pre-deliberate practice phase, with attention being more focused (on smaller number of sports) and driven by both, need for fun and enjoyment as well as want to improve ones' own skills (in other words, the importance of deliberate play and deliberate engagement is equal at this stage). The third stage, the investment years (typically between ages 15-18), is characterized by sole focus on a single sport driven by the need for improvement of performance and becoming as best as possible. The final stage is characterized by sport engagement with purpose of perfecting and maintaining skills and performance in competition.

Although less maladaptive outcomes of early diversification pathway have been reported in the literature so far (Baker & Farrow, 2015), the available evidence seems to suggest that diversification alone, albeit beneficial, is not enough for nurturing elite athletes long term (Baker et al, 2009). Domain-specific deliberate practice is ultimately required for one to achieve expert levels of performance. Therefore the determination of optimal timing and intensity of specialized training, alongside purposeful diversified training, are needed to be considered in the context of peak age and performance demands of the sport in question. Early engagement pathway attempts to provide this bridge between the two (Ford et al, 2009), by proposing that the optimal pathway to development is reflected in minimal diversity in engagement in (other) sports, but with high levels of deliberate play and deliberate practice, during the sampling years, in the primary sport of interest. In other words, early engagement highlights the need to derive an appropriate balance between (domain-specific) deliberate practice and deliberate play in order to develop expert levels of performance (Ford et al., 2009).

Because early engagement pathway is relatively new, and not yet supported by a wide breadth of empirical evidence, Chapter 4: Snowball effect of grit on (deliberate) practice will focus on the

[12] In their work, Côté specified that even though there were typical age ranges of when of the stages occur provided within the DMSP, those were not fixed and will differ from sport to sport – however, regardless of when exactly they happen, the stages follow the same order and have proportional length of duration to proposed ones (Côté, 1999).

Developmental Model of Sport Participation, and its implications, in more detail. It is also worth pointing out here that numerous studies have, since the publication of the module, confirmed some of the aspects of DMSP and assumptions that model brings in different sports (for a review please see Côté & Erickson, 2015; Côté & Vierimaa, 2014; Wall & Côté, 2007). In general, the (repeated) finding is that early childhood engagement in playful and enjoyable activities leads to a relatively rapid improvement in performance and motivation, which begins to plateau sometime later (Newell & Rosenbloom, 1981). When that happens, expert athletes' start planning and engaging with deliberate practice to overcome the obstacle and continue improving their abilities (Ford et al., 2013).

Impact of practice on expert performance

Given that starting age differs greatly between different sports, as well as within the same sample of athletes in the same sport, the number of accumulated practice hours required to attainment of expertise will be prone to wide variation. On top of that, number of hours required for achieving expert performance (within own sport) will be impacted by several other, non-practice and ability related, factors such as nature and popularity of a sport, characteristics required to become and expert athlete, extent to which other athletes accumulate practice hours in the domain, et cetera (Ford et al., 2015). Therefore, it is much more fruitful, when looking into impact deliberate practice has on performance, to discuss proportion of variance in skill/performance that (the amount of) deliberate practice can explain.

Even utilizing this approach, the amount of variance in skill, deliberate practice can explain, varies from study to study (although some amount of explained variance has been consistently noted): 16% in recent meta-analysis on impact of deliberate practice on sports (Macnamara et al., 2016); 61% when redefined using stricter criteria (Ericsson & Harwell, 2019); 28% in dart throwers (Tucker & Collins, 2012); 29, 31 and 63% in different groups of Olympic swimmers (Hodges et al., 2004); 53% for swimming component of Olympic triathlon athletes, but 38% for their running component (Hodges et al., 2004).

Even more troubling are the studies conducted on experts only (instead of typical expert versus novice designs), which show that impact of deliberate practice on performance is even smaller and, on occasions, even negative (Güllich, 2014; Johnson et al., 2006; Macnamara et al., 2016). Part of the reasons behind this outcome might be that, due to the nature of the sample, restricted range of performances suppresses the relationship between different variables (Vaci et al., 2014), it is indicatory

of the role factors other than practice might have on expert performance and attainment (Donner & Hardy, 2015; Ford & Williams, 2012; Tucker & Collins, 2012).

Conative underpinnings of expertise

As Simonton (1999) pointed it out, it is not enough to focus only on the factor that has the biggest contribution to the development of expertise (albeit the magnitude of that contribution varies, as mentioned previously) – researchers ought to investigate all the other factors that contribute to the development as well. Hambrick and colleagues (Hambrick et al., 2016), in their general framework for multifactorial perspective on expertise, map out predictors of factor they named domain-specific knowledge. They propose that ability factors (basic cognitive, perceptual and physiological traits), developmental factors (age and starting age) and domain-specific experience (training and other forms of experience) have a direct impact, whilst non-ability factors (personality, motivation and temperament) and background factors (socioeconomic status, country of origin, parental involvement) have an indirect impact, through domain-specific experience. Finally, gene-environment interplay has an impact on all of the levels as well. In other words, to better understand expert performance and its development, on top of investigating expert abilities and practice, one needs to look into developmental factors, non-ability factors, background factors and the role of gene-environmental interplay.

In this thesis, I focus on impact of a specific conative (non-ability) factor grit, that has recently been shown as relevant for practice in sport (Duckworth et al., 2019; Hodges et al., 2017; Tedesqui & Young, 2018), as well as the role age plays in maintenance and decline of expertise, both will be discussed below.

Grit and its neural correlates

Personality trait grit is defined as persisting interest and determination to achieve long-term goals, in spite of setbacks and challenges one comes across (Duckworth et al., 2007). It is composed of two facets: 1) *Consistency of Interest (CI)* – continuous interest, through the course of a lifetime, in a single life-goal, instead of focusing on different superordinate goals over shorter periods of time (as is the case with conscientiousness); and 2) *Perseverance of effort (PE)* – one's ability to maintain

prolonged effort despite obstacles and difficulties they come across (Duckworth & Quinn, 2009). Or, in simpler terms, CI represents direction of one's passions while PE represents the amount of effort set forth in pursuit of those passions (Tedesqui & Young, 2017).

Before continuing on discussing findings on grit, it should be pointed out that there is an ongoing discussion on (hierarchical) structure of grit, that started with a recent publication of meta-analysis conducted on studies on grit in academic domain (Credé et al., 2017). The meta-analysis has demonstrated that out of the two subscales only PE explains variance in performance and has significantly stronger criterion validity than CI. In other words, analysing grit as a composite score of the two subscales might not be optimal. In follow-up publications Credé and colleagues, as a solution, proposed to analyse the subscales as separate constructs (Credé, 2018, 2019), and further discussion about (and work on) grit as a scale and as a construct is currently ensuing. Since the findings leading to this recommendation stemmed from a non-sport domain, in this thesis, I approached girt in both ways – as a singular, higher-order, construct as well as two separate facets (CI and PE).

Even though relatively new as a concept, grit has been shown, on multiple occasions, to be related to performance, in academic and non-academic settings, and to explain performance even when one accounts for practice and ability, especially in cognitive domains (Akos & Kretchmar, 2017; Duckworth & Gross, 2014; Duckworth et al., 2007, 2011, 2019; Duckworth & Quinn, 2009; Eskreis-Winkler et al., 2014; Jachimowicz et al., 2018). Furthermore, early neurological studies conducted in academic domain, indicate possible functional and structural neural correlates underlying individual differences in grit. They stipulate that the local activity of prefrontal cortex (PFC) and PFC-striatum connectivity may play a role in the development of grit, while gray matter structures in several PFC-striatum regions (dorsolateral PFC, putamen, nucleus accumbens) may serve as a neuroanatomical marker for individual differences in grit (for more in depth review see Wang & Li, 2021). Having said that, since the sample sizes in these studies were relatively small, and since these studies were the very first to look into brain structures underlying grit, it may be premature to make firm and clear conclusions about neural correlates of the grit at this point.

Grit in sport

When it comes to sports domain, research on grit is still in its infancy and findings are, at times, in contradiction with each other. Studies researching relationship between grit and other factors relevant for expertise (such as abilities, performance, practice, and so on) are still very scarce in the

field of sport (Cormier et al., 2021). Grit has been shown to differentiate between athletes of different skill levels (Sigmundsson et al., 2020) and to retain some predictive power even within homogenous samples of highly skilled athletes (DeCouto et al., 2021; Larkin et al., 2016). Most studies found a positive relationship between girt and various measures of athletes' performance (Ansah & Apaak, 2019; Doorley, 2021; Doorley et al., 2022; Elliott, 2018; Shaver, 2017), while those who failed to capture it used smaller sample sizes, e. g. N=9 (Criticos et al., 2020).

Theoretically speaking, there should be a relationship between grit and deliberate practice as, per motivational constrain (Ericsson et al., 1993), one needs to be highly motivated to be able to repeatedly subject themselves through highly effortful, non-enjoyable, activity in order to improve their performance (Duckworth et al., 2011; Ericsson, 2020). Most studies on their relationship in sport domain (Fawver et al., 2020; Larkin et al., 2016; Tedesqui & Young, 2017) demonstrated findings that are aligned with theoretical predications, however some studies did not (Tedesqui & Young, 2018). Overall, grit seems to be mostly positively related to measures of performance and practice, but that finding is not universal (Cormier et al., 2021).

Most of these findings, however, came from studies that analysed grit as a single, higher-order, composite - when it comes to relationship between individual grit factors and different outcome measures of expertise, the picture becomes even blurrier. Only recently has a trend of analysing two subscales of grit individually begun in domain of sport. The findings, unlike the meta-analysis that started the whole debate by pointing out only PE as relevant (Credé et al., 2017), indicated that both, PE and CI, were predictive of future success in sport (Ansah & Apaak, 2019); that only CI was associated with longer tenure in chosen domain (Cousins et al., 2020) and that only PE, but not CI, was able to differentiate between athletes of different skill levels (Tedesqui & Young, 2017, 2018). To make the matters worse, some of the studies (Cazayoux & DeBeliso, 2019; Tedesqui et al., 2018; Tedesqui & Young, 2018; Ueno et al., 2018), when looking into relationship between the two subscales claimed greater importance of either one of them, or even completely dismissed one of them, without introducing them both in a single model to formally (and statistically) compare them (Credé, 2018). In this thesis, to address that, I analyse them both within the same model.

Underpinnings of grits' influence in sport expertise

Although there seem to be a positive relationship between grit and different factors of expertise, the overall influence of grit, and mechanisms by which it is achieved, is still unclear. The

literature seems to insinuate that grit's impact on skill (and therefore performance) is mediated through (deliberate) practice, however, the only two studies that formally investigated the mediation link were both from academic domain (Duckworth et al., 2011; Lee & Sohn, 2017). Findings from both of them were aligned – grit did not predict successful performance directly, but only (indirectly) through (deliberate) practice. Even so, given that other findings from sport domain do not quite align with findings from non-sport domains, it is still unclear whether this relationship is to be expected on sample of expert athletes. Furthermore, the way in which grit impacts accumulation of practice, especially for highly skilled athletes (who already practice as much as they possibly can), and if (and how) that changes throughout athlete's development, remains answered.

In Chapter 3: Grit - Deliberate practice mediation on performance and Chapter 4: Snowball effect of grit on (deliberate) practice of this thesis, I try to tackle these problems by answering following questions:

	Chapter 3: Grit - Deliberate practice mediation on performance	Chapter 4: Snowball effect of grit on (deliberate) practice
1.	Can non-ability factors (grit) influence expert skill/performance (especially for elite athletes)?	How is practice accumulated in elite youth athletes? In other words, what is the process of practice acquisition?
2.	Is the influence direct or indirect? And can it go above and beyond influence of practice?	Is grit related to the pattern of practice acquisition?
3.	How big of an influence there is and does it differentiate between skill levels?	/
4.	Which "types" of practice does it influence the most and through which does it have an effect on performance?	/
5.	How does a non-ability factor influence expertise (directly)?	/
6.	Are there any differences between impacts of consistency of interest (CI) or perseverance of effort (PE)?	

Aging and sport expertise

Finally, since the impact of non-ability and ability factors has been discussed, discussion of the impact of developmental factors on expert performance is left (Hambrick et al., 2016). In other words, since expert ability, its cognitive and neural underpinnings, as well as role practice and personality traits play in attainment of expertise and expert performance, the logical next step is discussing the retention, and finally decline, of expert skills over the span of a lifetime (Vaci et al., 2015). There has been recorded consistent, linear increase in human life span in the past 170 years, despite previous scientific predictions of biological limitations of life duration (Horton et al., 2015). Predicted boundaries were typically proven wrong, not too long after they have been postulated, as life span extended even after the proposed ceiling (Oeppen & Vaupel, 2002). These moving goalposts in life expectancy brought upon with them constantly moving expectations regarding the age of attainment of peak performance, the length of its maintenance and strategies utilized to manage age-related decline of the said performance.

Even though this decline is inevitable, the rate of it will depend on various factors, as well as on skills that are being measured (Horton et al., 2015). Bortz and Bortz (1996) proposed that decline of 0.5% per year, after attainment of peak performance, represents an average, general biomarker of aging. However, this percentage of decline has since been heavily debated as the process of aging is usually reflective of multiple additional changes, such as changes in behaviour, that may impact the score. Horton and colleagues (2015) provide such demonstration by showing that percentage of engagement with different sporting activities, on a Canadian sample, drops only 2% when comparing groups of 15-19 years old with a group of 55 years old, despite much larger drop being expected if Bortz and Bortz's (1996) proposal were true. The varying speed of (performance) decline will further have impact on expectations of typical length of athletes' professional careers.

Baker and colleagues demonstrated (2013), on the sample of athletes playing in the four major North American professional sport leagues (NBA, NHL, NFL, and MLB), that the length of professional career varied not only between the sports, but also within the sports (the difference was recorded even between different positions players occupied), and suggested that the difference stemmed from risk of injuries one was exposed to rather than simple age-related changes. Furthermore, they showcased, as one would expect, that longer professional careers were related to superior performance. Their findings emphasize how understanding maintenance of highest levels of performance could inform our comprehension of changes in ability that occur across the whole lifespan.

Theoretical approaches to performance maintenance

Despite the obvious importance of understanding the length of time athletes are able to spend at the highest levels of performance, and mechanisms employed to prolong the period of peak performance and slow down the rate of decline, research in this area has been severely lacking (Horton et al., 2015). Existing developmental models, such as Côté's Developmental Model of Sport Participation (Côté, 1999; Côté & Vierimaa, 2014), primarily focus on early childhood and young adulthood, the period characterized by skill acquisition and expertise attainment. However, there are no models explaining, or even describing, age-related changes that happen during the other periods of ones' career and life. As with the (expert) ability in general, there are two main theoretical approaches to understanding expert skill maintenance over the life span, paralleling nature versus nurture debate, *preserved differentiation* and *selective maintenance.*

Galton's (1870) idea of importance of innate capacity, ability to work hard and zeal for determining excellence is what underlines the preserved differentiation (or general factor) account. This account represents a genetic explanation of expert performance and proposes that experts have innate capabilities that facilitate their performances across all stages of life. These inherent capabilities help them develop their skills in childhood and sustain their performance throughout the lifespan. On the other hand, the theory of selective maintenance proposes that through prolonged focused practice of the most relevant (aspects of) skills for the performance, abilities stay retained with age (Krampe & Ericsson, 1996). In other words, athletes' through deliberate practice (and engagement with sporting activities), continuously reinforce acquired knowledge structures, which prevent them from decline in later stages of life.

Even though current models of skilled performance propose more nuanced view of nature versus nurture aspects of age-related changes (Horton et al., 2015), the studies on expertise, in wide variety of domains, demonstrated importance of practice for long-term skill maintenance (Bloom, 1985; Ericsson et al., 1993; Young et al., 2008). Furthermore, older (Master) athletes have been shown to have different training patterns when compared to younger athletes (for example they tend to train fewer hours a week), while still managing to maintain their superior performance (Starkes et al., 1999; Weir et al., 2002). This different training pattern is believed to be due to (more) limited resources older expert athletes have available at their age. Baltes and Baltes (1990) suggest that older expert athletes deal with these restrictions by utilizing combination of *selection* (a conscious choice of where to invest the resources), *optimization* (a choice that optimizes performance) and *compensation* (adaptation to accommodate for restrictions).

Theory of compensation is a 3rd major theory of maintenance of performance, although not as clearly positioned on the nature versus nurture dichotomy, and it provides methods for dealing with cognitive or physical declines related to age (Horton et al., 2015). Salthouse's work (1984, 2004) provided an empirical support of this theory, in which Salthouse's demonstrated the strategies older expert typists used to maintain their level of performance on the same level as younger expert typists, despite the recorded decline in performance on related general measures of functioning (such as digit symbol substitution test, finger tapping speed, choice reaction time). Similarly to that, one could expect older athletes' to develop strategies to compensate for their weakening physical abilities (for example basketball players refining how they enter into jump shot sequence to provide themselves more space between the opponents and allow for more time needed to execute the shot).

Age-related changes in sport performance

As previously mentioned, there is but a handful of studies conducted in sports domain that addressed the issue of age-related changes in performance. Majority of them have typically focused on either social factors, such as racial inequalities, impacting the length of athletes' careers (Best, 1987; Hoang & Rascher, 1999) or medical treatments that might prolong peak performance (Brophy et al., 2011). The few studies that did investigate age-related decline in performance, have typically done so on samples of Master athletes – older athletes who train and competitively involve in sporting activities, in leagues of their own (separate from the typical competing leagues).

Due to their prolonged, consistent and purposeful engagement with sporting activities, any performance changes are suggested to reflect (important) indicators of physiological (and cognitive) aging (Anton, 2004; Anton et al., 2004). These studies typically looked into rates of decline of (different groups of) endurance and power Master athletes, indicating faster decline for sports requiring more complex movement sequences (Anton et al., 2004; Baker & Tang, 2010; Donato et al., 2003; Fairbrother, 2007; Young et al., 2008; Young & Starkes, 2005). Furthermore, three studies (Baker et al., 2006, 2007; Schorer & Baker, 2009) investigating rate of decline in skilled based sports, golf and handball, demonstrated that different components of expert skills deteriorated at different rates with components dependent on domain-specific knowledge showing slower rate of deterioration that components dependent on general physical abilities.

These findings could indicate that experts' domain-specific knowledge could be deemed a compensatory tool for decline in physical capabilities, helping them maintain their performance longer,

as is the case in cognitive domains (Vaci et al., 2015). However, none of studies tries to model expertise development through the whole lifespan, thus providing a link between skill acquisition and age-related decline in sport. To do so, in this thesis I use approach of lifespan psychology to examine the general principles of sport expertise development throughout the athletes' lifespan, that is, to describe the form of age-related changes.

Thus, Chapter 5: Aging curves of sport expertise provides answers to the following questions:

1.	What is the basic shape (form) of the age-related function in sport?
2.	Does the function differ between specific groups and individuals?
3.	How are more basic processes, the building blocks of age-related changes, influencing these (age-related) changes?

Overview of the thesis

In the Chapter 6: Conclusion, I will summarize the findings discussed in the individual chapters, and answers to questions stated above, discuss shortcomings and suggestions for future research directions, as well as state the original contribution to the pool of knowledge this thesis have made.

As indicated by the title of this thesis, I, overall, will investigate cognitive and conative underpinnings of sport expertise. In order to do so I focus my efforts on anticipatory skills of handball goalkeepers (cognitive factor); and influence grit (conative factor) has on both (deliberate) practice and performance. Furthermore, impacts on early skill development and throughout the lifespan will be looked into. By focusing on sport related engagement during early childhood of elite youth soccer players, the influence of conative factor, grit, on the accumulation of (deliberate) practice, and thus performance, is investigated. When it comes to age-related changes throughout the lifespan, I focus on several measures of performance, believed to capture different aspects of elite athletes' performance and therefore different cognitive (and motoric) processes, and track how they fluctuate during different stages of NBA players' careers.

It should be noted that this thesis is written in the format of journal format thesis. Chapter 2: Anticipation in handball and Chapter 5: Aging curves of sport expertise have already been published (Chapter 2: Anticipation in handball: here, Chapter 5: Aging curves of sport expertise: here), and their edited preprints (instead of full publication) have been provided in the thesis to avoid potential copyright issues with the stakeholders. Therefore, in order to stay consistent with their format, Chapter 3: Grit - Deliberate practice mediation on performance (currently under revision) and Chapter 4: Snowball effect of grit on (deliberate) practice (in preparation for revision) have been written in format ready for journal publication as well. Furthermore, it should be pointed out that the chapters have been done in collaboration with different groups of people. Chapter 2: Anticipation in handball was done in collaboration with Robert Prieger, who helped with data collection and provided me with irreplaceable expert insight, and Nemanja Vaci who helped with conducting more demanding and nuanced data analysis. Data used in Chapter 3: Grit - Deliberate practice mediation on performance and Chapter 4: Snowball effect of grit on (deliberate) practice has been collected by Paul Larkin, Donna O' Connor and Mark A. Williams (Larkin et al., 2016), while the general idea for research came from discussions with my principal supervisor, Merim Bilalić upon which further analysis and write up have been done by me (with the rest of the team providing invaluable feedback and guidance). Finally, Chapter 5: Aging curves of sport expertise was done in collaboration with Nemanja Vaci and Bartosz Gula who developed new (Bayesian) model for data analysis, while I provided the knowledge from the (sport) expertise domain – this is the only chapter where the biggest proportion of the text was not written by me, as it focuses more on the model itself. Even though (multiple) different versions (manuscripts) of the above mentioned chapters exist (with some parts now omitted/changed), I have chosen, and presented in this thesis, the versions which contained the most input by me.

Chapter 2: Anticipation in Handball

Abstract

The purpose of this study was to investigate the ability of anticipation in handball players. In speed-based sports that require fast reactions, the most accurate predictions are made once a player has seen ball trajectory. However, waiting to see trajectory does not leave enough time for appropriate reactions. Expert athletes use kinematic information which they extract from opponent's movements to anticipate the ball trajectory. Temporal occlusion, where only a part of the full movement sequence is presented, is a technique often used to research this phenomenon. Unlike many previous studies, we chose three time cuts in video-stimuli of penalty shooting in handball, based on the domain-specific analysis of movement sequences. Each of the time points revealed more information about the direction of the ball. Goalkeepers (experts) and students (novices) had to predict, as fast as possible, where, upon a penalty shot, the ball will end up (in the goal). The multivariate analysis showed that handball goalkeepers were overall more accurate and faster when predicting where the ball will end up. Furthermore, they are able to do so based upon different movement sequences than what novice used. These findings underline the importance of kinematic knowledge which underpins the anticipation ability in sports. Furthermore, these findings demonstrate the significance of carefully chosen occlusion points.

Key words: *expertise, anticipation, temporal occulsion, multilevel modeling, handball*

Introduction

The importance of sport in our society can be measured not only by the amount of material resources spent on it and income made by it (Gratton et al., 2000, 2006; Gratton & Dobson, 2002; Gratton & Taylor, 2000), but also by the amount of time and effort that sportspeople (as well as non-sportspeople) invest in it (De Grazia, 1962; Taks et al., 1994; Wall & Côté, 2007). Therefore, it shouldn't be surprising that people have been fascinated by and tried to understand what underpins seemingly supernatural powers of elite sport practitioners such as LeBron James in basketball, Yuzuru Hanyu in figure skating or Thierry Omeyer in handball (for other topics researched within the field of sport expertise please see Baker & Farrow, 2015; Janelle & Hillman, 2003).

Experts are defined as a group of people who produce clearly outstanding performances constantly and regularly (Bilalić, 2017). Therefore a sport expert would be someone who performs above average in the field of sport. Common approach to research within the field of sport expertise is comparing expert and novice performances on different tasks related to experts' domain of expertise (Ericsson & Smith, 1991). General belief that expert performance is based on superhuman abilities is not completely groundless. For example, if one analyses the process of returning a serve in tennis, while having in mind the average speed of the ball movement and size of the court, one might in fact conclude that a player must have extraordinary perceptual and motor skills to be able to see ball's trajectory and react to it in an adequate and timely manner. However, even though seeing trajectory of the ball results in the most precise predictions, findings have indicated that expert players actually rely on body movements of the opposing player preceding the racket's contact with the ball when anticipating where the ball will land (Hodges et al., 2006; Neumaier, 1985). Only in this way are they able to react in time and return the serve properly. Therefore the ability to anticipate opponent's movements is essential for success in sports in general, and especially in ball games which are associated with high speeds of movements (Hagemann et al., 2007).

Research on anticipation began around the end of 80s - beginning of 90s (Abernethy, 1991; Abernethy et al., 1993; Abernethy & Russell, 1987) and has since then consistently demonstrated that experts exibit the capability to react faster than novices (Hagemann et al., 2007; Williams et al., 1999). Research on sport expertise demonstrates that elite practitioners are not necessarily endowed with extraordinary reflexes, which enable them to react quickly (Starkes & Deakin, 1984). Rather, they rely on stored motor programs for recognizing the situation at hand and anticipating the outcome of the current scenario (Schmidt, 1975, 1988; Williams et al., 2019; Williams & Jackson, 2019; Wright &

Jackson, 2007). This advantage of experts over novices was shown in varieties of sports such as: tennis (Broadbent, Causer, et al., 2017; Broadbent et al., 2015; Broadbent, Ford, et al., 2017; Goulet et al., 1989; Jones & Miles, 1978; Singer et al., 1996; Ward et al., 2002), basketball (Abreu et al., 2012; Aglioti et al., 2008; Wu et al., 2013), squash (Abernethy, 1991; Abernethy et al., 2001; Howarth et al., 1984), cricket (Müller et al., 2006; Penrose & Roach, 1995), football (Savelsbergh et al., 2002; Williams, 1993) and handball (Gutierrez-Davila et al., 2011; Loffing & Hagemann, 2014; Schorer & Baker, 2009).

Anticipation in handball

Handball is complex, fast-based sport that consists of intense, intermittent activities, which include full-body participation: sprinting, jumping, throwing, blocking and pushing, as well as attack and defence tactics (both on individual and team level). Rule changes in the last couple of decades resulted in making the sport even faster, tougher and more complex than before, compelling the players to develop their skill sets quickly and efficiently (Alsharji, 2014). Based on their roles and movement patterns, one can distinguish two groups of players in handball – field players and goalkeepers. Even though they usually do not score the goals – goalkeepers' role is considered to be a vital one[13]. The goalkeeper is the last line of defence (often playing the essential role in team's win) and the first line of offense (a good initial pass from the goalkeeper can lead to easy scores made by other players on the court). Therefore it is crucial for goalkeeper's performance to be able to "read" opponent's movements and anticipate what is going to happen next (Gutierrez-Davila et al., 2011). It is due to this importance of goalkeepers' role that researchers of anticipation in handball often recruit goalkeepers for their expert subjects (Bideau et al., 2004; Cañal-Bruland et al., 2010; Cañal-Bruland & Schmidt, 2009; Rivilla García et al., 2013; Vignais et al., 2009)

Time necessary for a goalkeeper to receive information, process it, choose ideal motor response (necessary for the defence manoeuvre) and execute it sufficiently, is significantly greater than the ball-flight duration (time from the moment the ball leaves throwers hands until it reaches goalkeepers position). Therefore, in order to be able to defend the goal efficiently, especially for the throws that are 7 meters or less away, the goalkeeper has to throw their body in the correct direction even before the shot has been made, or, in other words, before the ball leaves the shooters hands and has a visible trajectory (Hatzl, 2000). In order to do so goalkeepers have to develop domain-specific

[13]There is a even saying in handball: "If you want to have a good handball team, get a good goalkeeper"

knowledge that allows them to identify relevant information quickly, recognize it correctly and implement the adequate motor response, all before the trajectory of the ball is visible.

Athletes who constantly have to make decisions under great time pressure develop a system of perception that enables them to selectively perceive only the kinetic information necessary for anticipation. This knowledge is acquired through exposure to relevant movement sequences during long periods of time. This makes expert athletes more familiar with the kinetic information and capable of grouping smaller pieces of information into schemas (chunks). That enables experts to recognize relevant bits of information more efficiently, increase the brain activation levels during recognition and shorten information identification period (Maxeiner et al., 1996). However, at the same time goalkeepers need to make a decision about the adequate defence manoeuvre, prepare it and execute it which shortens the time they have available for observing the opponents' movements (Maxeiner, 1988). In order to do so effectively, it is crucial that they spend as little time as possible observing – only briefly analysing the movement sequences and creating a simulation of possible outcomes based on that. Maxeiner (1988) has shown that asking experts to focus on specific aspects/details (of movement sequences) results in decrease in their performance. Therefore experts rely on forming meaningful constellations of features (chunks), when briefly viewing the individual characteristics, in order to successfully recognize already learned movement sequences and make a decision on the best motor response possible in a timely manner (Neumaier, 1983, 1985).

Hatzl (2000) examined what exact parts of the domain-specific knowledge, that goalkeepers possess, are relevant for their ability to anticipate or, in other words, which movement sequences of (which specific) body parts carry the most relevant information for their predictions. He found that vital factors are: 1) the direction of the ball and ball-carrying hand in the last stage of throwing phase; 2) rotation of the hip and upper body around its longitudinal axis; 3) how far the ball is from the body (to the side) and 4) relative shoulder width seen from the goalkeepers' perspective of view. This finding was later confirmed by several studies (Alhosseini et al., 2015; Bourne et al., 2011; Loffing & Hagemann, 2014; Rivilla García et al., 2013) who used occlusion techniques (more about this later) and eye-tracking equipment to check what were the expert athletes actually paying attention to and how had that impacted their performance.

Furthermore, Hatzl (2000) tried identifying the time period when the process of anticipation is happening by dividing the videos, of thrower shooting a ball, into 5 equal segments (the length of the segments was decided ad hoc) and analysing the impact that viewing the particular segment had on participants' performance (predictions). In other words, how much relevant information did a certain

segment have? He concluded that the most informative period, when it is most likely that anticipation happens, was between the defined turning point of the throwing motion (first body rotation) and the time when the ball-carrying hand and the head of the thrower make their last turns.

Anticipation in seven-meter throws (penalty shots)

In their analysis of handball matches, Foretić, Uljević and Prižmić (2010) found that average number of seven meter shots awarded per game is 3.68. Furthermore, Alsharaji (2014) argues that, at best, goalkeepers can reach a maximum quota of saving 50% of these shots. Given the distance between the thrower and the goalkeeper (which usually varies between 4-7 meters) and the velocity of the ball, it was calculated that the speed at which ball moves (in penalty shots) can reach up to around 26.2 meters per second (Fradet et al., 2004). These circumstances often lead to the goalkeepers being under a tremendous amount of stress which can affect not only their own performance, but also the overall gameplay and motivation of their whole team (due to the vitality of goalkeepers' role). It is therefore essential for goalkeepers to exhibit, as consistently as possible, a high level of expertise, acquired through the years of domain-specific practice.

However, their good performance is not as impossible as it might seem to be. The duration of ball flight after a shot, for the top shooters, is around 350 ms which corresponds to a speed of about 70 km/h. However, for amateur shooters, duration of the flight is around 420 ms which would mean that the speed of the ball movement is 60 km/h. In a typical penalty situation the goalkeepers usually position themselves one meter in front of the goal, to shorten the angle. Therefore, there is about 300-360 ms from when the ball leaves the thrower's hands until it hits the goalkeeper's body. During this short period of time the goalkeeper usually passes through several different phases of action, that can be grouped into cognitive reaction and movement execution phases. Compounded, time needed for those phases is usually referred to as response time of goalkeeper (Schorer, 2006).

The reaction times of handball goalkeepers vary between 200 - 250 ms[14]. In a typical seven-meter shot situation, the goalkeeper moves one meter in front of the baseline presuming the basic stance with hands spread to the sides and raised in line with the head. Time needed for this step-forward movement is between 100-140 ms for goalkeepers playing in the highest leagues, while it is

[14] For the reference: Emergency breaking (pressing the car breaks during emergencies occurred while driving) has an average reaction time of 450 ms; Average reaction time to an optical signal is between 150-200 ms.

130-180 ms for goalkeepers playing in lower leagues[15]. If the ball was thrown from 8.3 meters distance, by the best existing shooter, it can acquire the speed up to 105 km/h. Now having in mind that goalkeeper reaction time (including the step forward movement) can, at best be 300 ms, reacting after the ball has left the thrower's hand is not fast enough to be able to parry the throw. As mentioned before, duration of the ball flight is around 300 ms and would need to be significantly longer in order for goalkeepers to be able to stop it accurately. Their response time consists of not only reaction time (movement execution) but also of cognitive reaction period (period needed for identifying important information, recognizing the movement patterns, making the decision on the most appropriate movement sequence and initializing motor response sequence). Goalkeepers' response time in handball is usually about 600-1000 ms and can be reduced to 500 ms with a lot of practice and only if a good position play is conducted. Therefore, if we take into consideration the duration of the ball flight and time needed for response there is a difference of minimum 200 ms indicating that goalkeepers must start their reaction while the ball is still in opponents' hand (Schorer, 2006), by relying on motor information available in opponents' pre-throw movements, which is in line with all of the previously mentioned findings.

Choosing the time windows

Commonly used experimental method in anticipation research is occlusion paradigm (Farrow & Abernethy, 2007). As the name implies, in this paradigm parts of the body or the movement sequence are obscured from vision. For example, since hips rotation is important for anticipation of handball players one could occlude that part (via video editing) and measure how that action impacts participant performance and when is the impact the greatest. There are two types of occlusion techniques that can often be used in combination (Farrow et al., 2005): *spatial occlusion* – occluding some body parts or some parts of space relevant for decision making; and *temporal occlusion* – cutting videos of certain movements at different time points in order to manipulate the amount of information one receives when viewing shorter clips. Temporal occlusion technique offers the possibility to experimentally check which phases of movement impact the ability to anticipate the most (Abernethy et al., 2003). It also provides the opportunity to identify meaningful time windows, which provide the most relevant information for anticipation, for groups differing in their levels of expertise and compare group performances (Farrow & Abernethy, 2007).

[15] www.handballhaus.de/leistungstest/schnellkraft/wurfkraft.html

In a typical experiment using this research technique videos are made out of the sport-specific situations, such as seven-meter shots in handball, usually either from the perspective of a player in the game or a person watching it from the side-lines. These videos are then cut at different time points, based upon the decided methodology of the experiment, resulting in different number of shorter video clips. These clips differ from one another in length, amount of relevant information they carry, and the moment (time window) when they were cut (Abernethy et al., 2003). Participants are most commonly asked to make a prediction, based on the information available in the video clips, of what the opponent is going to do or what will be the end result of the opponents' movement. Prediction is considered valid if its accuracy is greater than the chance level (Farrow et al., 2005). Also, reaction time is another commonly used dependent variable in these experiments as well. Accuracy of predictions and reaction time(s) are then compared between different time windows, and between groups varying in their level of expertise, giving us insights about what time windows are the most relevant for each of the groups and how does their relevance change with inclusion of more information.

The common finding in these experiments is that regardless of expertise level precision of accuracy increases (and reaction time decreases) the later the cut in the video is made, and is at its highest level once the ball leaves the hands of the player that is watched - or in other words once the participants are able to see balls' trajectory and when the player's actions cannot impact that trajectory any longer (Farrow et al., 2005). No matter how much sports can differ from one another this pattern of results is consistent and can be found in tennis (Jones & Miles, 1978), badminton (Abernethy & Russell, 1987), football (Williams, 1993), cricket (Penrose & Roach, 1995), basketball (Aglioti et al., 2008) and handball (Alsharji, 2014; Loffing & Hagemann, 2014).

However, the literature does not specify exact timings of the time windows when videos should be cut. The duration and number of cuts (consequentially leading to different number of video clips to view) differs not only in different sports but also within the same sport and even within the same task (specific situation) in a sport (Farrow et al., 2005). There are two major strategies to solving this problem and making a decision on when and how many cuts (occlusion points) should be made. One of the strategies is to choose one critical event in the video and then cut the video in equally long intervals (as the length of the chosen cut) before and after the event (a good example of use of this strategy is Williams and Burwitz's study (1993) in which they have chosen the contact of the foot with the ball as the critical point and then divided the video based on that). This strategy provides the possibility to make non-weighted comparisons between different time-intervals as they all last equally long. However, this does not guarantee that these clips will carry the same amount of information, nor that the information that they carry will be of equal importance for anticipation.

The other strategy relies on choosing essential nodes or phases of executed movement and dividing the video into clips contacting them (good examples of usage of this strategy are studies done by Loffing et al.,(2014) and Müller et al.(2006)). This strategy enables manipulation of the quantity and the relevance of information each clip contains, but can often lead to having time-intervals that are not equal in duration thus needing additional weighting to incorporate for the length effect. There is also the problem of number of cuts (video clips) that should be made. General consensus is that the minimal number is 3, but this number can go up to 9 (or more) time points per each video (Abernethy et al., 2001; Abreu et al., 2012; Jones & Miles, 1978; Loffing & Hagemann, 2014). Even though it might seem that the more time windows one has the more detailed the analysis can be – the number of statistical comparisons (and their correction) can lead to decrease (or even a complete nullification) of the effect sizes. Therefore, it becomes harder to pinpoint a time window which is the most relevant for experts' ability to anticipate - the one were the growth of accuracy and/or decrease in reaction time is the largest. That leaves us with the knowledge of general gradual growth, but not with the knowledge about significant differences between consecutive time windows.

Therefore, we've decided to apply the second strategy of choosing the most relevant time-points for cutting the videos. However, in order to improve on previous studies and make our data more meaningful (in terms of importance and quantity of the information contained in the video clips) we've chosen our occlusion points by closely following Hatzl's analysis (2000) of relevant body movements (in handball penalty shots), but we have also kept the length of the occlusion periods (time windows) constant. In this way, we ensured that each clip contained more information relevant for anticipation than its predecessor. The first occlusion point (see Figure 2.1) showed the beginning of the shooting and contained almost no relevant information; while the second and third occlusion points contained additional 300ms each, containing information pointed out as relevant in Hatzl's analysis (2000) for anticipation in handball (see Method for in-depth description).

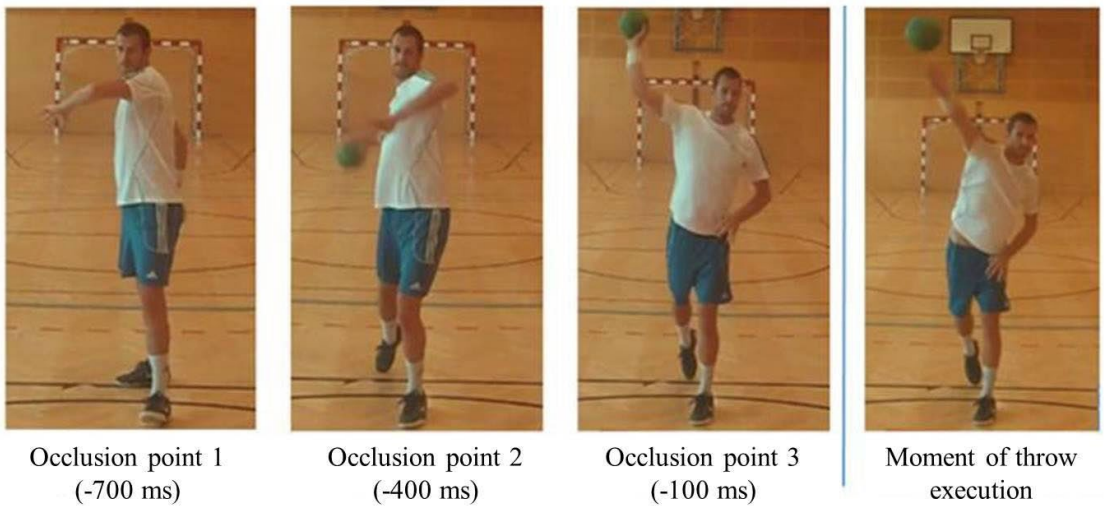


Figure 2.1. Movement sequence and the occlusion points. The first occlusion point (far left panel) happens 700ms before the ball is released and contains no relevant information for anticipation. The second occlusion point (mid left panel), 400ms before the ball release, contains the important information about the rotation of the hip and upper body. The third and final occlusion point (mid right panel), just 100ms before the ball release, in addition to the previous information, entails the ball-carrying hand and the shoulder width information. The last panel (far right) shows the moment when the ball leaves the shooter's hand. This panel was not shown to the participants and is here for illustrative purposes only.

Based on the previous studies (Farrow et al., 2005; Maxeiner, 1988; Maxeiner et al., 1996) we expect no significant difference between the experts and novices in the first occlusion point and we expect performance (accuracy) around chance level, due to the fact that at this time point there is no relevant information presented. The second occlusion point was the crucial one because it contained the most relevant information for expert goalkeeper anticipation (Loffing & Hagemann, 2014). We expect clearly above the chance performance of expert group while novices' performance should be around the chance level. The final occlusion point provides more information, but given that this information is not crucial for experts, we do not expect a large increase in experts' performance compared to the second occlusion window. In contrast, this information may help novices to finally reach performance above the chance level. We expect the same pattern of results with the reaction time. (Please note that we provide all the data, including the sample of stimuli, and the analyses reported in the manuscript here: https://osf.io/4kn8f/.)

In order to answer the question whether systematic manipulation of the quantity of relevant information, in different time sequences, impacts anticipation we've designed a 2x4 study (expertise level x throw direction) with dependent variables being reaction time and accuracy of prediction.

Method

Participants

Experts were 10 handball goalkeepers (Age M = 30.5, SD = 5.5 years, range 23-39, all male) who, at the time of the study, played in the top three Austrian leagues. They had on average 17 years of handball goalkeeping experience (SD = 3.8, range between 12 and 25 years). The group of novices consisted of 10 participants (Age M = 26.4, SD = 3.7, range 22-34, all male) who were familiar with the rules and the dynamics of the game (including the seven-meter shots and have seen them before) but had never played organized handball[16]. All participants signed a written consent and the local ethics committee in Klagenfurt approved the study.

Our sample is similar in size to those of other studies researching anticipation in handball: *N* = 20 in Alsharji (2014), *N* = 37 (14 experts and 23 non-experts) in Loffing & Hagemann (2014), and *N* = 10 in Rivilla-García et al. (2013). Since Loffing & Hageman used the most similar research method to the one we used, we relied on that study when conducting the power analysis. In the study, effect size for the main effect of expertise (experts versus non-experts) is $\eta_p^2 = .40$ ($F = 23.39$, $p < .001$) and for the main effect of temporal occlusion (5 time points) is $\eta_p^2 = .42$ ($F=25.4$, $p < .001$). Interaction between the two effects was not significant ($p = .39$); however, polynomial contrasts revealed a linear trend (of accuracy improving with later temporal occlusion) with effect size $\eta_p^2 = .71$ ($F = 83.81$; $p < .001$). Both main effects are large enough to detect, even with fewer participants (8 participants per group for the conventional 0.80 power; 12 for 0.95 power) for the within factor analysis; however, effect sizes are not quite large enough to detect, for the between factor analysis (15 participants per group for the conventional 0.80 power; 24 for 0.95 power). There are no studies that could be used to estimate the effect size for the interaction between expertise and time occlusion (e.g., Alsharji study uses only a group of experts, while other studies use a different approach to research). Therefore, in order to ensure adequate statistical power, we have predefined time windows (where we made cuts) based on previous studies, making them more relevant to the research question. We also used linear mixed-effect regression, which takes into account all individual stimuli and therefore improves overall power of the design (van Rij et al., 2020).

16 These participants are essentially beginners, but we refer to them as novices in this chapter in accordance with the usual practice in this kind of research.

Equipment and stimuli creation procedure

Videos used as stimuli in this study were recorded at the University Sport Institute (USI) in Alps-Adriatic University of Klagenfurt (Alpen-Adria-Universität Klagenfurtprigodan). The process of making stimuli took two days. During the first day we chose adequate camera settings for recording, as well as optimal lighting conditions. Ideal ball colour was chosen (blue) among a few different ones so that it was as distinguishable from the floor (colour) as possible. We examined parquet condition in order to stay clear from the possible damaged parts which could impact the way the ball bounces. Finally, ideal hall temperature was chosen.

Each of the four corners of the goal were taped so that it was clearer to handball player, that was to be filmed, which parts of the goal he was supposed to target while shooting penalty shots (hence making the precision of shots as high as possible). All specificities in this setting were chosen in accordance with a professional handball goalkeeper's counsel. Upon setting everything up, trail filming was conducted with a professional handball goalkeeper.

Based on the insights from trail filming on the first day, optimal time window was chosen (4 hours) with the best possible conditions for filming. Also, upon viewing trail material, we designed a detailed flow chart of how the process of filming is to be conducted. It was decided that the order of where seven-meter (penalty) shots are going to be shot at was to be randomized.

During the second day we recorded footage that was used in the experiment. We used GoPro Hero 4 camera for filming itself. It was on a camera stand positioned at typical spot for a handball goalkeeper – in the very middle of the goal and about one meter in front of it. The lenses of the camera were set on the height of 180cm. Precise orientation and rotation of camera was done by mobile phone application, GoPro RM, on a Samsung Galaxy 3 Mini (camera and phone were connected via Bluetooth). In addition to the goalkeeper's opinion, another handball player's advice was taken into account while deciding the best possible camera orientation for filming videos. Two hundred videos were recorded in this setting.

In order to make the footage as ecologically valid as possible we recruited a professional handball player, with 20 years of experience, who plays for Carinthain 2nd league club SC-Ferlach. He was asked to shoot penalty shots as precise as possible (as if his team's win was depending on the shots he was making). As mentioned before, each corner of the goal has been marked, and we've assigned numbers to the corners so that instructions were as clear as possible (see Fig. 2.2)

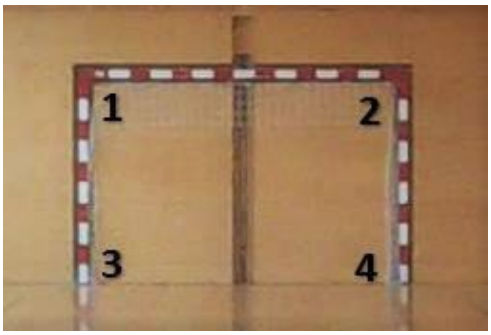


Figure 2.2. Goal marking

Order of where the ball was to be shot was randomized. Targeted corners of the goal were visually signalled just before each throw was conducted. This was done in order to ensure that the movement during seven-meter shots is as authentic as possible. There were not trick/fake throws – the shooter was instructed to throw the ball as straight as possible to the assigned corner. The player made all of the throws with his right hand.

Out of 200 videos that have been made (50 shots in each corner of the goal) we've chosen 15 best ones, per corner, based on how precise the shots were, how clear the video was et cetera. Therefore a total of 60 videos were used for testing purposes.

Stimuli and design

A professional handball player was filmed performing penalty shots, with the task to shoot at one of the four corners of the goal. The camera was centred a meter in front of the middle of the goal, making the distance between the shooter and camera 6m. The camera was set at 180cm height with angular viewpoint between the shooter and camera (goalkeeper point of view) being 17° 59'. In the end, we used 60 videos, out of 200 filmed. There were 15 shots going top left, 15 going top right, 15 going bottom left, and 15 going bottom right. All 60 videos were cut into three different time points (occlusion points one, two, and three), which resulted in 180 videos (clips) that were used as stimuli. The videos were filmed and cut in accordance with Hatzl's analysis (2000), so that each clip captures relevant kinetic information. The length between the occlusion periods was kept constant to ensure that each clip contained more information relevant for anticipation than its predecessor. The videos were

chosen in collaboration with a professional handball goalkeeper, following these criteria: 1) no hesitation when executing the shot; 2) no tricks/fakes; 3) no shots that deviate (in the slightest) from the targets (four corners of the goal); 4) must include clear movements distinguished by Hatzl (2000) as relevant (if the movement was blurry or unclear the video wasn't included). Upon choosing and cutting the videos, another Australian Handball Bundesliga (1st league) player checked the stimuli and validated our selection. The analysis of individual videos demonstrated that there was little variation across the chosen videos as individual participants responded (RT and accuracy) similarly to all 60 videos (see Results and Appendix B).

We edited the best 60 videos using editing software GoPro Studio version 2.5.7. Optimal brightness, contrast and saturation were chosen and equalized across all the videos. In order to implement temporal occlusion we cut the videos in three different time points, hence resulting with 180 videos that were used as stimuli.

Videos that were cut at the first occlusion point showed the very beginning of the shooting sequence (see Figure 2.1) and they lasted around[17] 400ms. The ball cannot be seen, and the player's body is turned sideways, blocking the view of his ball-throwing arm, therefore containing almost no relevant information. The videos cut at the second occlusion point contained both the movement shown in the first video and another consecutive movement (see Figure 2.1). They lasted around 800ms. Now, the ball can be seen, as well as the ball-throwing hand, and the direction of the head and body has changed - they are facing the camera more. This group of videos provides information about hip and upper body rotation, as well as the distance of the ball from the body, that Hatzl (2000) identified as relevant for anticipation. Finally, the third group of videos consisted of the movement seen in the first two groups and the finishing movement of execution (see Figure 2.1). However, the videos were stopped before the ball leaves the player's hand, so that the ball trajectory cannot be seen and used to make predictions. In these videos, further body rotation towards the camera is shown, the ball-throwing hand can be fully seen, and the position of the shooter's right leg and his head direction can be used to make predictions. This group of videos additionally contained information about the ball-carrying hand and the shoulder width during the last stage of the throwing phase deemed as relevant for anticipation (Hatzl, 2000). Total duration of the videos in this group was around 970ms. The start time of (all of) the videos relative to the ball release point was around -1100ms.

[17] Video clips, for the same time windows, somewhat varied in length (25-30ms) in order to ensure that they included the complete movement sequence deemed relevant for anticipation.

Procedure of the experiment

1. Familiarization with the equipment:

We explained to all of the subjects that they are going to see the videos of seven-meter shots from goalkeeper's perspective of view and that their task was to try and predict in which corner of the goal will the ball end up going. They were sited, in a comfortable posture, watching the videos on a 15 inch HD laptop screen (distance between participants and the screen was 70cm, with the height of shooter image (on screen) of 8cm, making angular viewpoint between the shooter on screen and a participant 6° 32'; with angular viewpoint between actual shooter and camera (goalkeeper point of view) 17° 59'. We used OpenSesame, version 2.9.7, for presenting the stimuli (Mathôt et al., 2012).

In order to ensure optimum/equal gaze direction the participants were shown a fixation dot, before trial presentation, on which they were to focus their gaze. Then video stimuli were presented, after which participants were asked to make a decision where the ball will go by pressing one of the buttons on they keyboard (Q, P, X, or M). The buttons were assigned so that they visually represented each corner of the goal (from the goalkeeper's perspective) hence making it easier for participants to make predictions (see Fig. 2.3)

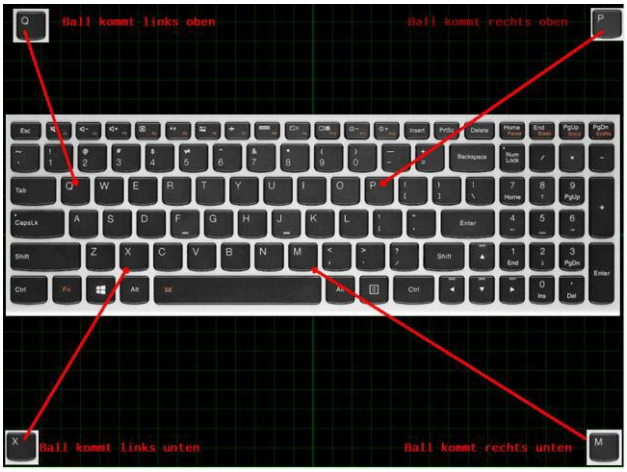


Figure 2.3. Positions of the response letters on the keyboard

2. Practice:

Participants were shown 13 videos (different from the ones used in the main part of the experiment) on which they practiced. They were given feedback on correctness of their answers and they were allowed to ask questions or to ask for additional explanations at this point. After they were done practicing and it was made sure that they understood their task, it was proceeded to the main testing part.

3. Experiment:

Participants were shown all 180 vidoes in randomized order. They were asked to make a decision where in goal the ball would end up as fast as they could. In order to prevent decrease in their performance participants were allowed to take breaks in between videos if needed. Upon finishing, they were thanked and debriefed. If they asked for it, a detailed feedback regarding their performance was sent to them via e-mail. The whole procedure lasted for about 45 minutes.

Results

Reaction Time

The reaction time results (Figure 2.4) show that experts were getting consistently faster in making their decisions as more information is revealed (later occlusion points). In contrast, while novices were also getting faster in deciding as more information was revealed, their improvements were not constant.

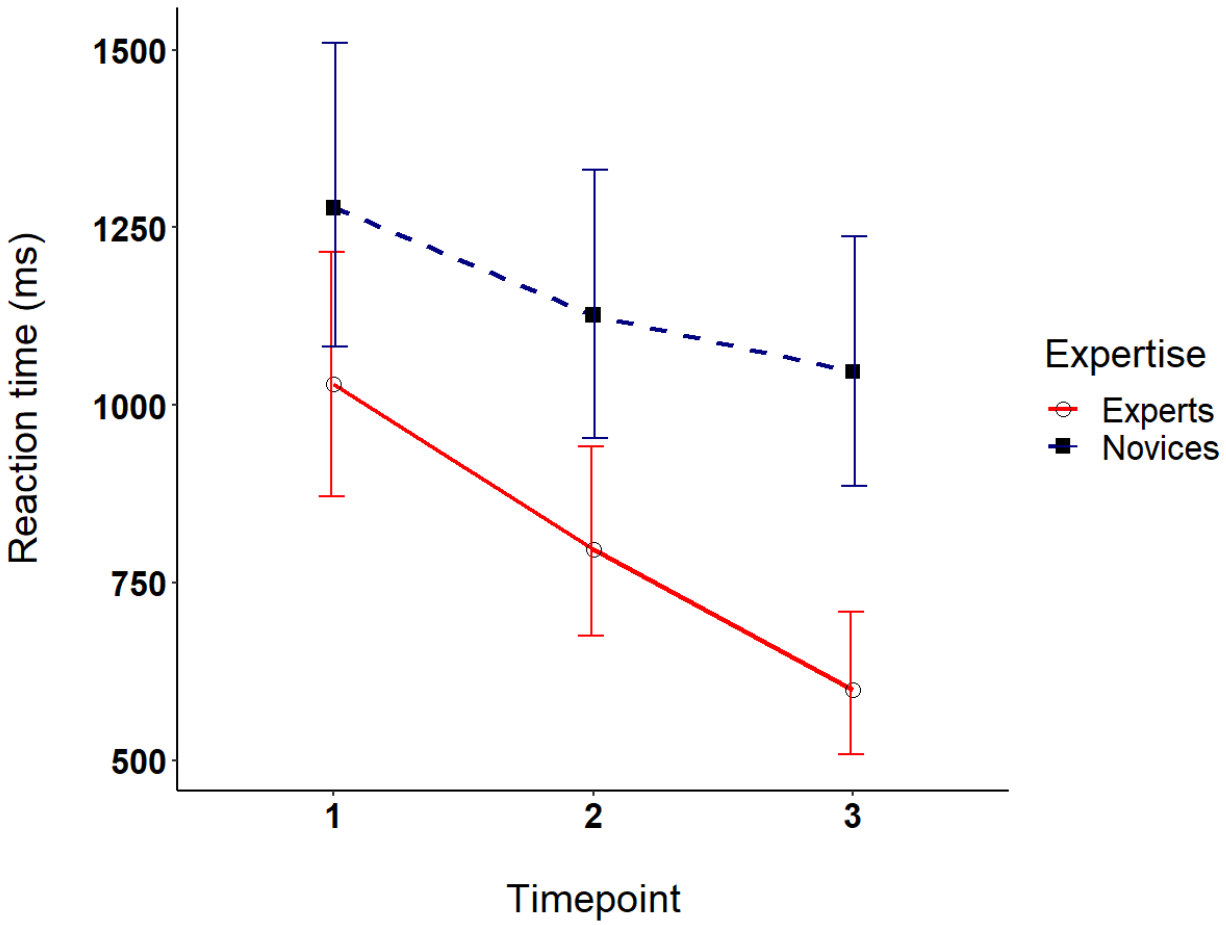


Figure 2.4. Reaction time of experts and novices at three occlusion points. Error bars represent one standard error (SE).

To statistically check the effect of temporal occlusion on the speed of the reaction when predicting the outcome of the penalty shots in handball (and later the accuracy), we used linear mixed-effect regression in R statistical environment (Wood, 2006; R core team, 2018 – for the sake of completeness, we provide the classical ANOVA table in Appendix A). The main idea of this method is to control additional sources of variability in the dependent variable, which are not influenced by the manipulated factors (fixed effects). In the case of experimental designs with repeated measurements for individual participants, intra-individual variations are often of lesser interest to the researchers. Because of these additional variations, practitioners use group averages as an input for the general linear model (i.e. ANOVA). The linear mixed-effect analysis handles responses from individual trials by treating the grouping factors as sources of additional variability (random-effect structure). Contrary to the ANOVA, that uses average data (per item or per participant for each condition), mixed-effect models use individual (raw) data as input to calculate regression coefficients. The mixed-effect model

utilizes individual reaction times/accuracy rates for all participants in the experiment across all conditions. A statistical feature that allows such modelling is a specification of a random structure, that is, the inclusion of factors or experimental information that can influence the results but is not manipulated in the experiment. The random effects are represented by one parameter: standard deviation of the particular grouping factor. When treating individual participants as random effects, the estimates of the random structure added to the fixed effects (manipulated factors) provide an estimate of the participant's performance. These estimates constitute a compromise between the overall mean of performance for all players and the individual data of the participants. This way, the outliers and participants with missing data are drawn towards the general mean of performance (van Rij et al., 2020). The linear mixed-effect modelling proves extremely useful when modelling repeated measurements data where the variability of the dependent variable comes from multiple different sources, as well as in the case of the data with non-Gaussian distribution and missing data. The standard estimation of the parameters in the linear mixed-effect analysis is a comparison between the combinations of the factors used in the experiment, which is parallel to the post-hoc comparison in the ANOVA analysis. Similarly, as with factorial models, we can calculate omnibus tests and investigate the overall significance of the factors in the model.

In the case of this study, the reaction time was used as the dependent variable in the linear mixed-effect model. To approximate the normal distribution, we log-transformed the raw reaction times (see Baayen & Milin, 2010). After we estimate the model, the log-transformed values can be easily reverted to the original reaction time values by applying the exponential transformation. In the fixed-effect structure, we included the information about expertise level (experts versus novices) and temporal occlusion points (1st, 2nd, and 3rd), while participants and individual items were included as random-effect in analysis: that is, novices and the second and third occlusion points were compared to them.

Table 2.1 summarizes the results of the analysis. The linear mixed-effect analysis utilizes standard dummy coding of categorical predictors to estimate the regression coefficients. In particular, one level is dropped from each factor and serves as a referential level with which all other levels and their combinations are compared. The intercept in this type of analysis represents the predicted value of dependent variable (reaction time) for a combination of baseline categories, that is, excluded levels (Expertise: experts, Occlusion point: 1st time point). All other factor levels and their combinations (shown in the Table 2.1) are consequently compared with the baseline combination of levels. Therefore, the results show that there were no overall significant differences between experts and novices at the first occlusion point ($b = 0.21$, $t = 0.91$, $p = .35$). Experts reacted more quickly at the 2nd ($b = -0.25$, $t = -8.79$, $p < .001$) and the 3rd occlusion point ($b = -0.53$, $t = -18.63$, $p < 0.001$) than on the

1st time point. Finally, this difference between the 1st and the 2nd time point was smaller for novices than for experts ($b = 0.12$, $t = 3.14$, $p < .01$), as well as, the difference between the 1st and the 3rd time point ($b = .34$, $t = 8.30$, $p < .001$). To be able to estimate changes from the 2nd to the 3rd occlusion point, we set the 2nd occlusion point as reference level and re-run the model. As expected, the difference between the 2nd and the 3rd was significant for experts ($b = -0.12$, $t = -3.14$, $p < 0.01$), while still weaker for novices than for experts ($b = 0.21$, $t = 5.17$, $p < 0.001$). The model with these two factors and by-participant and by-item random structure explained 57% of the variance in reaction time. The variance for intercept adjustment was estimated stronger between participants (variance = 0.27 log RT) in comparison to the variance between items/videos (variance = 0.01 log RT). In other words, different participants respond consistently slower or faster, while different stimuli elicit equally fast responses. The Appendix B illustrates random adjustments for each participant and each item in the reaction time (see Figure B1) and accuracy analyses (see Figure B2).

Table 2.1. *The results of the linear mixed-effect model on the reaction time.*

Parametric coefficients:				
	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	6.93	0.16	41.46	< 2e-16
Expertise(novices)	0.21	0.23	0.917	.358
Time(2)	-0.25	0.02	-8.797	< 2e-16
Time(3)	-0.53	0.02	-18.63	< 2e-16
Expertise(novices): Time(2)	0.12	0.04	3.144	0.00168
Expertise(novices): Time(3)	0.34	0.04	8.306	< 2e-16
Approximate significance of smooth terms:				
	Edf	Ref.edf	F	p-value
s(Subjects)	17.91	18	203.240	< 2e-16
S(Items)	92.58	179	1.073	1.48e-14

Accuracy

The experts were unsurprisingly more accurate than novices (see Figure 2.5), but they have already achieved respectable accuracy levels by the 2nd occlusion point (keep in mind that chance level is 0.25 in our study). The additional information available in the third occlusion point improved experts' performance, but it had more effect on novices who only here could, with some success, predict where the ball would land.

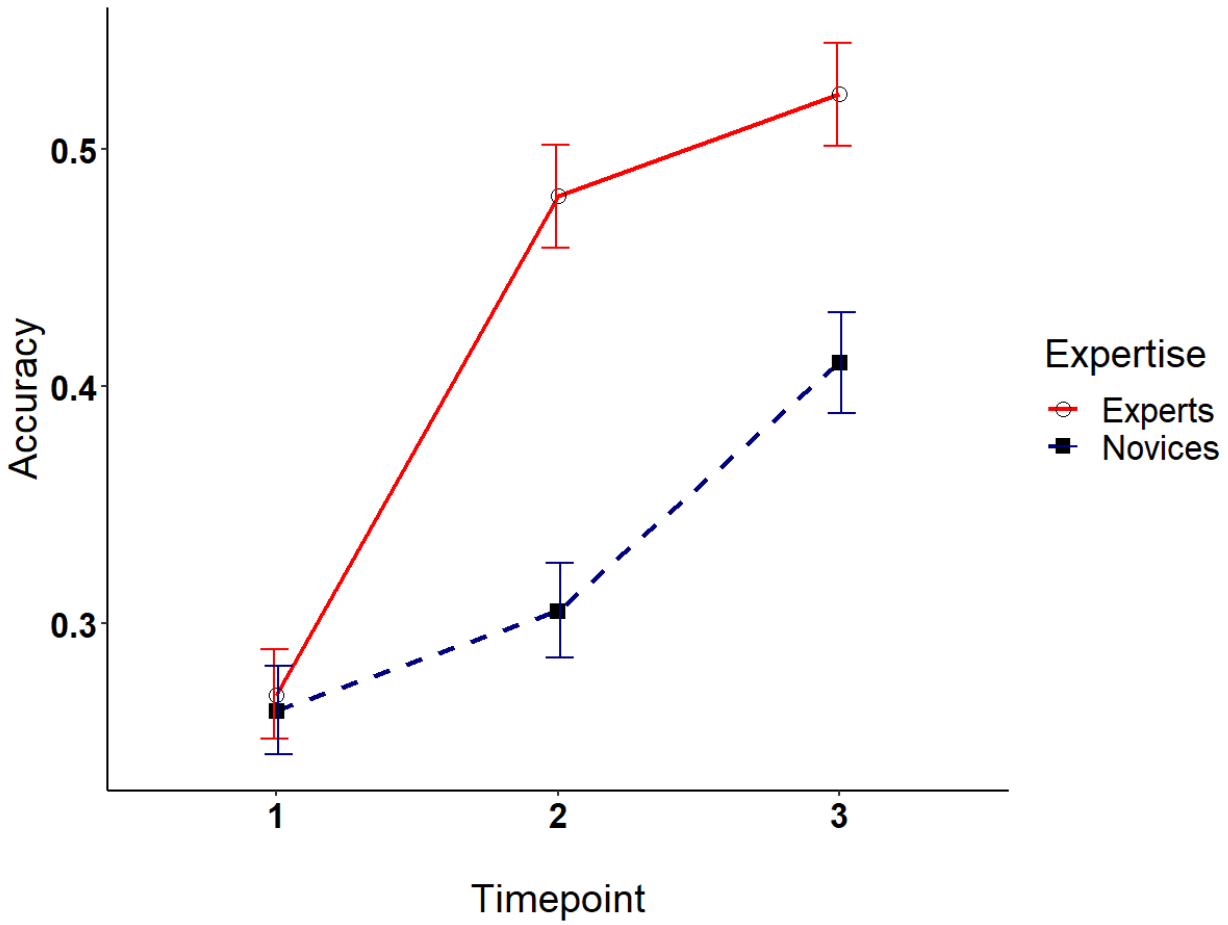


Figure 2.5. Accuracy (proportion) of experts and novices at the three occlusion points.

In the case of the accuracy, we used the logistic mixed-effect analysis with the same fixed and random-effect structure as in the analysis of reaction time. Table 2.2 presents overall significance of factors and their interactions. Similar to the mixed-effect model run on reaction time data, the model built on accuracy also uses individual data (non-averaged measures), while random effect structure adjusts the estimates from the model by specifying the repeated (clustered) measurements. We specified that dependent variable is following binomial distribution forcing model to calculate regression coefficients in the log-odds space. In other words, we did not separately transform the input to the model, e.g. calculate probability or frequencies per condition, but used the outcomes in their natural format.

Similar to the reaction time analysis, results show significant interaction between temporal occlusion points and expertise level. The experts and novices do not differ on the first occlusion point (b = -0.03, z = -.025, p = .80). Experts extract more information at the second (b = 0.90, z = 7.28, p = < .001) and the third occlusion point (b = 1.07, z = 8.65, p = <.001) in comparison to the first occlusion point, that is, their accuracy increases when answering the experimental task. As with the reaction

time, the extraction of information from the 1st to the 2nd (b = -0.69, z = -3.90, p < .001), as well as, from the 1st to the 3rd (b = -0.41, z = -2.35, p = < .05) time point is much better utilized by experts than novices. They are generally more accurate and are superior in reading the movement, in comparison to novices, already at the second occlusion point.

We also investigated changes of accuracy in anticipation from the 2nd to the 3rd occlusion point between experts and novices by changing the referential level of time occlusion factor. In contrast to the results on the reaction time, results show that experts do not benefit from more information between the 2nd and the 3rd time point (b = 0.16, z = 1.45, p = .14), while novices tend to improve more but the differences did not quite reach the significance level (b = 0.28, z = 1.67, p = .09). The model with these two factors and by-participant and by-item random structure explained 5% of the variance in accuracy. Unlike the reaction time analysis, the estimated variance of random intercepts was higher for items/videos (variance = 0.14) than for subjects (variance = 0.004). The weak contributions of the random structures indicate that all participants respond to the task with similar baseline accuracy, while all stimuli elicit similarly accurate responses (see Figure B2 in Appendix). Contrary to this, most of the differences in the accuracy are observed due to the manipulated factors.

Table 2.2. *The results of the logistic mixed-effect model on the accuracy.*

Parametric coefficients:				
	Estimate	Std. Error	z-value	Pr(>|t|)
Intercept	0.98	0.09	-10.04	< 2e-16
Expertise(novices)	-0.03	0.13	-0.251	.801
Time(2)	0.90	0.12	7.286	< 2e-16
Time(3)	1.07	0.12	8.656	< 2e-16
Expertise(novices): Time(2)	-0.69	0.17	-3.908	9.31e-05
Expertise(novices): Time(3)	-0.41	0.17	-2.359	0.0183
Approximate significance of smooth terms:				
	Edf	Ref.edf	F	p-value
s(Subjects)	3.68	18	4.587	0.213
S(Items)	43.63	179	57.33	0.003

Discussion

In order to successfully parry a penalty shot in handball, goalkeepers need to anticipate the final destination of the ball even before the ball leaves the thrower's hands. Our results demonstrate well-developed anticipatory skills in handball goalkeepers. Even 400ms before they saw the ball

trajectory (occlusion point 2), experts could judge where the ball is going to go, considerably above the chance level. This ability is acquired, as novices, with far less experience, were consistently worse in anticipation. Both experts and novices could extract more useful kinetic information as the amount of information increased in the subsequent occlusion points (see also Farrow et al., 2005; Maxeiner et al., 1996). However, experts were able to identify and utilize the relevant information better and more rapidly than novices (see also Gredin et al., 2018; Maxeiner, 1988).

Importance of meaningful occlusion points in anticipation research

The first occlusion point, which ends 700 ms before the ball is thrown, contains no relevant information (Hatzl, 2000). The accuracy performance is therefore around the chance level as even experts could not rely on their knowledge. The second occlusion point contained the information about rotation of the hips and upper body, both important indicators of anticipation (Hatzl, 2000). This resulted in significantly better performance in both groups when compared to the first occlusion point. The third and final occlusion point contained additional important information (for anticipation) about the direction of the ball-carrying hand, which improved the anticipation additionally in both groups.

Although both groups improved their performance with additional information, there were important differences. The accuracy increase for experts was the highest in the second occlusion point (from 26% to 50%). In contrast, novices showed a particular increase in performance in the third and final occlusion point (from 30% on the second occlusion point to 42% on the third). The differing pattern makes it clear that the two groups use different kinematic clues for their performance. Experts can base their decision on the information about the rotation of the hips and upper body, which is present in the second occlusion point (Neumaier, 1983, 1985). The additional information about the shooting hand improves the experts' anticipation only to a certain extent. In contrast, novices benefitted considerably from the information about the ball-carrying hand.

These results underline a large body of research that demonstrates experts' ability to make informed decision about an outcome before it actually happens. Experts in all sport domains extract the necessary information for prediction from the body movements that precede the shot/motion execution (Bideau et al., 2004; Gredin et al., 2018; Loffing et al., 2014; Penrose & Roach, 1995; Vignais et al., 2009; Williams & Burwitz, 1993). Our study goes beyond the previous ones because it pinpoints the crucial time for anticipation as well as the exact kinetic information on which experts' decisions are based upon. The analysis that includes the identification of meaningful occlusion points may go a long way toward explaining inconsistent findings in previous research. For example, Loffing and Hagemann (2014), while examining anticipatory ability in seven-meter shots, chose five different time

points before the ball was released. However, the time windows were so close to each other (40 ms between time windows) that it was hard for experts to pick up and respond to additional information, therefore resulting in no differences between consecutive time periods.

Similarly, Alsharji (2014) also defined five time windows in his analysis of the ability to anticipate seven-meter shots in handball. However, out of five, two time windows were after the ball was already released and three prior to ball release – only they included the throwing motion. As mentioned before, reacting after the ball has been released will not result in a successful save (Schorer, 2006) as it does not leave enough time for goalkeepers to make an informed decision, and then choose and execute an adequate motor response program. Therefore, information from the last two occlusion points in Alsharji's study (2014) is not relevant for successful anticipation. Even though the first three occlusion points contained pre-throw movement sequences, the starting point of the sequence was chosen to be in the middle of the movement execution (when the body was already rotated and one could see the thrower's hand clearly). This ignores the analysis of relevant movements for anticipation (e.g Hatzl, 2000) and has consequently resulted in no significant difference between consecutive time windows.

Reaction time in anticipation research

Our results also emphasize the importance of complementing the measure of accuracy with the measure of reaction time in studies on anticipatory skill (for similar analysis in different sport domains, see Farrow et al., 2005; Mann et al., 2007). The reaction time data underlines the anticipatory ability of expert goalkeepers in handball, as we asked the participant to react as quickly as possible, simulating the actual goalkeeping reaction. Only at the last occlusion point (Figure 2.4), when they have 100ms before the ball is released, do expert goalkeepers no longer have enough time to decide on and execute the defensive motor program. This scenario is based on Schorer's analysis (2006), which found that: a) the ball travels for about 300-360 ms before it reaches the goalkeeper; b) the reaction time of goalkeepers for initiating the movement is between 200-250 ms; c) the time it takes for one step defensive movement is between 100-180 ms. According to this analysis, the goalkeepers will have between 400 and 460ms (time from 3rd occlusion point to ball release + time to reach the goalkeeper) to decide on and execute the motor movement. Our experts needed on average about 600ms for their response, but one needs to consider that the actual button press also takes around 200-300ms (Helm et al., 2016; Klemmer, 1956; Niemi & Näätänen, 1981; Przednowek et al., 2019; Teichner, 1954). Subtracting the time for simple reaction would leave experts with around 300-400ms decision time.

Since one also needs to execute the defensive movement (100-180 ms), it becomes clear that successfully parrying the penalty shot may become rather difficult.

However, at all other time points, experts will have plenty of time to parry the shot. In order to make a save, the participants' reaction time would have to be between 1000-1100 ms in the first occlusion point and 700-800 ms in the second one. Taking into account the aforementioned analysis by Schorer (2006), experts were able to react in good time in the first two occlusion points, and possibly in the third one too. On the other hand, novices' reaction times are too slow for successful defence, even when we account for the simple reaction time included in their total reaction time. They do get significantly faster with the increase in information, but the time window for successful reaction is shorter in subsequent occlusion points. This provides ecological validation for the results. Although novices may be able to predict the outcome of penalty shots after a certain amount of information is available (occlusion points two and three), their decisions are not fast enough to successfully parry the shot.

The combination of accuracy and reaction time can also be used to determine the ecological validity of the study. For example, in the German handball Bundesliga, arguably the strongest handball league in the world, goalkeepers save on average about 20% of seven-meter penalties (see here). Other research also indicates that the efficiency of the goalkeepers is around 20% on penalty shots in local competition (Greek premier handball leagues – Hatzimanouil et al., 2017), World Cup (Hansen et al., 2017), or over a long period of time at the top level (Espina-Agulló et al., 2016). This may appear to be a low success rate, given that our goalkeepers, who are arguably not as good as the best Bundesliga professional goalkeepers, manage one in two successful reactions already at occlusion 2 point (see Figure 2.4). One needs to consider, however, the fact that in the real game the players are able to throw the ball to more than four predefined spots. The goalkeeping decisions are also made more difficult by the use of deception techniques such as fake throws or adding different amounts of spin to the throw. Both these factors will decrease the success of anticipation.

Future directions and conclusion

Besides using meaningful occlusion points and the combination of the accuracy and reaction time measures, our study featured, for the first time in the research on anticipation skill (to our knowledge), multilevel analysis. Analyses that make use of all individual trials instead of manipulating averages of individual participants are gaining considerable popularity in psychological research (Baayen et al., 2008; Gelman & Hill, 2007; Pinheiro & Bates, 2000). In comparison to the classical analysis, multilevel models perform better in the case of unbalanced designs, not normality in

dependent variable, and repeated measure covariates (Baayen, 2008; Barr et al., 2013; Radanovic & Vaci, 2013; van Rij et al., 2020). In other words, these models represent a more sensitive statistical tool at researchers' disposal. Our hope is that our study paves the way for the use of multilevel modelling in research on anticipation skill in sports; for this reason, we provide access to the commented code used for the analysis of our data in the online supplement.

Our results also point out a couple of future avenues worth exploring. We have identified the rotation of the hips (occlusion point two) as the early kinetic information available to experts. To confirm its importance for anticipation, one could employ eye movement recordings of experts (Kredel et al., 2017; Kurz et al., 2018). Similarly, the spatial occlusion technique, where one occludes different body parts, may provide a definitive answer regarding the role of this particular information (Dicks et al., 2017).

Given that, in the experimental conditions, participants' viewpoint of shooter is not only two-dimensional (as it appears on screen), but is also less than half the retinal size of the real-life image, the issue of ecological validity could be raised (Mann et al., 2013). Therefore, in future research, a more naturalistic approach may be the use of liquid-crystal occluding goggles (Milgram, 1987) in the real simulations of the seven-meter penalty. The goggles could be externally manipulated to block the vision at crucial moments, thus simulating the occlusion paradigm in the real world. This technique, which has been successfully used in other sports (Farrow & Abernethy, 2003; Féry & Crognier, 2001; Starkes et al., 1995), would allow goalkeepers to really execute the defensive movement. This may be particularly relevant in this study because we noticed that some experts, that participated in this study, upon seeing the stimuli, moved their hands reflexively, as if they were actually defending their goal, before pressing the button. This pattern of behaviour, which was not noticed among novices, may have suppressed the reaction time. The liquid plasma goggles would, among other things, also deal with this particular problem.

Our study demonstrates that kinetic knowledge is the essence of expertise in sport. It also underlines the importance of the definition of meaningful occlusion points in the research on anticipation. Only carefully chosen occlusion points allow insights into how different patterns of movement impact experts' ability to anticipate. The importance of this finding extends beyond the laboratory, as only the findings based on meaningful occlusion points can serve as the basis for the training of future experts. Our study identified the crucial occlusion points based on the typical movement analysis (Hatzl, 2000) as well as the time reactions of experts (Schorer, 2006).

Chapter 3: Grit - Deliberate practice mediation on performance

Abstract

Practice is arguably one of the most important predictors of skill. Becoming an expert requires long-term immersion in a domain, which enables development of the mental structures necessary for outstanding performance. Deliberate practice (DP), focused repetitive activities with corrective feedback, is particularly beneficial for building such mental structures. The amount of accumulated DP does indeed differentiate well between experts and novices. However, the predictive strength of DP weakens considerably when it comes to differentiating between differently skilled experts, leaving a way clear for other non-practice related factors to exercise their influence. Here we demonstrate in a large sample (388) of elite youth soccer players, that one such factor, the personality trait of Grit, predicts the expertise level both directly and indirectly. Grittier players accumulated more Coach-led team practice, the activity in sports which is closest to DP in team sports, which in turn predicted the skill level. Other practice activities, such as self-training or playing with friends, were not predictive of skill levels, nor were they influenced by Grit. Most importantly, Grit continued to exert a direct positive influence on the skill level of players even after the amount of DP was accounted for. Overall, a standard deviation of change in the Grit score resulted in almost half a standard deviation improvement in skill. Situations where the predictive power of traditional expertise factors, such as practice, is limited highlight the need for the inclusion of additional factors in theoretical frameworks. Grit, for example, could be used as a complement to practice in both the theoretical explanation and talent identification.

Keywords: Expertise, Deliberate Practice, Grit, Soccer, Mediation, SEM, Path Analysis

Introduction

While, in Chapter 02, we have discussed the cognitive underpinnings of sport experts' perceptual-cognitive skills (kinetic knowledge being the essence of expertise in sport), in this chapter we further the investigation of predictors of those expert skills by focusing on the role and impact (of interplay) of (deliberate) practice and conative factor, grit, on expert performance.

To become an expert, immersion in a domain is necessary. It is no surprise then that practice is often taken to be the main factor driving the acquisition of skill (Bilalić, 2017; Ericsson et al., 1993). In some expertise domains, such as sports, the association between the amount of practice and performance is often over $r = .50$ (Helsen et al., 1998; Ward et al., 2007). However, when we only focus on elite practitioners, the ability of practice to differentiate between more and less skilled experts considerably weakens (Macnamara et al., 2014). In sports, for example, the correlation between practice and performance in elite samples is typically around $r = .10$ (Macnamara et al., 2016; Memmert et al., 2010). This leaves the door open to other factors whose influence on skill would be otherwise diminished by practice-related activities in classical expert vs. novice studies. Here we demonstrate that one such factor, the personality trait of "Grit", explains the differences among a large sample of elite youth soccer players. Grit's influence on skill was both indirect and direct. Grittier youth players accumulated more beneficial types of practice throughout their immersion in the domain, which in turn led to a higher skill level. However, Grit differentiated among elite youth players also beyond the influence of practice - grittier players were more skilled even when the differing amounts of practice were accounted for.

Deliberate practice in experts' performance

Extensive and prolonged exposure to an activity is necessary for becoming proficient in that particular activity. All practice activities, however, do not have equal impact on performance. According to the Deliberate Practice framework (Ericsson, 2008; Ericsson et al., 1993), only goal-directed activities that feature repetitions combined with constant feedback aimed at identifying weaknesses and improving current performance are considered beneficial to performance. Solitary practice, designed and supervised by a coach/teacher was the prototypical form of deliberate practice (Ericsson & Harwell, 2019). In soccer, for example, the individual practice designed, monitored, and evaluated by a coach with a goal of improving a striker's weak foot, would constitute deliberate practice. Playing street soccer with friends, however, does not afford the same opportunities for improvement as practice does.

There are not only fewer opportunities for practicing with the weak foot, but also the corrective feedback would be missing. Similarly, competitive matches are unlikely to afford the same amount of repetitions and they do not lend themselves to using underdeveloped techniques as any inaccuracy could be costly.

Deliberate practice is assumed to be particularly effective in acquiring necessary mental structures that enable experts' performance. Expertise domains are inherently complex environments which require adjustments of the human brain. Picking up regularities in the environment and learning how to deal with certain situations is at the heart of every kind of expertise (Bilalić, 2017; Chase & Simon, 1973; Degroot, 1978; Gobet & Simon, 1996). The mental structures that support experts' performance are primarily based on domain-specific knowledge (Broadbent et al., 2015), which can be, depending on the domain, cognitive and/or kinetic in nature (Bilalić, 2017). In either case, the knowledge enables experts to quickly orient themselves in their domain by activating already acquired knowledge structures, which then automatically provide appropriate responses. Immersion in a domain is necessary for the development of these knowledge structures, but it is a fair assumption that some activities, particularly those that mimic the underlying perceptual, cognitive and motor demands of a sport, are more beneficial than the others (Hendry & Hodges, 2018; Roca & Williams, 2017).

Early studies on deliberate practice demonstrated its explanatory power regarding experts' performance. For example, world-class musicians did not differ in the overall amount of time spent on activities in their domain than their less accomplished peers who were training to become music teachers, by the time their careers diverged in their early twenties (Ericsson et al., 1993). However, the difference was clear when only deliberate practice activities (e.g. practice with the goal of improvement) were investigated, as world-class musicians were found to have accumulated over 10,000 hours (of deliberate practice) compared to only 8,000 of music teachers. Similar findings were found in numerous other (and vastly different) expertise domains, ranging from chess (Burgoyne et al., 2019; Charness et al., 2005) and sport (Ford et al., 2009; Helsen et al., 1998; Hendry et al., 2018; Sieghartsleitner et al., 2018), to academic performance (Nandagopal & Ericsson, 2012; Plant et al., 2005).

Recent studies cast a doubt on the extent of the impact deliberate practice has on experts' performance (Hambrick et al., 2016; Macnamara & Maitra, 2019). A couple of meta-analyses (Macnamara et al., 2014, 2016) estimated that (deliberate) practice alone explained 26% of performance in games (average r = .51), 21% music (r = .46), 18% in sports (r = .42), 4% in education (r = .16), and as low as 1% in professions. However, when the activities were more precisely

differentiated between deliberate and other types of practice, these estimates of the influence of deliberate practice improved considerably, with 61% of the performance explained across the different expertise domains (Ericsson & Harwell, 2019). The current controversy on what exactly constitutes deliberate practice (Ericsson, 2020a, 2020b; Ericsson & Harwell, 2019; Macnamara & Hambrick, 2020) highlights inherent difficulties in identifying deliberate practice activities in some domains. It is possible that an extension of the original definition of deliberate practice is required (for some recent suggestions, see Baker et al., 2020).

Deliberate practice in sports

Much of the scientific study of expertise development in sport stems from Ericsson and colleagues' classic study of musicians (Ericsson et al., 1993), whereby solitary practice was the prototypical form of deliberate practice, given the intense, purposeful, self-directed nature of the activity. Soccer, however, is an invasion team game which puts unique perceptual-cognitive and motor demands on its athletes. Training together with teammates under the instructions of a coach (e.g. positioning and timing of the flat four defensive system) would represent beneficial practice even if it is not individual training with a coach. Indeed, structured interactive "team practice" has been shown to discriminate between experts and their less accomplished peers in team sports (Baker & Young, 2014; Ford et al., 2009; Helsen et al., 1998; Hodges et al., 2004; Zibung & Conzelmann, 2013). Individual training prescribed by a coach, on the other hand, is rare and may be bereft of the key perceptual-cognitive conditions that are likely to facilitate transfer and development of mental structures necessary for performance improvement (Ford et al., 2010). Furthermore, individual training prescribed by a coach typically does not show any discriminatory value across skill levels to the extent that it is often collapsed with team practice in sport related studies (Ford et al., 2009; Ford & Williams, 2012; Hendry et al., 2019; Ward et al., 2007). Recent analyses of team practice environments in soccer (Ford, Yates, et al., 2010; Ford & Whelan, 2016; O'Connor et al., 2017; Partington & Cushion, 2013) have demonstrated that coaches indeed spend two to three times more time on interactive team practice (e.g. replicating the demands of the game via small-sided games) than individual practice (e.g. isolated drill activities).

Other informal sport activities such as street soccer or pick-up basketball are also related to the development of expertise (Ford et al., 2009; Ford & Williams, 2012; Hendry et al., 2018; Uehara et al., 2018). These informal, peer-led activities may elicit similar perceptual-cognitive conditions that could engender the development of skill without the specific intention to improve performance (Côté &

Vierimaa, 2014; Uehara et al., 2018). Yet, it is difficult to square how playing street soccer (with or without others) can elicit the same improvement benefits as those gained from practice conditions often found in elite sport settings with best players, facilities, coaches, and sport science support (Hendry et al., 2018; Hendry & Hodges, 2018; MacNamara et al., 2015).

Finally, competition has typically showed little in the way of predictive or discriminatory value in sport expertise research. It is unclear whether these findings can be attributed to a lack of extrinsic, coach directed feedback or if they occur because of a relatively homogeneous (and restricted) competition schedule set for developing elite athletes. However, there is some anecdotal and empirical evidence that optimally challenging competition can benefit expertise (Cook et al., 2014; Hendry & Hodges, 2019; Holt & Dunn, 2004).

Irrespective of the operational definitions used to outline deliberate practice, domain specific practice activity is obviously an important factor of expertise (for reviews, see Baker & Young, 2014; Ford & Coughlan, 2019). However, it remains unclear whether it is not only necessary, but also sufficient (Campitelli & Gobet, 2011; Hambrick et al., 2016). Deliberate practice explains a considerable amount of experts' performance, but a large chunk is still left unresolved. Even more troubling for the sufficiency claims of deliberate practice is that its explanatory power weakens within elite samples. The correlation between deliberate practice and performance among heterogeneous samples, which include a range of skill levels from novices, through intermediates, to experts, regularly reaches incredible heights (e.g. almost perfect correlation between practice and performance in (Ward et al., 2007)). However, within the samples of experts, where the differences are considerably smaller, this association often becomes small (Macnamara et al., 2016), or even negative (Güllich, 2014; Johnson et al., 2006). This is certainly a consequence of the restricted range which suppresses relations between variables (Pearson, 1902; Vaci et al., 2014), but it is also an indication that other factors may be at play, in particular at the highest level of expertise (Ford & Williams, 2012; Hardy et al., 2017; Tucker & Collins, 2012).

Non-practice factor in expertise – Grit

The amount of explained performance in heterogeneous, and especially in homogeneous, samples leaves the door open to other (explanatory) factors. One such factor, which has recently started to attract scientific interest, is the personality trait of Grit (Duckworth et al., 2019; Hodges et al., 2017; Tedesqui & Young, 2018). Grit is an aspect of the Big Five personality trait

conscientiousness (Duckworth et al., 2007) and corresponds to interest and determination in achieving long-term personal goals. It is particularly predictive of persistence in the face of challenges and obstacles. As such, it is related to performance in academic and non-academic activities (Jachimowicz et al., 2018). It also explains performance even after one accounts for practice and ability, at least in cognitive domains (Akos & Kretchmar, 2017; Duckworth et al., 2019; Eskreis-Winkler et al., 2014). Grit is composed of two facets: *Consistency of interests (CI)* and *Perseverance of Effort (PE).* CI refers to continuous interest, throughout time, in a single life-goal instead of focusing on different superordinate goals over short periods of time. PE refers to the ability to maintain effort in the face of difficulties (Duckworth & Quinn, 2009). In other words, CI represents direction of one's passion, while PE represents magnitude of effort put forward in pursuit of that passion (Tedesqui & Young, 2017).

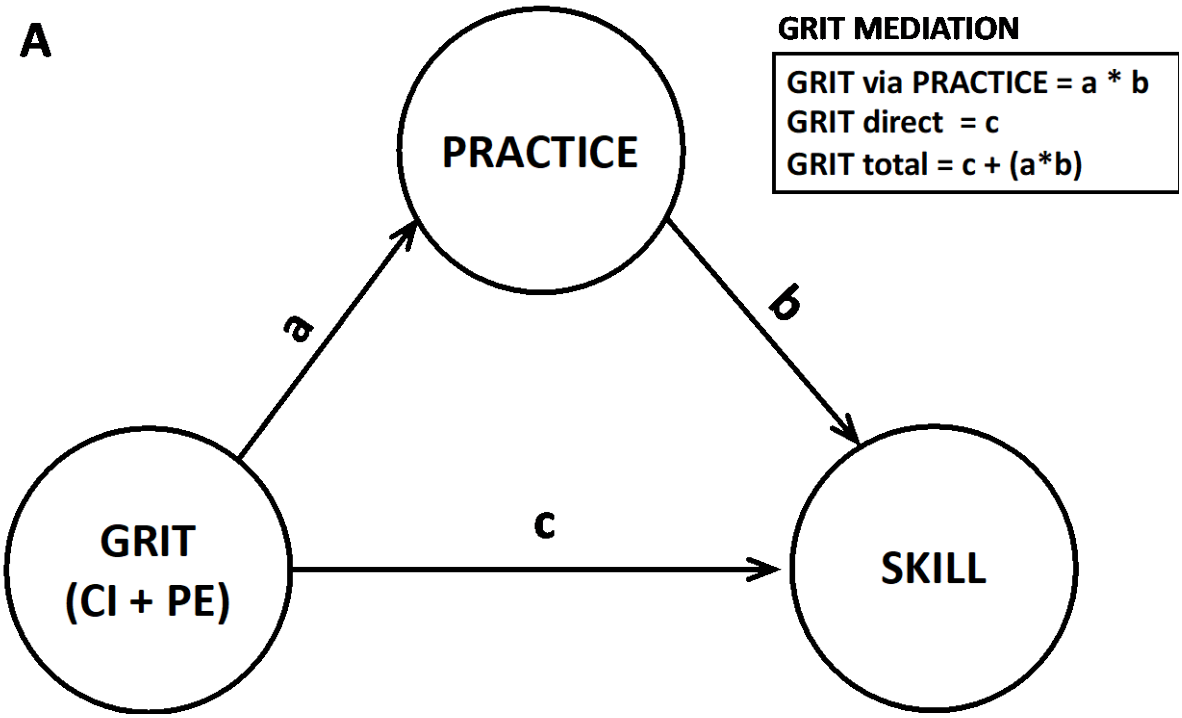
In sport domains, Grit differentiates between more and less able athletes (Sigmundsson et al., 2020) and retains some its predictive power within skilled samples (DeCouto et al., 2021; Larkin et al., 2016). Grit should also be related to deliberate practice. Experts who have more pronounced personality trait of Grit are more likely to spend more time on their chosen activity and persist despite obstacles, when compared with their less gritty peers (Duckworth et al., 2011; Ericsson, 2020b). This is the case in the majority of studies in the sport domain (Fawver et al., 2020; Larkin et al., 2016; Tedesqui & Young, 2017), but not necessarily all (Tedesqui & Young, 2018). Overall, Grit is mostly positively associated with both: performance in athletes and time spent on practice (see Cormier et al., 2021).

Most of the findings above feature the single composite Grit score. Recently, there has been a trend to investigate both components of Grit, CI and PE, separately. One of the reasons for the sudden shift is a (relatively) recent meta-analysis, which demonstrated that PE is much more predictive of success in the academic setting than CI (Credé et al., 2017). The situation is, however, somewhat different in sport domains. PE, and not CI, differentiated between differently skilled athletes (Tedesqui & Young, 2017, 2018), but in other studies, both were predictive of future success (Ansah & Apaak, 2019), while only CI was associated with longer tenure in the chosen domain (Cousins et al., 2020).

Grit – Practice mediation

The positive association of Grit with both Practice and Skill has consequences for the overall influence of Grit on skill in sport domains. There is not only direct impact of Grit on Skill (relations c

in Figure 3.1A, and c_1 and c_2 in Figure 3.1B), but also an indirect impact through (deliberate) Practice (relations a and b in Figure 3.1A, and a_1 / a_2 and b in Figure 3.1B). The assumption of the interplay between Grit and Practice follows directly from the literature. The mediation link between Grit and Practice has only been formally tested in studies on the spelling bee competitions (Duckworth et al. 2011) and college academic performance (Lee & Sohn, 2017). In both instances, Grit did not directly predict success, but rather indirectly, through (deliberate) Practice. To our knowledge, the assumption of this mediation has not been empirically investigated in sport domains.



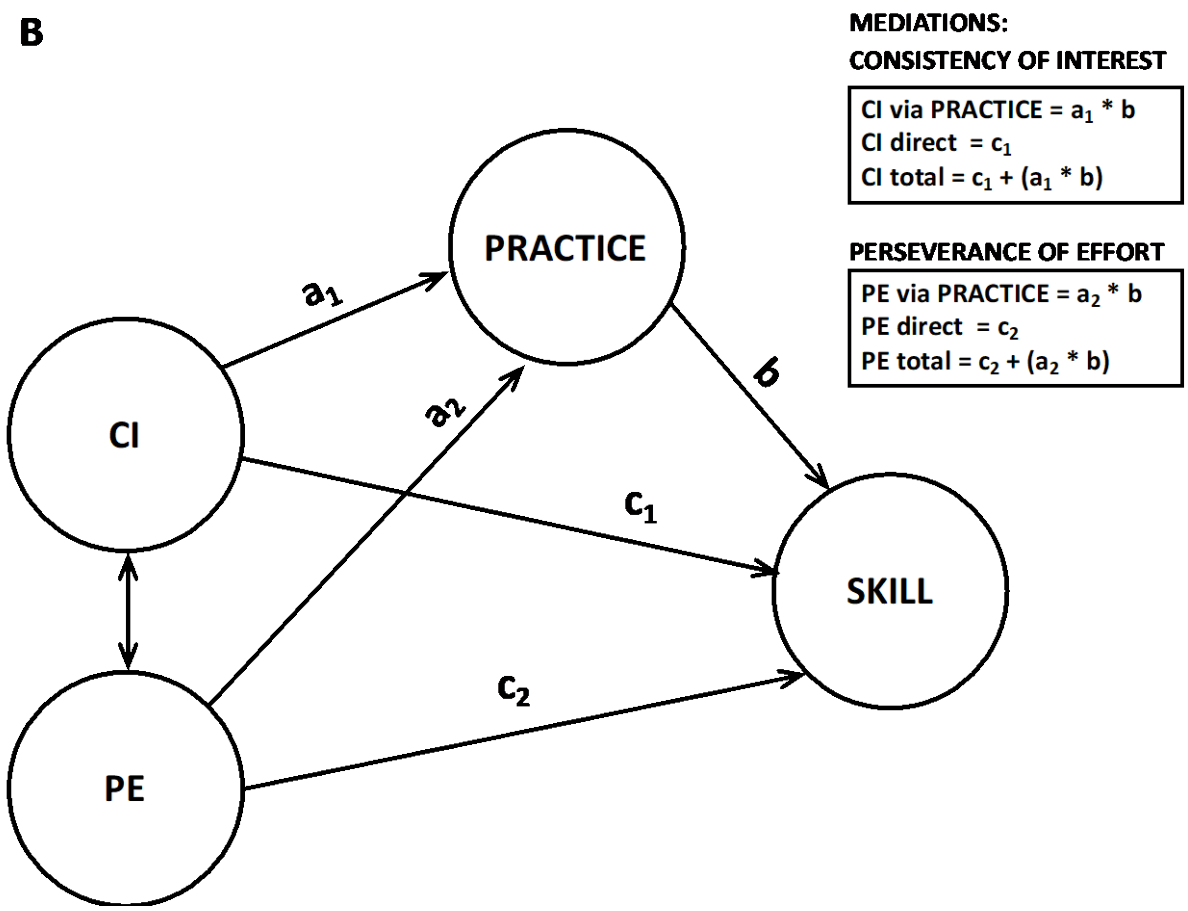


Figure 3.1. Theoretical model of mediation between Grit, Practice, and Skill. (A) Grit, as a single construct, is being mediated by practice. Mediation is the product of the Grit's relation with Practice (a) and that of Practice with Skill (b). The total effect of Grit on Skill is sum of the direct (c) and the indirect, mediation effect (a * b). (B) Grit's components, CI (Consistency of Interest) and PE (Perseverance of Effort), are mediated by Practice. The mediation and total effects of CI and PE are calculated using the same procedure as with the single Grit measure.

The lack of mediation studies precludes us from knowing whether Grit influences expertise beyond practice, that is directly, in addition to its indirect influence through practice. This is unfortunate, since these assumptions carry theoretical and practical importance. For example, the influence of Grit on practice would provide a currently lacking explanatory mechanism for differing amounts of practice even among experts (Campitelli & Gobet, 2011; Hambrick et al., 2016). Most importantly, a possible direct influence of Grit on expertise may provide the crucial missing factor that differentiates even in experts (only) samples.

Current Study

Larkin and colleagues (2016) have conducted a study on a large sample of highly skilled Australian youth soccer players, investigating, among other things, link between grit and sport-specific engagement as well as link between grit and perceptual-cognitive expertise. In this study, they found that grittier players accumulated more hours being engaged in sport related activities. Additionally, they found that grittier players outperformed less gritty peers on the assessments of performance (on the perceptual-cognitive skill tests). Despite demonstrating the link between grit, engagement in sport related activities and skills, and having the data available, Larkin and colleagues have not looked into the mediated relationship of grit and practice on skill. That is why, in collaboration with them, we ran secondary data analysis of data collected in their study (Larkin et al., 2016) to answer this research question. We will describe the relevant variables, instruments and procedures from their study, necessary for understanding the findings of the current study, as well as the data analyses conducted in our own study further bellow.

We investigated the relations between Practice and Grit on the one side, and Performance on the other, in a large sample of highly skilled Australian youth soccer players (Larkin et al., 2016). The players estimated their involvement in different soccer activities retrospectively starting from the age eight. It is worth nothing that the grouping of sport related activities into categories, although somewhat similar, was not the same as it was done by Larkin and colleagues in the original study (2016). This was done in order to be able to distinguish between more and less structured activities, as well as between activities that the players themselves had different levels of (self) control. One category of activities was *Coach-led (team) Practice*, which, in our context, comes the closest to the classical deliberate practice definition (Ford et al., 2009; Helsen et al., 1998). The other highly structured activity type was *Competition*, which is considered as highly relevant to development of athletes (Baker, 2003; Ford et al., 2015; Hendry et al., 2019). The other three activity categories, which we call "Unstructured Practice", were *Self-led (individual) Practice* (no coach supervision), *Play with peers* (for fun), and *Indirect Involvement* (e.g. watching games on TV, playing football video games).

The players also answered questions about their persistence and interest in soccer as a part of the Grit questionnaire (Duckworth & Quinn, 2009). Most importantly, they underwent extensive testing of their cognitive and perceptual soccer abilities. These non-motor tests, that Larkin and colleagues employed (2016), feature domain-specific situations which require correct anticipation and regularly correlate highly with objective and subjective measures of skill (Dugdale et al., 2020; Sieghartsleitner et al., 2019).

Based on the Deliberate Practice framework (Ericsson, 2020; Ericsson & Harwell, 2019), we expect that Coach-led Practice influences Perceptual-Cognitive ability of young elite soccer players. Coach-led Practice should also mediate the influence of Grit on Perceptual-Cognitive ability. Competition is also a structured development activity but should be less predictive of skill development as it provides fewer opportunities for repetitive activities with immediate feedback. The research on the effect of unstructured activities (e.g., self-led training, play with peers, indirect activities) on skill in sport domains has been riddled with inconsistent results (Ford et al., 2009; Helsen et al., 1998; Hendry et al., 2018; Hodges et al., 2004; Williams et al., 2012; Zibung & Conzelmann, 2013). However, these activities are theoretically unlikely to optimally challenge players' perceptual-cognitive-motor systems to be positively associated with expertise.

Grit should positively impact the amount of practice the players accumulated, in particular when it comes to unstructured activities which are under players' control. The structured practice (e.g., coach-led training and competition) may be mostly outside of players' control, but even there one can assume differences between more and less gritty individuals (e.g. they can attend more practice sessions and competitions and give their best). Consequently, we believe that Coach-led Practice should mediate the influence of Grit on Perceptual-Cognitive ability.

We do not expect, however, that Practice will mediate the whole influence of Grit on performance. Our sample is highly homogenous, including the very best youth players in Australia. In such a homogenous sample, the performance range is restricted, which often results in low associations between practice and performance (Pearson, 1902; Vaci et al., 2014). Consequently, other factors, including Grit may continue to influence performance once we have accounted for practice.

We do not feel confident in predicting the impact of individual Grit's components, CI and PE, on skill. The studies on the separate components are still rare and so far have produced inconsistent results (Ansah & Apaak, 2019; Cousins et al., 2020; Tedesqui & Young, 2017, 2018). Most importantly, almost all studies used the subcomponents separately, one without the other, in models. In order to establish the relative importance of Grit's components, it is necessary to introduce both in a single model (Credé, 2018). Only like this can they be formally subjected to a statistical tests and their possible interplay investigated. That is why we analysed two variations of the mediation models in this study: one where the Grit is defined as a single predictor (composed of CI and PE); and another where Grit's components CI and PE are separate predictors.

Unlike many studies in expertise that suffer from small samples, our study featured 388 elite youth soccer players. The large number of experts enables us to soften the restriction of range problem

that regularly plagues studies involving elite practitioners. The effects of interest may not be as large as they would be in a more heterogeneous sample, but the sheer sample size enables us to detect complex relations if they exist (see the power analysis in the method section).

Methods

Participants

In their study Larkin and colleagues (2016) recruited 388 elite youth male soccer players, all of which volunteered to participate in the study. The participants were selected by their regional youth soccer development programs and were competing at national youth soccer championships in Australia, thus representing the best Australian youth male soccer players. All of them were around the age of 14 (years) at the time of testing. Although almost all participants took part in the perceptual-cognitive tests (with only six missing), some participants did not complete Grit (16 players) and/or Practice Questionnaires (between 16 and 25 players, depending on the specific sport related activity). In the end, the analyses were conducted on 345 players (M_{age} = 13.8, SD_{age} = .8). The institutional research ethics board of Sydney University approved the study and the written parental consent was obtained, by Larkin and colleagues (2016), for all youth players prior to data collection.

Power Analysis

In the Grit – Practice – Performance relation, the association (standardized regression coefficient) between Grit and Deliberate Practice in similar contexts is around .30 (Duckworth et al., 2011; Lee & Sohn, 2017; Tedesqui & Young, 2017, 2018). The Deliberate Practice – Performance association in samples similar to ours, which include elite and sub-elite young practitioners, is around .40 (Hendry et al., 2018; Macnamara et al., 2016). Finally, the direct Grit – Performance relations in similar settings is around .10 (Duckworth et al., 2011; Lee & Sohn, 2017; Moles et al., 2017). Taking into account these relations, one would need 233 participants to detect the Grit – Practice – Performance mediation with .80 power (Schoemann et al., 2017).

Measures

Grit.

Larkin and colleagues (2016) assessed Grit using the child adapted version of the Short Grit Scale, Grit-S (Duckworth & Quinn, 2009). This questionnaire is a general personality inventory, containing either self-report items, and it has established construct and predictive validity and test/retest reliability (Duckworth & Quinn, 2009). An example of items form the Grit-S would be "Setbacks (delays and obstacles) don't discourage me." and "I bounce back from disappointments faster than most people", where participants respond on a 5- point Likert scale from 1 (not like me at all) to 5 (very much like me). Scores on each of the item are added up (and divided by 8) to create an average Grit-S, with higher values representing higher levels of grit. The internal reliability of this questionnaire in the original study was $\alpha = 0.63$ (Larkin et al., 2016).

Considering the recent controversy about the uniformness of the Grit construct in general (Credé, 2018; Credé et al., 2017) and sport specifically (Cormier et al., 2019, 2021; Tedesqui & Young, 2017, 2018), we conducted confirmatory factor analysis (CFA). The one factor model (only Grit) had a suboptimal fit, while the model with two factors, interest and perseverance, was clearly superior (see Section 1 in the Appendix C). However, even the two-factor model was merely a good fit. The culprit proved to be one of the questions in the perseverance of effort items ("Setbacks don't discourage me. I don't give up easily."), which had already been identified in other studies as the reason for poor fit (Dunn et al., 2021; Shields et al., 2018; Tedesqui & Young, 2017, 2018). After removing this item, the fit of the model was excellent and significantly better than when the item was present (see Section 1 in Appendix C). We consequently performed all analyses excluding this item, which was a procedure adopted in other studies (Dunn et al., 2021; Shields et al., 2018; Tedesqui & Young, 2017, 2018).

Practice.

In the original study, Larkin and colleagues (2016) used an adapted version of the Participation History Questionnaire, PHQ (Ward et al., 2007) to gather data relating to the players' date of birth and soccer-related activities that players had undertaken from the current season back to 8 years of age. The items in the questionnaire obtained the information relating to the number of hours participants engaged in soccer-related activities at a specific age. Participants were asked to recollect the number of hours per week and the number of months per year engaged in five soccer-related activity categories, including Match Play (i.e., competitive soccer matches), Coach- led Practice (i.e., soccer practice with

a coach), Individual Practice (i.e., soccer activity by oneself), Peer-led Play (i.e., soccer activities with peers, including small-sided games), and Indirect involvement (activities of non-physical nature, such as playing soccer computer games and watching soccer games). Within the Australian Football development pathway, it is from the age of eight that the games more closely represent match play conditions, with 7 vs. 7 games on a quarter sized pitch, with line markings, a goalkeeper and a referee; therefore retrospective recall was only considered from that age (eight) onward. Prior to this, players only participate in 4 vs. 4 small sided games without a goalkeeper (Australia, 2013 - FFA National curriculum). In section 2 of Appendix C we provide CFA for the PHQ. While one factor model had a poor fit, a two factor model fit data well and was significantly better at describing the data. In other words all practice activities do not belong together – however Structured activities and Unstructured activities do go well together and load well on their own factors.

Perceptual-cognitive Ability.

Larkin and colleagues (2016) used a film-based paradigm, using the temporal occlusion method, to determine Perceptual-Cognitive abilities of the participants. In order to measure the participant's level of perceptual-cognitive expertise, two activities were conducted in the original study. The first activity, decision making, was designed to evaluate participant's ability to make an informed decision of what game action to perform next with reference to the presentation of a sequence of play that was occluded at a key moment. During this activity, the participants were presented with 20 video clips of offensive soccer sequences. Participants were instructed to watch the clip and at the point of occlusion make an informed decision regarding the next game action, as if they were the players on the ball (i.e., What would you do next?). Larkin and colleagues (2016) gave the participants three possible decision outcomes to choose from: (a) pass the ball, (b) run with the ball, or (c) shoot at goal. While the participants were thinking about and providing the response, a picture of the last frame of the video was provided to help them to indicate the game action (i.e., run with the ball, pass, or shoot), as well as to provide the direction in which the game action would take place (i.e., draw an arrow in that direction). The procedure used in the original study is consistent with the protocol used in previous research (Roca et al., 2012; Ward & Williams, 2003). Each trial was scored out of 2, with 1 point being allocated for the correct direction (as indicated by the arrow) and 1 point for indicating the correct game action (i.e., pass, run, or shoot). A total score of 40 points was possible, with the total score for all trials being used for analysis purposes.

The second activity, situational probability, was designed to evaluate each participant's ability to assess soccer-specific situational information by identifying the likely options for the player in

possession of the ball (Williams et al., 2012). During this activity Larking and colleagues (2016) presented participants with 20 video clips of an evolving passage of play for approximately 6 to 10 s, and at a critical moment in the footage, 120ms prior to the player in possession of the ball making a pass, the footage was frozen. This last frame was presented for 15 s. Participants were required to indicate, on an image of the last video frame (in the duration it was presented), the three most threatening players to the defence, if they were to receive the ball next. The next task for the participants was to rank the most threatening players (they have just identified) from one to three in order of most threatening (i.e., 1) to least (i.e., 3) threatening to the defensive team. Larkin and colleagues (2016) scored each trial out of 10 points, with the scoring weighted to reward correct responses. The correct identification of the most threatening player scored 6 points, second most threatening scored 3 points, and the third most threatening player scored 1 point. When a participant identified an option as being higher or lower than the identified correct ranking (that was done by a group of expert coaches (n = 5)), the total available points were subtracted from the participants' ranking of the player. Therefore, if a participant identified the top-ranked player as the third most threatening player, the participant would receive 3 points for that player (6 – 3 = 3). The total score for all trials were calculated for analysis.

Procedure

In the original study, Larkin and colleagues (2016) had the participants complete the Grit-S questionnaire first, with the completion time ranging from 5 to 10 minutes. Following that, PHQ was then administered, requiring approximately 1 hour to complete. During this time, Larkin and a research assistant were available to provide any needed clarifications, further explanations and answer questions that participants may have had. Finally, the participants completed the perceptual-cognitive activities. They started with decision-making activity and, upon successful completion, followed up by the situational probability activity. Three familiarization trials, preceding tasks within each of the activity, were presented to ensure that participants were comfortable with each of the tasks. The videos were projected on a screen (2.1 m), whilst the participants were seated in front of it, with a clear view of the screen (approximately 5–7 m away).

Data Analysis

We used the SEM approach as the (latent) variables of interest had two or more indicators/variables. We therefore constructed latent variables for Perceptual-Cognitive ability out of Decision Making and Situational Probability tests. Since one of our goals was to investigate how

different practice activities influence soccer skill, we followed a step by step approach in constructing the latent Practice variable. We first use the Coach-led training as the indicator of Practice because we expect this kind of activity to be the most predictive of soccer skill. The second model adds Competition to the Coach-led training as the part of the Practice construct, as both activity types are Structured activities. The third and final model adds other three Unstructured activities as an independent latent construct so that we have two practice (group) types in the model (see Section 2 in the Appendix C for CFA on the practice activities): Structured practice (Coach-led training and Competition) and Unstructured practice (Self-led training, Play with peers, and Indirect Activities).

The Grit subscales, Consistency of Interest (CI) and Perseverance of Effort (PE), were made from individual items confirmed by the CFA (see Appendix C, Section 1). One model always featured a second-order latent factor – Grit, made out of these two latent constructs of interest and perseverance. This has been a common way of dealing with the Grit scale in most of the studies (Cormier et al., 2021). We do have an alternative version of the model, however, where the CI and PE are included directly in the model, that is, without the overreaching Grit factor. This approach has been suggested recently because CI and PE can be easily considered as separate constructs (Credé, 2018; Credé et al., 2017).

All measures were normally distributed except the Practice activity, which was positively skewed. To alleviate the non-normality issues in the Practice measure, we log-transformed the variables. Given the small amount of missing data (< 5%), and the fact that the individuals with missing data did not have differing values from the individual with available data on the variables of the interest, we assume that the missing pattern was random (Van Buuren, 2018). Consequently, we analysed the data using the standard imputation techniques (Rosseel, 2012). The additional details and results of the SEM analyses are available in the Appendix C.

Results

Descriptive Analysis

The elite players started the activities rather early, around age of five, and by the age of 14 they have already accumulated over 5,600 hours of soccer-related activities (see Table 3.1). The estimates are in line with those reported from elite players in other countries (Ford et al., 2015). Their Grit estimates (average 3.7 on a 5-point rating scale) are generally high and similar, for example, to

those of West Point graduates (Duckworth et al., 2019). The consistency of interest subscale of Grit had a lower average than the persistence of effort subscale (3.7 vs. 4.2). The performance on the Perceptual-Cognitive ability is generally high as the players correctly answered around two thirds of the problems (see, also Larkin et al., 2016).

The inter-correlations followed expected patterns of results. Perceptual-cognitive abilities were significantly related to structured activities (Coach-led Practice and Competition) and Grit. Unstructured activities (Self-led (individual) Practice, Play, and Indirect Involvement) were, however, not significantly correlated to Perceptual-cognitive abilities (with an exception of Indirect Involvement for one of the perceptual-cognitive tests). The relations between constructs reflect the fact that we are dealing with a homogeneous, highly skilled sample. They often reach significance due to the large number of participants, but they are considerably lower than in similar research with heterogeneous samples (Ward et al., 2007).

Table 3.1. *Intercorrelations between main constructs: Perceptual-Cognitive ability (1-2), grit (3), Grit's subcomponents (4-5), and Practice (4-8).*

	1	2	3	4	5	6	7	8	9	10	M	SD
1. Decision Making	—										20.34	4.7
2. Situational Probability	0.28*	—									125.2	11.5
3. Grit	0.15*	0.17*	—								3.7	0.50
4. Consistency of Interest	0.13*	0.16*	0.90*	—							3.7	0.64
5. Perseverance of Effort	0.12*	0.12*	0.72*	0.34*	—						4.2	0.55
6. Coach-led Practice	0.13*	0.14*	0.18*	0.18*	0.11*	—					1003	497
7. Competition	0.12*	0.16*	0.22*	0.24*	0.09	0.42*	—				324	163
8. Self-led Practice	0.03	0.07	0.22*	0.21*	0.14*	0.36*	0.25*	—			794	707
9. Play with Peers	-0.01	0.06	0.15*	0.17*	0.06	0.20*	0.22*	0.55*	—		882	668
10. Indirect Involvement	0.17*	0.09	0.23*	0.24*	0.11*	0.25*	0.33*	0.35*	0.34*	—	2614	2002

* $p < .05$

Structural Equation Modelling (SEM) analysis

We used Structural Equation Modelling (SEM) to investigate the interplay between Practice and Grit in respect to Perceptual-Cognitive ability (see Figures 3.2-3.7). The Perceptual-Cognitive ability was always constructed by two manifest variables (Decision Making and Situational Probability), whereas Grit was either the second order factor made of consistency of interest (CI) and perseverance of efforts (PE) components or was represented directly by the components (CI and PE). The CI and PE latent constructs were created from the individual items (see Method). For the Practice construct, we first used Coach-led Practice as it is the closest construct to deliberate practice in sport domain. In the second model, we added Competition activities to the practice construct (in addition to Coach-led practice) as Competition represents another Structured activity and was shown to belong together with Coach-led practice in an independent CFA (see Section 2, Appendix C). Finally, the third model featured both structured (Coach-led practice and Competition) and unstructured practice (Self-led practice, Play with peers, and Indirect activities) as separate latent factors. In all three models, we provide formal tests between the models with Grit as the second-order factor and CI and PE as separate factors. At the end, we provide formal tests between the three models, as between coefficients of interest (e.g., CI vs. PE). We depict the standardized coefficients in the figures. The raw estimates and the associated standard errors can be found in the Appendix C, Section 3.

Coach-led practice model.

The first model (Model 1A) with Coach-led practice as Practice and Grit as the second-order factor is presented in Figure 3.2. Practice mediates the influence of Grit on Perceptual-Cognitive ability. Grit is a significant predictor of (Coach-led) Practice (standardized beta = .33; see Section 3 in the Appendix C for raw estimates), which in turn directly determines Perceptual-Cognitive ability (.22). The results of the formal mediation analysis (Hayes, 2017) indicate that the indirect effect of Grit on Perceptual-Cognitive ability (.07) is not quite significant (p = .061). The SEM model shows that Grit continues to exert considerable influence on Perceptual-Cognitive ability beyond the influence of (Coach-led) Practice. The direct effect of Grit on skill (.36) just failed to reach the significance level (p = .051). However, when one considers both the direct (.36) and indirect effect (.07), the total effect of Grit on skill is considerable (.44) and significant (p = .028). Overall, a change of a standard deviation in the (standardized) Grit score leads to a change of almost a half of standard deviation in the (standardized) Perceptual-Cognitive ability score (more precisely, .44).

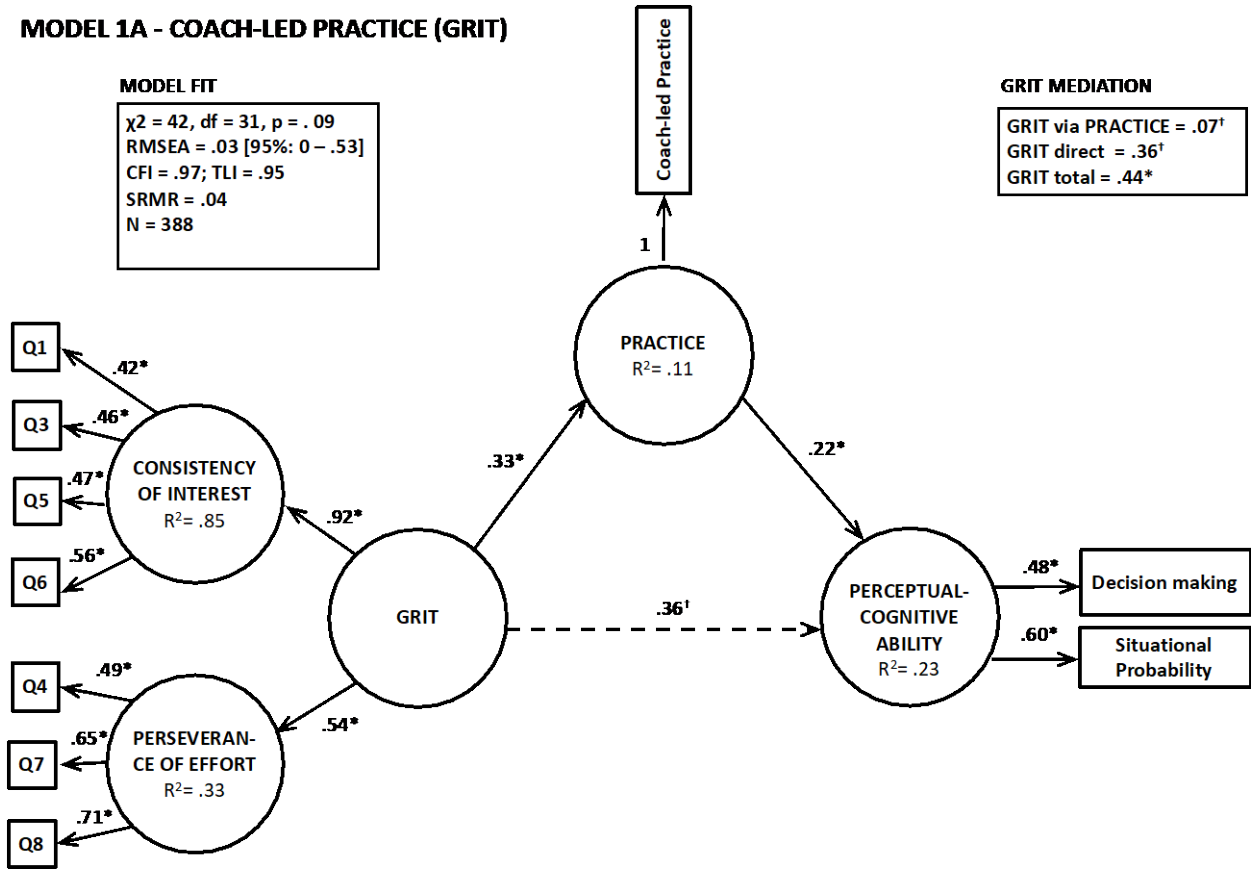


Figure 3.2. SEM model for Practice defined as Coach-led practice and Grit (Model 1A). The interplay between Practice and Grit (the predictors) and their influence on Perceptual-Cognitive ability (dependent variable). Dotted lines indicate non-significant relations, dashed lines borderline significant ones, while full lines indicate significant relations. The numbers on the line are standardized SEM model coefficients. The indirect influence of Grit on Perceptual-Cognitive ability through Practice is formally tested in a mediation model (upper right box). Model fit indices are presented in the upper left box. $^{*}p < .05$, $^{\dagger}p < .06$.

The same model can be estimated with CI and PE as separate latent constructs instead of Grit as the second-order latent construct (Model 1B). Now it is these two constructs that predict the skill levels directly and indirectly through Practice (see Figure 3.3). CI and PE are related constructs, as can be seen by their association (see also Table 3.1), but it is only CI that is relevant for the Perceptual-Cognitive ability. CI predicts positively Practice (.31), which in turn predicts the skill level (.24). This

mediation through Practice (.07) is not quite significant (p = .066), as is CI's direct association with skill (.26; p = .099). However, when both direct and indirect effects of CI on skill are included, the overall CI's effect on skill (.34) is statistically significant (p = .04). In contrast, PE does not affect the Practice (0) and its direct influence on skill (.10) is also not significant.

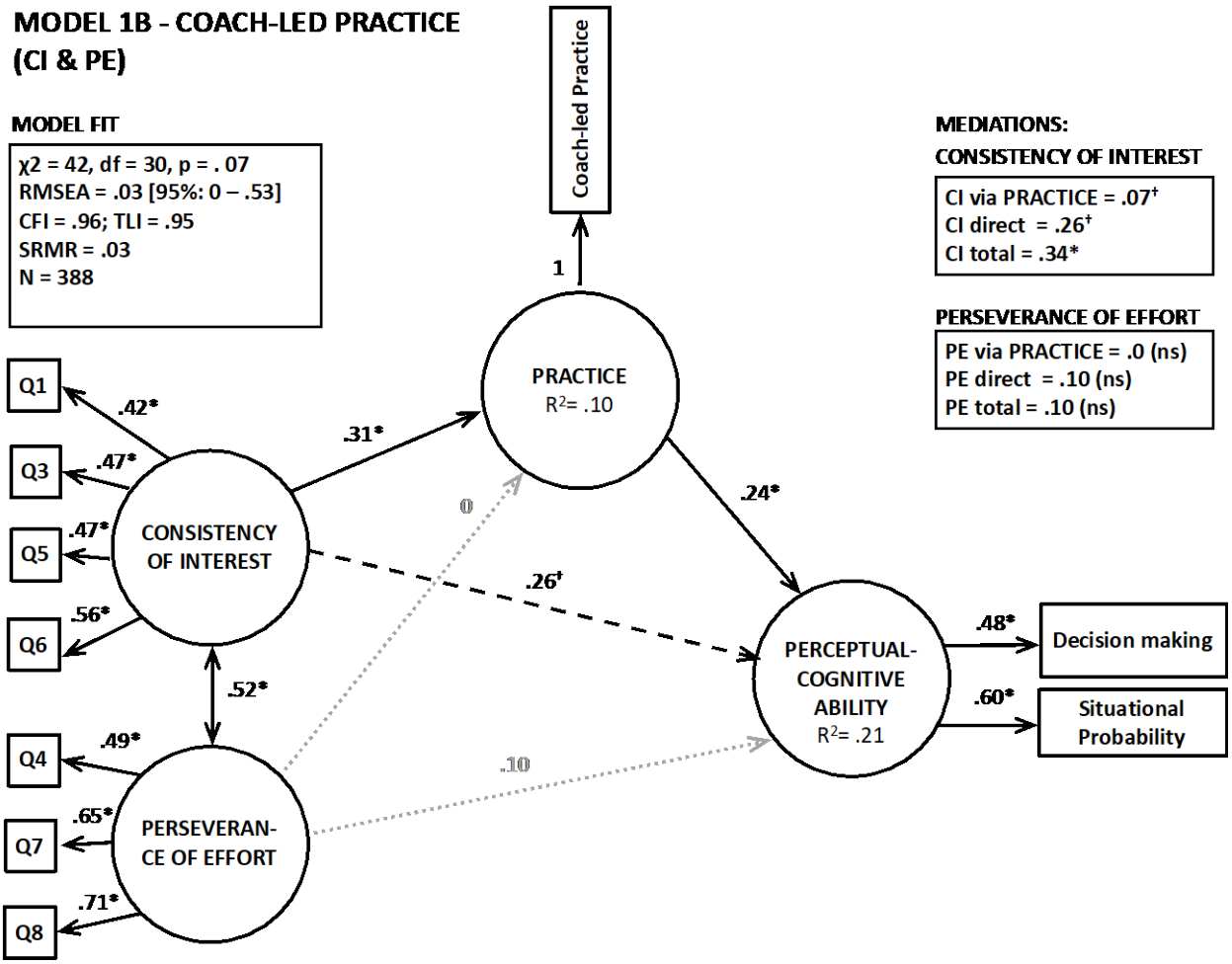


Figure 3.3. SEM model for Practice defined as Coach-led practice and CI & PE (Model 1B). The interplay between Practice, CI, and PE (the predictors) and their influence on Perceptual-Cognitive ability (dependent variable). Dotted lines indicate non-significant relations, dashed lines borderline significant ones, while full lines indicate significant relations. The numbers on the line are standardized SEM model coefficients. The indirect influence of CI and PE on Perceptual-Cognitive ability through Practice is formally tested in a mediation model (upper right box). Model fit indices are presented in the upper left box. *p < .05, †p < .06.

Both models, with Grit (Model 1A) and with CI and PE instead of Grit (Model 1B), explain the data well (see the upper right box in Figures 2 and 3). Formally, there is no difference between the two models either ($\chi^2 = .3$, df = 1, $p = .59$).

Coach-led practice + Competition model.

We extended our initial model by adding Competition, another Structured Practice, to the latent construct of Practice. Figure 3.4 shows the model where Grit is made of CI and PE (Model 2A). The results were similar to the previous model: Grit influenced Practice (.44), which then influenced skill (.33), whereas Grit explained skill beyond and above Practice too (.25). The actual mediation (.15) was significant ($p = .048$), unlike the direct effect (.25; $p = .15$). The overall influence of Grit on skill, directly and indirectly, was considerable (.40) and significant ($p = .04$).

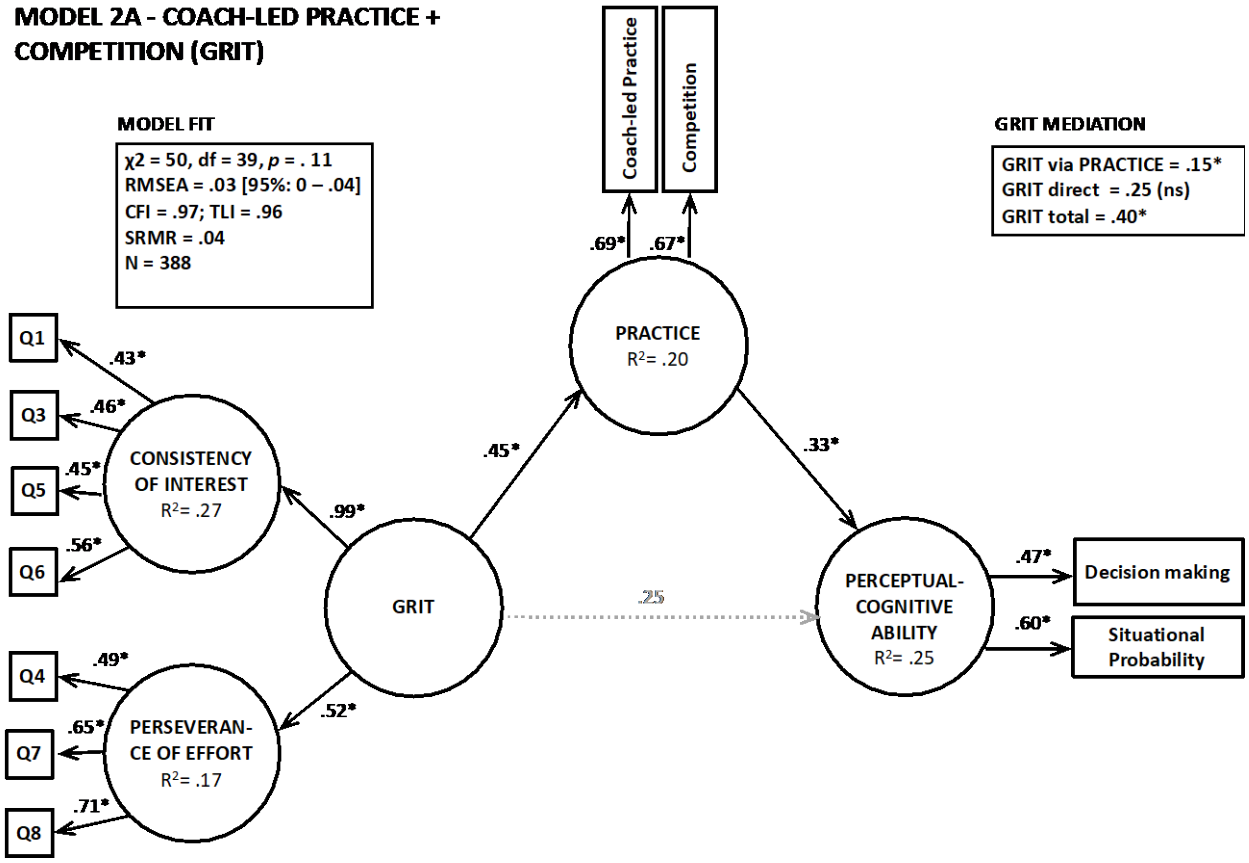


Figure 3.4. SEM model for Practice defined as Coach-led practice + Competition and Grit (Model 2A). The interplay between Practice (Coach-led practice and Competition) and Grit (the predictors) and their influence on Perceptual-Cognitive ability (dependent variable). Dotted lines indicate non-significant relations, dashed lines borderline significant ones, while full lines indicate significant relations. The numbers on the line are standardized SEM model coefficients. The indirect influence of Grit on Perceptual-Cognitive ability through Practice is formally tested in a mediation model (upper right box). Model fit indices are presented in the upper left box. $^{*}p < .05$, $^{\dagger}p < .06$.

When we modelled CI and PE as separate, albeit related, latent constructs (Model 2B), the results are similar to those found in Model 1B. Figure 3.5 shows that only CI is a significant predictor of Practice (.49), whereas the PE does not significantly predict how much players will practice (-.06; $p = .63$). Consequently, only CI has a significant indirect effect on skill through Practice (.17; $p = .049$). The direct effect of CI on skill (.19) was not significant ($p = .35$), but the overall effect of CI on skill, which includes the direct and indirect effects, was large (.36) and significant ($p = .038$).

Both models, with Grit (Model 2A) and with CI and PE instead of Grit (Model 2B), explain the data well (see the upper right box in Figures 3.4 and 3.5). There is formally no difference between the two models either ($\chi^2 = .9$, df = 1, $p = .33$).

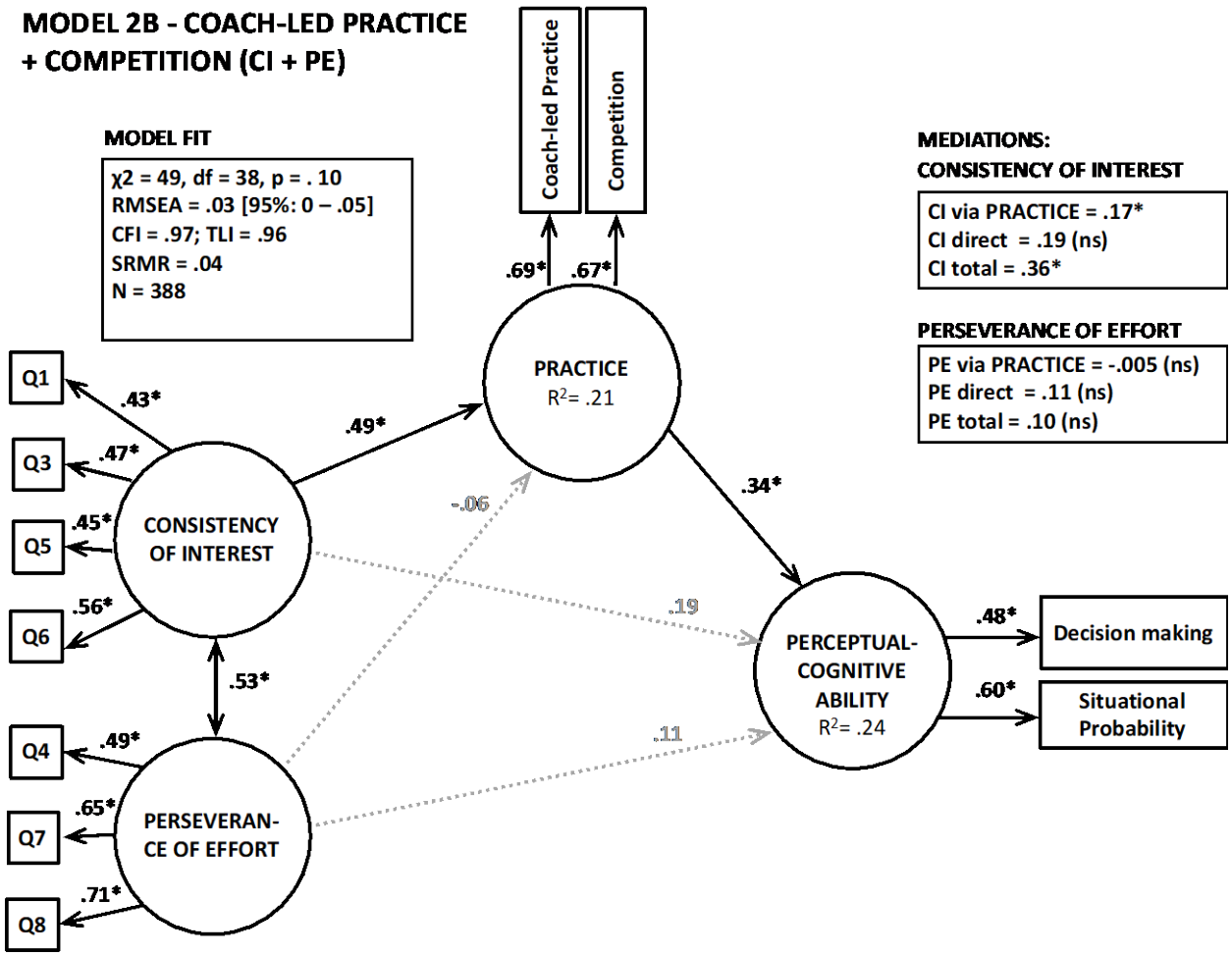


Figure 3.5. SEM model for Practice defined as Coach-led practice + Competition and CI & PE (Model 2B). The interplay between Practice (Coach-led practice and Competition), CI, and PE (the predictors) and their influence on Perceptual-Cognitive ability (dependent variable). Dotted lines indicate non-significant relations, dashed lines borderline significant ones, while full lines indicate significant relations. The numbers on the line are standardized SEM model coefficients. The indirect influence of CI and PE on Perceptual-Cognitive ability through Practice is formally tested in a mediation model (upper right box). Model fit indices are presented in the upper left box. *$p < .05$, $^{\dagger}p < .06$.

Structured and Unstructured Practice model

Finally, the last model included the Unstructured Practice activities, such Self-led practice, Play with peers, and Indirect activities, in addition to the Structured Practice activities. Model 3A had two latent Practice constructs which were predicted by Grit, and which predicted Perceptual-Cognitive ability (Figure 3.6). Grit was a positive and significant predictor of both Structured (.43) and

Unstructured (.43) Practice activities. Only Structured activities, however, were significantly predictive of skill level (.37). Unstructured activities had essentially no relation to Perceptual-Cognitive abilities (-.06). The mediation of Grit's influence on skill through Structured Practice was considerable (.16) but not quite significant (p = .66). The same was the case with the direct influence of Grit on skill (.28), which was not significant (p = .12). The overall Grit effect on skill was, however, large (.44) and significant (p = .037).

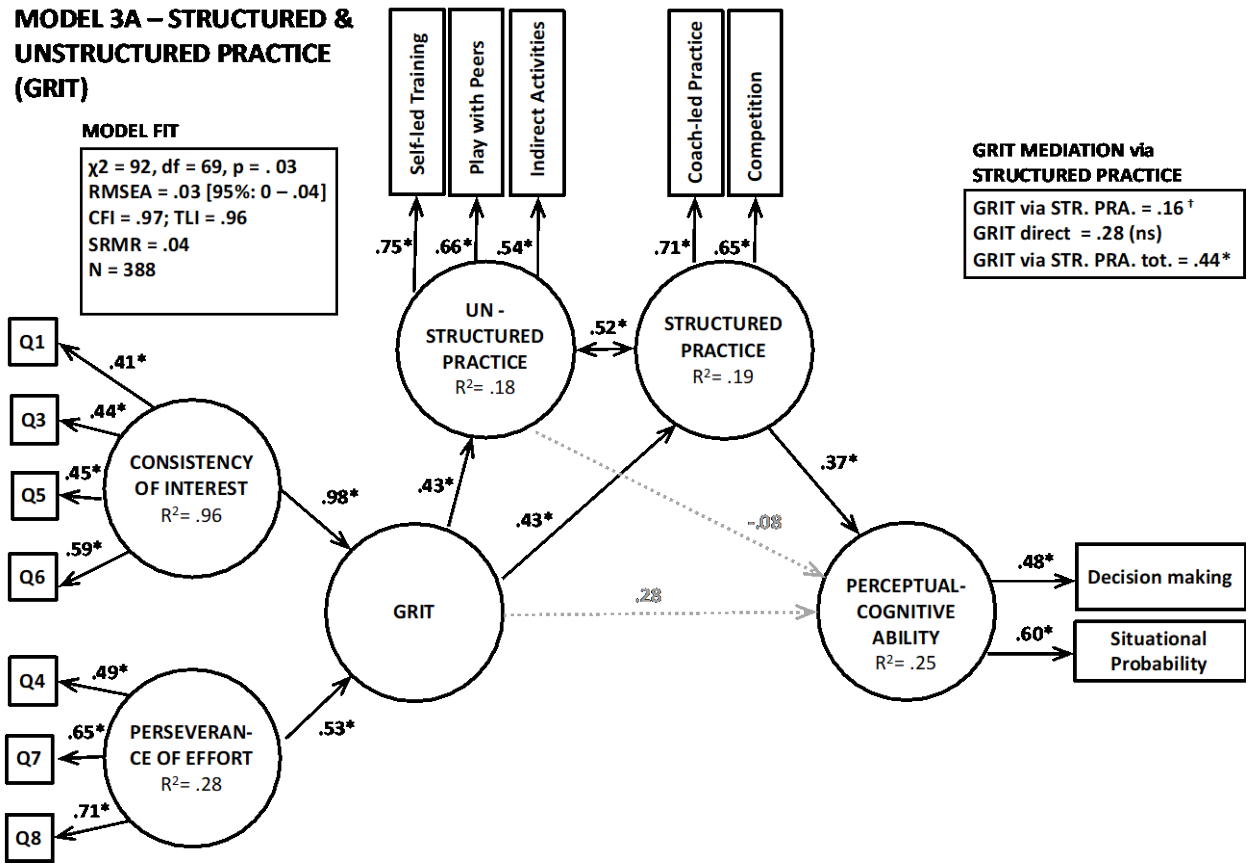


Figure 3.6 SEM model for Practice defined as Structured + Unstructured practice and Grit (Model 3A). The interplay between Structured (Coach-led practice and Competition) and Unstructured Practice (Self-led training, Play with peers, and Indirect activities), and Grit (the predictors) and their influence on Perceptual-Cognitive ability (dependent variable). Dotted lines indicate non-significant relations, dashed lines borderline significant ones, while full lines indicate significant relations. The numbers on the line are standardized SEM model coefficients. The indirect influence of Grit on Perceptual-Cognitive ability through Structured Practice is formally tested in a mediation model (upper right box; mediation through Unstructured Practice is not shown as it is negligible and not significant). Model fit indices are presented in the upper left box. *p < .05, †p < .06.

The alternative model where CI and PE are separate latent constructs, instead of a single Grit construct, produced similar results (Model 3B, Figure 3.7). Only CI was a significant predictor of Structured (.47) and Unstructured Practice (.41). Only the Structured Practice in turn was predictive of the skill level (.38). Consequently, the CI's impact on skill was mediated only through the Structured Practice. The mediation effect (.17) was again not quite significant (p = .065), similar to the direct CI's effect on skill (.17; p = .32). The overall CI's effect on skill (.35), which includes both direct and indirect effects, was also not quite significant (p = .051).

Both models, with Grit (Model 1A) and with CI and PE instead of Grit (Model 1B), explain the data well (see the upper right box in Figures 3.2 and 3.3). There is formally no difference between the two models either (χ^2 = .9, df = 2, p = .63).

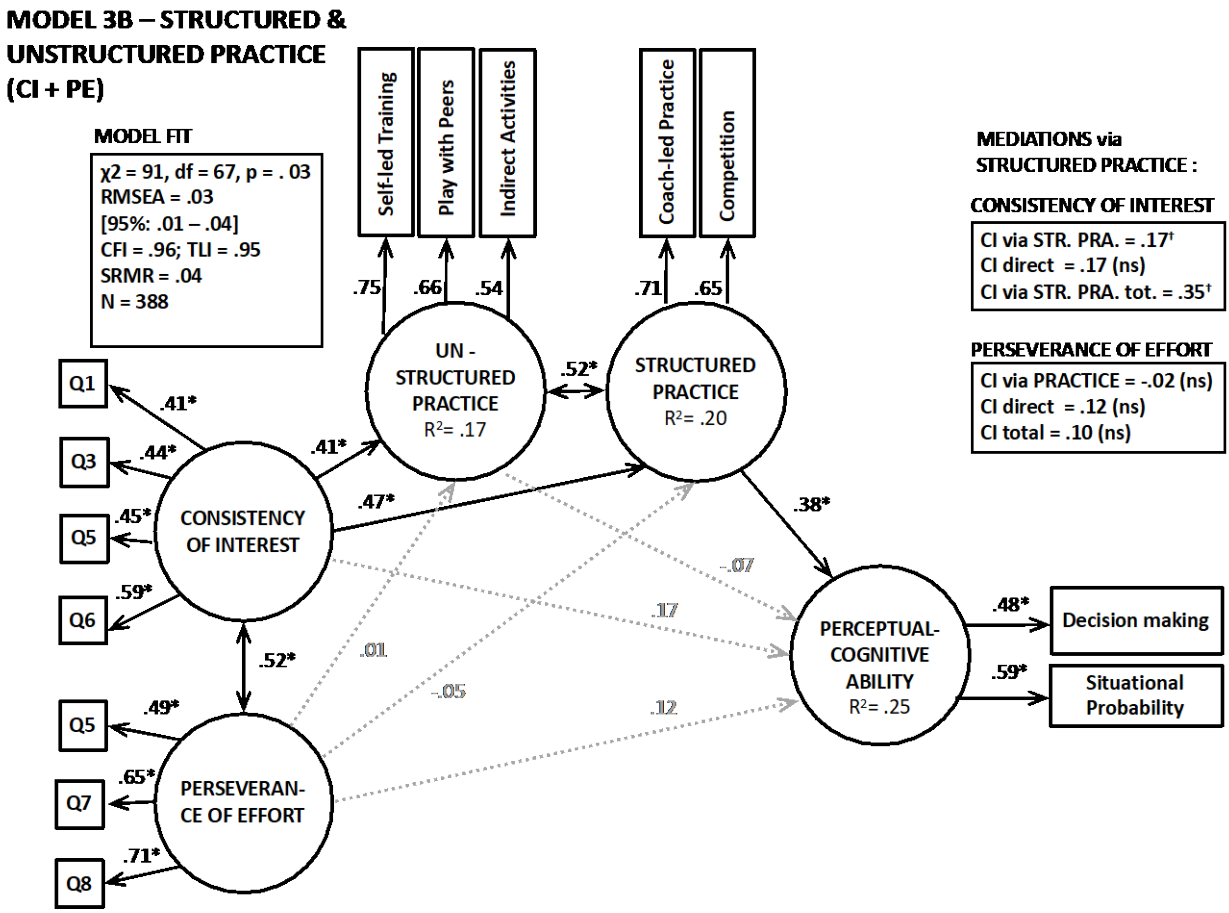


Figure 3.7. SEM model for Practice defined as Structured + Unstructured practice and CI & PE (Model 3A). The interplay between Structured (Coach-led practice and Competition) and Unstructured Practice (Self-led training, Play with peers, and Indirect activities), and CI and PE (the predictors), and their influence on

Perceptual-Cognitive ability (dependent variable). Dotted lines indicate non-significant relations, dashed lines borderline significant ones, while full lines indicate significant relations. The numbers on the line are standardized SEM model coefficients. The indirect influence of CI and PE on Perceptual-Cognitive ability through Structured Practice is formally tested in a mediation model (upper right box; mediation through Unstructured Practice is not shown as it is negligible and not significant). Model fit indices are presented in the upper left box. $^{*}p < .05$, $^{\dagger}p < .06$.

Comparison between models.

As shown above, there were no difference between two versions of the same model – one with Grit as a higher-order latent construct, and another with CI and PE as separate latent constructs. There were essentially few differences between the three models. The first two models had an excellent fit, while the third model, with Structured and Unstructured Practice, had a merely very good fit (see Model Fit box in Figures 3.2 through 3.7, left upper corner). The difference was, however, not significant. The difference between Model 1 (Practice as Coach-led training) and Model 2 (Practice as Coach-led training and Competition) is negligible. The first model fit somewhat better than the second, but the difference was not significant ($\chi^2 = 8.2$, df = 8, $p = .42$ for models with Grit, and $\chi^2 = 7.5$, df = 8, $p = .48$ for the models with CI and PE). The first model was better at describing the data than the third model, but the difference was not statistically significant ($\chi^2 = 49.8$, df = 38, $p = .09$ for models with Grit, and $\chi^2 = 49.1$, df = 37, $p = .09$ for the models with CI and PE). The same situation was found when we compared the fit of the second and the third model ($\chi^2 = 41.6$, df = 30, $p = .08$ for models with Grit, and $\chi^2 = 41.6$, df = 29, $p = .06$ for the models with CI and PE). Consequently, all three models could be used for practical purposes.

Consistency of Interest (CI) vs. Persistence of Effort (PE).

The CI was consistently more significant predictor of Practice (and sometimes Perceptual-Cognitive ability) than PE. One should not, however, assume that the CI was significantly stronger predictor than PE. For that statement, one would not only need to check the significance in relation to other constructs (e.g., CI is a significant overall predictor of skill, whereas PE is not), but one would need to a) compare the actual coefficients of the two constructs directly or b) compare models (fits) with one construct and without the other. Our SEM models allow for such direct comparisons of either coefficients or differing models. Although the differences between CI and PE's overall influence on

skill are considerable (e.g., .34 vs. 10 in Model 1B – see Appendix C, Section 4) they are not reliable enough to produce statistical significance in any of the three models (*p* between .10 and .20 – see Appendix C, Section 4). Similarly, when we estimate Model 1B (or Model 2B and 3B) with CI and without PE, as well as with PE and without CI, the two models are not significantly different (*p* between .08 and .30).

Discussion

We demonstrated that the personality trait of Grit influences both indirectly and directly the development of sporting expertise. The indirect influence is through practice, as youth soccer players who display more persistent effort and consistent interest accumulate considerably more highly structured and effortful practice than their less gritty peers. The accumulated Structured Practice then determines the level of Perceptual-Cognitive ability because the players who spent more time on soccer-related activities demonstrated higher levels of perceptual-cognitive skill. However, Grit trait still influences the level of skill (directly) even when its influence via Practice has been accounted for. Overall, total Grit influence on the development of soccer expertise is sizeable. A Grit score higher for only one standard deviation leads to almost half a standard deviation better performance score. Most of Grit's influence on skill is direct (.36 / .44 = 81%), but a considerable chunk is indirect, through (deliberate) practice (.17 / .44 = 19%).

Grit's role in development of skill

It is not surprising that individuals, who are more interested, and more willing to exert effort, accumulate more domain-related activity. The difference in Grit or Conscientiousness traits has been regularly found between experts and novices across multiple domains (Duckworth et al., 2009, 2011, 2019; Eskreis-Winkler et al., 2014), including sports (Hodges et al., 2017; Tedesqui & Young, 2018). The effect of grit in our study is remarkable because it differentiates within elite (youth soccer) players. It is feasible that small initial differences can snowball to large effects over time. Grittier players probably continuously log more practice time than their less persistent peers. The differences may not be large at the beginning, but with time, they become more and more visible. By the time they are teenagers, the accumulated hours under the influence of Grit differ even among the very best athletes in the country.

Arguably the most important result of our study was that the non-cognitive personality factor Grit influenced the skill level among elite youth soccer players even after the influence of Practice was accounted for. The extent of Grit's influence was also considerable and comparable to that of Practice, which is regularly a primary determinant of skill level (Ward et al., 2007). The indirect influence of Grit on expertise through Practice is predicted through theory (Duckworth et al., 2011; Ericsson et al., 1993). Gritty players spend more time on domain-related activities, particularly those important for skill acquisition as they tend to be less inherently enjoyable. This in turn leads to the acquisition and development of mental structures that enable experts' outstanding performance (Ericsson & Pool, 2016). But how does a non-cognitive factor influence expertise directly, as we found to be the case in this study?

One possibility is that gritty players would be able to perform better on perceptual-cognitive tests due to sheer effort on the test, at least not to the extent found in our study. Other studies have found that Grit incrementally predicts achievement over and above the influence of other factors (Akos & Kretchmar, 2017; Duckworth et al., 2007; Eskreis-Winkler et al., 2014). However, none of these studies looked for mediated effects of time on the performance. The sole exception is the study on contestants in the spelling bee contest which found that Grit mediates spelling performance through deliberate Practice (Duckworth et al., 2011). In contrast to our study, the direct relation between Grit and performance was not significant once the (deliberate) Practice was accounted for.

More likely, however, it is that Grit affects performance through the influence of another cognitive factor that we have not taken in our account in our study. Grittier players, for example, may engage more in metacognitive processes than their less accomplished peers, reflecting upon and evaluating decisions made in training sessions as a means of analysing and ultimately improving performance. The metacognitive processes then influence performance. Jonker and colleagues (2012) showed that the metacognitive process of "reflection" successfully discriminated between athletes competing internationally from those competing nationally. The authors argued that the propensity for elite athletes, across multiple sports, to reflect upon performance, effectively extended the learning benefits from practice beyond the confines of the practice session. The results of the current study showed grittier players perform better on skill-related tasks (see, also Hodges et al., 2017). Future studies should investigate whether the link between Grit and experts' performance is mediated through metacognitive ability.

Consistency of Interest (CI) and Perseverance of effort (PE)

Unlike most of the studies involving Grit (Cormier et al., 2021), we investigated both Grit as a unified single measure, and CI and PE separately as Grit's components. In the latter instance, we featured both CI and PE in a single model (instead of separately assessing them), which enabled us to directly compare their influence. Our analyses show that CI is a better predictor of both (deliberate) Practice and skill than PE. CI had higher simple correlations with Practice and performance indicators than PE (see Table 1), as well as considerably higher overall influence (direct + indirect) on skill (.34 vs. 10 in Model 1; .31 vs. .10 in Model 2). The overall effects of CI on skill were significant, unlike those of PE (see Figure 3 and 5). However, here comes the caveat, which is applicable to some of the previous studies on CI and PE - which claimed that one is stronger than the other based on one component being statistically significant predictor, while the other is not (Lee & Sohn, 2017; Tedesqui & Young, 2018). When the influence of CI on skill was formally compared to its PE counterpart, the differences were not statistically significant either when they were directly compared or when the models with and without the individual components were pitted against each other (see Appendix, Section 4).

It is noteworthy that our finding of CI being seemingly more important than PE bends the current trend of research on these two components of Grit (Credé et al., 2017). PE is the sole predictor of success in academic settings (Crede et al., 2017) and has been shown to differentiate between differently skilled athletes (Tedesqui & Young, 2017, 2018). One possible explanation for the trend in our study is that the soccer players were all around 14-15 years of age, unlike in most of the other studies which featured older participants. According to the early diversification pathway in Cote's developmental model of sport participation (Côté, 1999; Côté & Vierimaa, 2014), athletes of that age would be making the transition from "sampling years" during childhood (6-12 yrs.) to the "specialization" years during adolescence (13-18 yrs.). During the sampling years, when children are exploring different sports and developing interest in sport engagement, CI would be a prime candidate for developing skill through consistent interest in the sport activity. In contrast, during the specialization phase, when developing elite players focus on more complex and demanding forms of practice within a single sport, PE may exert more of its influence.

(Deliberate) Practice in sports

Grit only exerted influence through highly Structured Practice such as team training led by a coach (see Fig. 3.2 and 3.4). This is not an unexpected result given that this kind of practice is most

challenging (Hendry et al., 2019) - something that grittier players should deal with easier than their less gritty peers. This kind of highly structured practice was also predictive of the soccer skill, which again calls for rethinking of the definition of deliberate practice in certain domains. Although it is not solitary training, designed and monitored by a coach who provides feedback, which would constitute the classical definition of deliberate practice (Ericsson et al., 1993; Ericsson, 2020b), it is arguably more related to performance than individual training with a coach would be (Hendry & Hodges, 2018). Soccer is after all a team sport where coordination of all 11 members is a prerequisite of success. Interactive practice with other team members under the correcting supervision of the coach(es) is essential for the acquisition of mental structures necessary for developing skill in team sports. It is no wonder then, that the interactive team practice has been regularly shown to be one of the best predictors of skill in team sports (Ford et al., 2009; Helsen et al., 1998; Hendry & Hodges, 2018; Hodges et al., 2004; Starkes et al., 1996; Zibung & Conzelmann, 2013) and as such, it should constitute a part of deliberate practice activities in team sports.

A number of practice activities, such as playing with peers (Play), watching soccer on TV (Indirect Involvement), and even self-training (Self-led individual practice) were not predictive of soccer skill (see Figures 3.6 and 3.7). None of these activities involve the necessary immediate augmented feedback, which is prerequisite for successful learning (Bilalić, 2017; Ericsson et al., 1993). They are also much less effortful than interactive team practice, which is reflected in the smaller influence of Grit on the Unstructured Practice compared to the Structured Practice. It is then expected that they are not going to be relevant in differentiating between skill levels of a homogenous elite sample, as it was the case in our study. What was less expected is that the actual time spent in official competitions was highly predictive of soccer skill. The finding runs counter the deliberate practice framework, as in official competition there should not be enough opportunities for repetitive-corrective practice of certain weaknesses (Ericsson et al., 1993)

However, this finding may demonstrate the opportunities within the talent development pathway for youth players to engage in official competition games. For example, more skilled players may have had the opportunity to play in more competitive games as a result of being selected to play in numerous competitions such as school, regional, state and national team competitions. A potential benefit of playing competitive games is the environment promotes athletes to execute technical and tactical skills within a performance environment. Therefore, engaging in more competitive games may provide greater opportunities to refine these skills for effective performance (Ford et al., 2015). This notion is supported by previous research which has indicated that competitive experiences do influence technical and tactical skill development in open skill sports (Nielsen & McPherson, 2001).

Despite our large sample, which circumvented the typical restriction of range problem in expertise studies, we still tested a highly homogeneous sample. It is likely that including less successful children who, by the time of testing, in their early teenage years, either ceased the activity or played considerably less, would have produced different results. We assume that practice may trump all other factors to such an extent that we would be able to find only an indirect influence of grit (through practice) on performance. The homogeneity of our sample is also reflected in a relatively low explained variance of performance – 23%. The same variables, even Practice alone, regularly explain a much larger share of experts' performance in heterogeneous samples (Hendry & Hodges, 2018; Vaci et al., 2019; Ward et al., 2007). It is possible that the addition of other cognitive and non-cognitive variables such as physical ability and motivation may improve the explanatory power of the model.

The Grit scale turned out to be far from perfect. As in other studies, one of the items in the PE component did not fit well and had to be discarded (Dunn et al., 2021; Shields et al., 2018; Tedesqui & Young, 2017, 2018). The obtained factor structure (see Section 2, Appendix C), did fit the data but the associated measurement error was considerable. This is evident by the small loadings to the latent constructs of CI and especially PE, as well as the little explained variance in these latent constructs (see, for example, R^2 in Figures 3.2 and 3.4). Unlike other statistical procedures, such as path analysis, SEM considers the associated error measurement into the further calculation of the structural model (here the mediation). The consequence is that even very large coefficients may not reach statistical significance level due to the associated variance. This is the case in our study where we have a paradoxical situation that the direct influence of Grit on skill is considerably larger than that of Practice on skill (.36 vs. .22 in Figure 2), but does not quite reach the statistical significance level, unlike the practice coefficient. The unreliability of the Grit scale is evident in all Grit-related relations, including the large but not quite significant indirect effects.

We used the short grit scale (Grit-S), which features 4 fewer items than the original Grit scale (Grit-O). However, there is evidence that the difference in reliability and validity of the two scales is minimal (Hasan et al., 2020), or that the shorter scale has even better psychometric properties (Credé et al., 2017). This problem with the Grit scale has been long well concealed, despite some recent critiques (Credé, 2018; Tedesqui & Young, 2017). One of the reasons is arguably the use of composite scores, whether for the overall Grit scale, or for the CI and PE components. The composite scores, which are then used in regression analyses, carry the assumption that there is no measurement error (i.e. that the constructs have been perfectly captured). This, in turn, supresses variance and leads to inflated coefficients and its significance. For example, in our study the use of the composite scores in a path analysis would have increased the size of all relations for about 30% and considerably

improve their statistical significance (see Section 4 in the Appendix C). Therefore, future studies should consider using more appropriate statistical tools, such as SEM, which account for the unreliability of the actual measurements of the constructs, as well as adapt the Grit scale (for recent recommendation of adaptations of Grit scale see Tynan, 2021).

Our results point out the importance of personality factors in expertise. Their importance may be particularly pronounced in elite samples where classical factors, such as practice and talent, may explain only a small chunk of performance. This is evident in our study which demonstrates that one such factor, the trait of Grit, had, overall, a bigger impact on the performance of elite youth soccer players than practice. However, the relative unreliability of the Grit scale may preclude practitioners from its inclusion, at least in the form that is in now, in their talent identification and development process assessments. Nonetheless, that should not stop future researchers and practitioners from taking into considerations other conative factors.

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Data and materials availability

The data and the code used for the analyses can be retrieved here.

Chapter 4: Snowball effect of grit on (deliberate) practice

Abstract

To master any skill, an extensive immersion in that domain is necessary. Practice is therefore often considered one of the main components of expertise development. Little is known, however, about the process of practice acquisition and even less why people practice in first place. Here we demonstrate, in a large sample of elite young Australian soccer players, that players acquire different amounts of practice at different stages of practice acquisition. Starting from the age of eight, the players engaged in a similar amount of domain-specific activities every year until the age of 13. The logged hours suddenly increased at the age of 13, producing an accelerated and curvilinear pattern of practice acquisition. More importantly, the practice acquisition process is heavily influenced by the personality trait of grit at its every stage. Grittier players start accumulating more practice hours already at the beginning and continue to consistently log in more hours throughout the years. That way, initially small differences in engagement snowball into sizable ones at the age of 15. The impact of grit on practice acquisition is, however, more subtle at the level of its two components, consistency of interest (CI) and perseverance of effort (PE), as they exert a different pattern of influence. CI is the driving factor of the initial differences and their consistent snowball effect until age of 13, while it is the PE that impacts the acceleration period from age 13 to age 15. We elaborate how our findings about practice acquisition process and its motivational factors extend current theories of expertise development in sport.

Keywords: Sport Expertise, (Deliberate) Practice, Grit, Soccer, Longitudinal study, Multilevel analysis

Introduction

While, in Chapter 03, we have discussed the role and impact (of interplay) of (deliberate) practice and conative factor, grit, have on expert performance (perceptual-cognitive skills); in this chapter we further that investigation by looking into, and discussing, how elite youth soccer players accumulate (their) practice hours, as well as, what is the role of the conative factor grit in that engagement accumulation.

It has been well established in the literature that for skill acquisition, especially perceptual-motor skill, practice is the key factor (Baker & Young, 2014; Ericsson, Krampe, & Tesch-Römer, 1993). Despite numerous academic articles and books researching, looking into and discussing the importance of practice (Campitelli & Gobet, 2011; Ericsson, 2020b; Macnamara & Hambrick, 2020), different practice types (Baker & Young, 2014; Ericsson & Harwell, 2019), or mechanisms of making practice as effective as possible (Ericsson & Pool, 2016), the questions of motivation, why people practice in first place, as well as its impact on practice, still remain unresolved. Among numerous biological and psychological factors impacting the motivation to practice (Hambrick et al., 2018), grit, a psychological trait of persistence and determination, seems to be a good candidate for understanding the reasons behind one's practice. Here we investigate the interplay between practice and grit in a large sample of elite young Australian soccer players. We show that an initially small difference between gritty and less gritty elite youth players in the amount of time accumulated (engaged in sport-related activities) snowballs into a difference maker as the grittier players consistently log more practice (than their less gritty peers) over the years. Grit's component, consistency of interest (CI), is the driving factor behind this snowball effect, but the other grit's component, perseverance of effort (PE), is the one that influences the acquisition of practice in the later phase when players become serious about their chosen domain.

Practice

Expertise, in any field, requires domain specific knowledge (Broadbent, 2015), which can be cognitive and/or kinetic in nature depending on the field (Bilalić, 2017). To enquire this knowledge, experts expose themselves to and immerse themselves in prolonged engagement in domain related activities(Baker & Farrow, 2015). Through that engagement, experts form mental structures necessary for development of their expert knowledge, and skills (Bilalić, 2017; Broadbent, 2015). That

knowledge helps experts to easily orient themselves in their domain and, upon stumbling on problems, automatically produce adequate solutions by activating appropriate mental structures that were previously required. In other words, one needs to be thoroughly immersed in a domain for prolonged time in order to become proficient in it (Ericsson, 2020b). Even though practice has been clearly outlined as necessary, underlying factor of expertise (Baker & Young, 2014; Ford & Coughlan, 2019), not all types of practice are equally beneficial for development of expert skills and knowledge - activities that mimic the underlying perceptual, cognitive and motor demands of a field considered more important (Hendry & Hodges, 2018; Roca & Williams, 2017).

Deliberate practice, a goal-driven activity focused on repetitions followed by feedback, aimed at improving performance and weeding out weaknesses, is deemed to be the key factor (Ericsson, 2008; Ericsson et al., 1993). According to Deliberate Practice Framework (DPF), the prototypical form of deliberate practice would be practice that was designed and supervised by a teacher/coach conducted in a solitary manner (Ericsson & Harwell, 2019). In line with that framework, in soccer, for example, only one-on-one practice designed and supervised by a coach on goalkeeper's catching technique, with constant feedback provided by the coach, would be considered deliberate practice. Playing with peers, practicing with the team or even playing in the matches would not afford the same amount of practice or feedback and would therefore lead to less improvement (plus mistakes would be very costly if made during the matches).

As discussed in Chapter 3, early studies on deliberate practice demonstrated its importance for predicting expert performance in various domains, sport (Ford et al., 2009; Helsen et al., 1998; Hendry et al., 2018; Sieghartsleitner et al., 2018) and non-sport alike (Burgoyne et al., 2019; Charness et al., 2005; de Bruin et al., 2008; Nandagopal & Ericsson, 2012; Ericsson et al., 1993; Plant et al., 2005). Recent reports and meta-analyses (Hambrick et al., 2016; Macnamara et al., 2014, 2016; Macnamara & Maitra, 2019), however, cast some doubt on the extent of the impact deliberate practice has on expert performance – showing that deliberate practice alone explained 18% of expert performance in sports (average r = .42), 26% in games (r = .51), 21% in music (r = .46), 4% in education (r = .16) and 1% in professions. Even more troubling are the studies showing that the impact of deliberate practice seemed to be even smaller and, in some cases, negative when only expert samples were taken into consideration (Güllich, 2014; Johnson et al., 2006; Macnamara et al., 2016). Although this can be contributed to restricted range of performance (Pearson, 1902; Vaci et al., 2014), which suppresses relations between variables, it indicates that, at the highest level, some other factors may be in play when explaining and understanding expert performance (Ford & Williams, 2012; Hardy et al., 2017; Tucker & Collins, 2012). Even so, Ericsson and Harwell (Ericsson & Harwell, 2019) demonstrated

that when activities are more precisely defined and differentiated between deliberate practice and other types of practice activities, estimates of influence deliberate practice has on expert performance increases to 61% of explained expert performance across various expert domains. Ongoing discourse on what exactly constitutes deliberate practice (Ericsson, 2020a, 2020b; Ericsson & Harwell, 2019; Macnamara & Hambrick, 2020) showcases the difficulties in identifying deliberate practice activities in some domains, particularly so in the domain of (team) sport. An extension/modification of the definition of deliberate practice may be required for application in domains that differ from the one the original definition was conceptualized in.

(Deliberate) Practice in sport

Originally, solitary practice that was devised and supervised by a teacher or a coach was the only type of practice considered deliberate. Nowadays, what is considered deliberate practice in team sports, such as soccer, is one of the contentious points in our understanding of it and may have played a role in meta-analytic findings casting the doubt on role of deliberate practice for expertise (Macnamara et al., 2014, 2016; Macnamara & Maitra, 2019). Baker and colleagues (2020) do an in-depth analysis on DPF, the lanes of research of DPF in sport, pointing out the commonalities in them, as well as current trends, and pointing out the two critical conditions for defining deliberate practice in sport: 1) deliberate selection and development of activities to improve performance (Deliberate design); and 2) athletes' concentration and conscious cognitive effort to make refinements throughout the iterations of DP activities (Deliberate engagement). In other words, according to Baker and colleagues' (2020) revision of definition, no particular activity could be considered deliberate practice in absolute terms – it is highly individualized, thus making it much harder for athletes to recall and utilize as a measurement in scientific studies (as different activities would be considered deliberate practice during different periods of expertise development). It is for this reason that a lot of studies investigating practice in sport domain, as well as its correlates, utilize so called „accounting approach" (Baker et al., 2020), where they simply take into count the number of hours athletes' spend in different sport-related activities and then group those activities, based on different criteria, and compare them against one another or against time spent in non-sport related activities (Baker & Farrow, 2015). Training together with the rest of the team, under a coach's supervision, in a structured pre-planned practice, would simulate competition conditions closely and be highly beneficial not only for individual players, but the team as whole. The importance of this type of practice has been shown empirically, as the amount of time spent in it was able to discriminate between experts and their less

accomplished peers (Ford et al., 2009; Helsen et al., 1998; Hodges et al., 2004; Ward et al., 2007; Zibung & Conzelmann, 2013). Analyses on the distribution of time coaches allocate to different types of practice whithin a practice session showed that they spend 2-3 times more time doing team activities than individual drills (Ford, Yates, et al., 2010; Ford & Whelan, 2016; O'Connor et al., 2017; Partington & Cushion, 2013). Individual training, even though closer to the original conceptualization of deliberate practice, is rarer occurrence and might lack perceptual-cognitive conditions needed to facilitate transfer of knowledge and development of mental structures necessary for improvement of performance (Ford, Low, et al., 2010). Leaving aside the current controversy (Ericsson, 2020b, 2020a; Hambrick et al., 2016; Macnamara & Hambrick, 2020) about whether practice (and what kind of practice) is sufficient (Ericsson, 2008; Ericsson, et al., 1993) or just necessary (Campitelli & Gobet, 2011; Moreau et al., 2019) component of expertise, practice is an essential ingredient as it helps in forming mental structures required for experts' outstanding performance (Bilalić, 2017). However, the questions regarding its sufficiency remain as there is still a large part of expert performance that remains unexplained.

(Deliberate) Practice through sport expertise development

Côté and colleagues (Côté, 1999; Côté et al., 2001; Côté & Hay, 2002; Côté & Vierimaa, 2014) provided a model of sport participation, based on data gathered from in-depth interviews with young elite athletes and all their family members, that describes (and predicts) ways in which youth athletes engage in sport-related activities during different periods of their development, called Developmental Model of Sport Participation (DMSP). They identified distinct stages of sport engagement that athletes pass through in order to attain expert performance: the sampling years (6-13), the specializing years (13-15), the investment years (15-18) and perfection/performance years (18+).

The sampling years are characterized by athletes participating in wide variety of sports and sport-related activities and are typically when athletes develop basic skills and fundamental movement mechanics (such as running, catching a ball in timely manner, et cetera). Athletes' parents are the ones that have the leadership role as they provide opportunities for their children to try out bunch of different sporting activities and enjoy sport in general. Fun and enjoyment are at the heart and focus of this period – overall sport participation is what is deemed more important than specific sport(s) athletes engage in (nor their level or performance). In other words, Côté and colleagues point out greater importance of deliberate play compared to deliberate practice during the sampling years.

The specializing years are when athletes begin to narrow their focus on a specific sport, increasing their interest in it, and participate in fewer activates that are not related to the main sport of interests (than they did during the sampling years). During this period athletes take over the leadership role from their parents and decide how they will spend time engaging in sport-related activities, while parental role becomes more supportive (in both, monetary and temporal terms). Fun and excitement are still central elements with sport specific skill development (through practice) emerging as equally important. That is, in specializing years the importance of deliberate practice increases and is equal to the importance of deliberate play.

During the investment years, athletes become devoted to a single sport and achieving elite level of performance is a sole purpose of their lives. Athletes are in full control of their sporting engagement, while the role of their parents is to support them and provide them with help during setbacks hindering training progression. Strategic, competitive and skill development characteristics of sport are the most important elements of this stage – deliberate practice is deemed much more important than deliberate play. Finally, perfection/performance years are marked by the maintenance and perfection of the developed skills, as well as their utilization in competitive contexts.

Following its publication, numerous studies have been conducted testing and eventually supporting DMSP and its postulates (for review, see Côté & Vierimaa, 2014). Even though DMSP provide us with an idea of what type of sport engagement could be expected from elite children athletes during different stages of their development, the question of motivation still remains. Reasons behind why one engages in such a practice to being with (despite the increasing sacrifices it requires) and how these motivating factors impact further engagement in sport-related activities are still unclear.

Grit

One of those factors could be a personality trait known as grit. Grit is defined as persisting interest and determination in achieving long-term goals in spite of challenges and setbacks (Duckworth et al., 2007, 2019; Hodges et al., 2017; Tedesqui & Young, 2018). Colloquially, it can be understood as persevering (at a long-term goal) despite obstacles and challenges (Duckworth et al., 2019; Roberts et al., 2014). Although it is seen as part of conscientiousness, one of personality traits from Big five, grit is differentiated from conscientiousness by its predicting strength and by emphasizing long-term stamina instead of short-term intensity that is relevant for conscientiousness (Duckworth & Gross, 2014; Duckworth et al., 2007).

Duckworth and Quinn (2009) conceptualized grit is a higher order construct, composed of two subordinate facets: *Perseverance of effort (PE)* and *Consistency of interests (CI).* PE refers to one's ability to maintain effort in face of difficulties, while CI refers to continuous interest, throughout time, on a single life-goal instead of focusing on different superordinate goals over short periods of time (Duckworth & Quinn, 2009). In other words, CI represents direction of one's passion, while PE represents magnitude of effort put forward in pursuit of that passion (Tedesqui & Young, 2017). However, construct validity of grit, as a higher order structure, has been questioned. A recent meta-analysis, done on studies conducted in academic domains, shows that only PE explains variance in performance and has significantly stronger criterion validity than CI (Credé et al., 2017). Therefore, it has been recommended that researchers, when studying grit, analyse these two facets separately instead of analysing grit as a composite score (Credé, 2018, 2019). Since these conclusions have been drown from the research in a non-sport domain, and since the participants differed in age and level of expertise compared to our sample, we used both grit as a composite, as well as two facets separately, in this study. Furthermore, studies (Duckworth & Gross, 2014; Duckworth et al., 2011; Duckworth & Quinn, 2009) demonstrated that grit questionnaires modified to refer to specific context that is being researched (i. e. behaviour in sport, behaviour in school, etc.), instead of measuring grit in general, provide better measures of grit. It is because of this that this study utilized adapted grit measures as well.

Girt has been shown to add onto the explanation of exert performance, in both academic and non-academic settings (including sports), beyond practice and ability (Akos & Kretchmar, 2017; Cormier et al., 2021; Duckworth et al., 2019; Eskreis-Winkler et al., 2014; Jachimowicz et al., 2018). Grittier athletes are more likely to persist and practice more, despite adversities, than their less gritty expert peers, who slightly underperform in comparison (Sigmundsson et al., 2020). Additionally, grit has been shown to have some predictive power even when measured only on highly skilled samples (DeCouto et al., 2021; Larkin et al., 2016). However, the studies investigating relationship of grit and (deliberate) practice, as well as their combined influence on expert performance, in both heterogeneous and homogenous samples, are scarce in the field of sport (for a review, see Cormier et al., 2021). Most studies have shown a positive association between grit and different measures of performance in various sports (Ansah & Apaak, 2019; Doorley, 2021; Doorley et al., 2022; Elliott, 2018; Shaver, 2017), while those which failed to capture that relationship (e.g. Criticos et al., 2020) tended to use smaller sample sizes (e.g. N = 9).

When it comes to practice, grittier athletes, overall, have been found to log in more hours of practice and persist despite setbacks (Fawver et al., 2020; Larkin et al., 2016; Tedesqui & Young,

2017, 2018) - a finding that is common in non-sport domains (i. e. Duckworth et al., 2011; Ericsson, 2020a). Cousins and colleagues (2020) found only one facet of grit, CI, to be correlated with number of years athletes spent practicing, while one replication study failed to capture this relation (Tedesqui et al., 2018). Finally, studies investigating combined influence of grit and practice on performance, although few in numbers, also exhibit the similar relationship and importance grit has for expertise. Previous chapter (Chapter 3: Grit – Deliberate practice mediation on performance), conducted on elite youth soccer players, showcased that grit not only impacted performance through practice, but that it also had direct effect on performance as well. This was consistent with findings on competitors of a national spelling bee contest (Duckworth et al., 2011), as well as in academic setting (Lee & Sohn, 2017).

Studies looking into grit facets, and their effects, individually (instead of as a composite score) in sport domain are even fewer, although the trend of investigating them separately is currently growing. Because of that scarcity the findings in these studies tend to be inconsistent: Tedesqui & Young, (2017, 2018) found that only PE differentiated between athletes of different skill level, on the other hand Cousins and colleagues (2020) found that only CI was associated with longer tenure in chosen domain, while Ansah and Apaak (2019) found that both of the grit facets were predictive of future success. Most importantly, almost all studies (looking into relationship of individual grit facets and any sport related variables) used the subcomponents separately, one without the other, in models. Some of them even going a step further and specifically claiming greater importance of either of the grit facets over the other, or even completely disregarding one of them, without actually comparing them statistically against one another (e. g. Cazayoux & DeBeliso, 2019; Tedesqui et al., 2018; Tedesqui & Young, 2017, 2018; Ueno et al., 2018). In order to establish the relative importance of grit's components, it is necessary to introduce both in a single model (Credé, 2018). Only like this can they be formally subjected to statistical tests and their possible interplay be investigated. That is why we analyse two variations of the mediation models in this study: one where the grit is defined as a single predictor (composed of CI and PE), and another where grit's components CI and PE are separate predictors.

Grit's effect on practice

Even though grit's importance for practice is theoretically clear (Ericsson & Pool, 2016), and has been demonstrated empirically (Duckworth et al., 2011), the question remains by which mechanism grit makes an effect on practice, and, therefore, performance. Grit's impact could be found at certain

stages of practice acquisition, but not in others. For example, it could lead to a difference only at the very early stage which would then remain constant over the years as illustrated in Figure 4.1A. Grit could also consistently impact the practice acquisition each year as grittier players would consistently log (the same amount of) more hours than their less gritty peers. That way an initially small difference would snowball into a bigger and bigger one throughout the years (see Figure 4.1B). Grit could, however, only influence the later stages of practice acquisition, when the domain-specific activities pick up pace as the players start to specialize in their expertise (Figure 4.1C). Finally, grit could have an effect at each stage as depicted in Figure 4.1D.

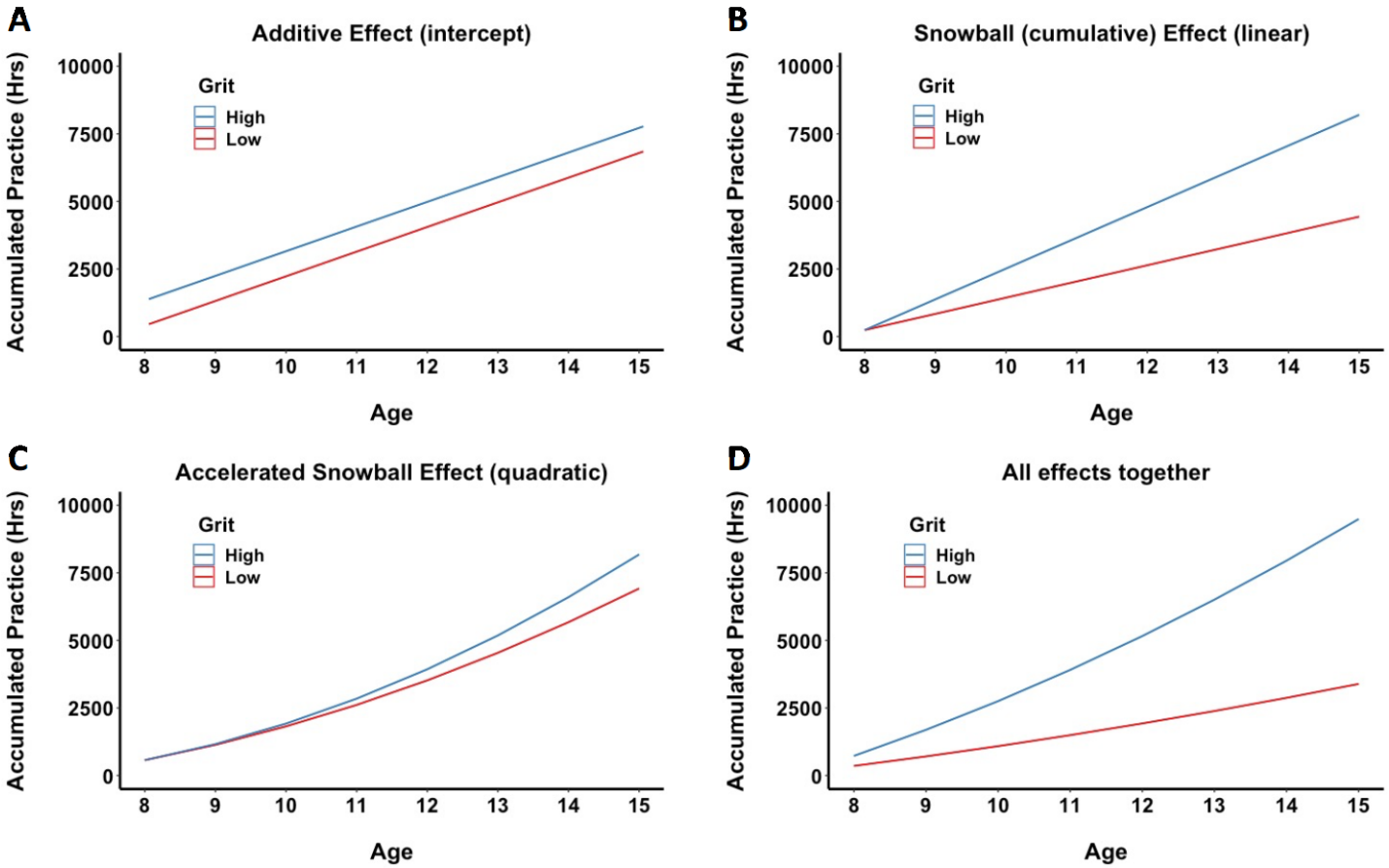


Figure 4.1. Hypothetical effects. Grit could have only an effect at the beginning, where the initial differences will be carried over to other years (A). Grit could also have a constant cumulative effect across the years where a small initial difference snowballs into a big difference over the years (B). Finally, grit could also play a role in the later phase where small differences exponentially increase over the later years (C). All three effects, together, could produce a huge difference over the years (D). The terms in the brackets in the title (intercept, linear, and quadratic) indicate the parts of the model (regression) with which grit interacts (see Method section for more details).

While there are many longitudinal studies on the acquisition of practice in sport (Baker & Farrow, 2015), they rarely identified the best (mathematical) function for describing the practice curve. Even more seldom did they look at the factors which could modify the shape of the practice curve. This is unfortunate as the findings should have both theoretical and practical implications. Theoretically, the shape of the practice curve would provide additional validation of the DMSP, which expects different amount of logged practice depending on the developmental stage. Knowing that a personality trait of grit impacts the practice acquisition would further enrich the theoretical framework behind the DMSP. Practically, it is beneficial to know the stages and driving actors of practice acquisition in young elite players. They could provide, for an example, information on what kind of effort and commitment is expected of future elite players at different stages of development.

Current study

As for the previous chapter (Chapter 3), data used for answering the research question of this chapter was collected by Larkin and colleagues (2016) for their study on the relationship between grit, practice and performance, among other things, on a large sample of highly skilled Australian youth soccer players. In their study (Larkin et al. 2016), the players who scored higher or lower on grit could be differentiated based on their engagement in sport-related activities. In other words, they found that grittier players accumulated significantly more total practice hours (amount of the practice hours when all logged in practice was added up together at the age of testing) than their less gritty peers. Despite demonstrating this relationship between practice and grit, they have not investigated the accumulation of practice over time (practice curve during skill acquisition) nor have they investigated how grit impacts that accumulation of the practice (how it modifies the shape of the practice curve). That is why, in collaboration with them, we ran secondary data analysis of data collected in their study (Larkin et al., 2016) to answer these research questions. We will describe the relevant variables, instruments and procedures from their study, necessary for understanding the findings of the current study, as well as the data analyses conducted in our own study further bellow.

Here we investigated effects of grit on practice in a large sample of highly skilled Australian youth soccer players. In order to assess player's level of grit, Larkin and colleagues (2016) asked players questions relating to their perseverance and interests that are soccer specific as a part of grit questionnaire (Duckworth & Quinn, 2009). The players also retrospectively, starting from the age of eight (to fifteen), estimated their involvement in five different types of soccer-related activities: 1) *Competition* – highly structured activity considered as highly relevant in sport settings; 2) *Coach lead*

(team) practice – highly structured activity which, in our context, we believe comes as close as possible to the original definition of deliberate practice; 3) *Play with peers* – no supervision and for fun activity; 4) *Self-led (individual) practice* – practice with no coach supervision and feedback; and 5) *Indirect involvement* – any soccer related activity that is not practice such as playing football video games, watching matches on TV, et cetera. As it was the case in Chapter 3, it should be noted here as well that the way the sport-related activities were grouped together into categories slightly differed in comparison to the categorization done by Larkin and colleagues in the original study (2016) to account for level of structure of the practice activities, as well as the level of (self) control players have over those activities.

This paper tries to answer three questions regarding engagement in sport-related activities, and grit's impact on that engagement, during the developmental period of elite youth athletes:

1) *How is practice accumulated in elite youth soccer players?*

As previously mentioned, there are two possible ways athletes may accumulate practice hours: they can log similar amount of practice hours each year, regardless of level of competition and grit (in other words fixed effect model) or they can log different amount of practice hours each year leading to bigger and bigger differences throughout the development (cumulative effect model). Given predictions of DMSP regarding the engagement in sport-related activities (Côté, 1999; Côté et al., 2001; Côté & Hay, 2002; Côté & Vierimaa, 2014), as well as increasing difficulties and complexity of sport and competition during the period for which Larkin and colleagues (2016) measured participation, we expect to find cumulative (snowball-like) effects. There are two types of cumulative growth that can be potentially observed in our data: linear (similar increase in amount of logged practice hours each year) or accelerated (similar increase in amount of logged practice hours until a certain point after which the increase is more rapid). We do not feel confident in predicting what type of snowball-like growth is to be expected, but, assuming that DMSP is correct, if there were to be a breaking point in our data, we would expect it to be in line with development stages postulated by the model. In other words in between first and second stage of development (sampling and specialization years), around 13 years of age, since our data captures the engagement in sport-related activities during those two periods only.

2) *Is grit related to this pattern?*

Based on the previous literature, we expect grit to be related to this pattern, with players higher in grit not only logging more hours than their less gritty peers, but also having a greater cumulative increase in practice hours. Based on the previous research, grittier players should already at the

beginning start to differentiate from their less gritty peers (initial additive effect – see Figure 4.1). The difference will become even more pronounced over the years as every year grittier players will constantly log more time (cumulative snowball effect – see Figure 4.1). Grit should also be one of the driving forces behind the accelerated accumulation of practice in the later stages (accelerated snowball effect – see Figure 4.1).

Even though Côté (1999), and the other colleagues that refined his original publication (Côté et al., 2001; Côté & Hay, 2002; Côté & Vierimaa, 2014), were not necessarily interested in grit and its role in engagement in activities necessary for expertise development, their model can still provide us with helpful information for forming our own expectations, especially when it comes to specific types of practice activities we would expect grit to impact more at this age. As mentioned beforehand, leadership role in sport engagement, during the first two stages of development (captured in our data) switches from parents (in the sampling stage) to young athletes (in the specializing stage), even though there are still some restrictions on the athletes (for example: athletes themselves cannot chose how often or for how long they will have coach-led practice sessions, nor whether they will make the team for the competition and, if so, how many minutes they will get to play). Given those restrictions, we hypothesize grit to be one of the drivers behind the switch of the leadership role and to have greater impact on activities under one's own control (self-led practice and indirect involvement) than activities that are under control of others (coach-led practice and competition) or the activities that are inherently enjoyable, thus not requiring athlete to be persistent and determined to engage in them (play with peers).

3) *Does it matter whether it is interest or perseverance?*

Even though Côté's developmental model (Côté, 1999; Côté et al., 2001; Côté & Hay, 2002; Côté & Vierimaa, 2014) indicates potentially greater importance of interest (CI) during the sampling years (when fun and enjoyment are the sole focus of engagement in sporting activities) and increasing importance of perseverance (PE) for the more challenging activities that start from the specializing years on-board. However, given the inconsistency of results in previous research (for a review see Cormier et al., 2021), we do not feel confident in predicting impact of individual grit's components on practice and will therefore have exploratory approach to this research question.

Methods

Participants

Larkin and colleagues (2016) recruited 388 elite youth male soccer players who volunteered to participate in the study (M_{age} = 13.8, SD_{age} = .8). All of the participants, at the time of the testing, were around the age of 14. These participants represent the best Australian youth male soccer players, believed to be future elite athletes, because, prior to the original study, they were selected by their regional youth soccer development programs and were competing at national youth soccer championships in Australia. However, some of them had missing data as 16 players did not fully complete Grit-S, and between 16-25 players have not fully completed Practice History Questionnaires (depending on the specific sport-related activity). Larkin and colleagues (2016) were granted ethical approval by the institutional research ethics board of Sydney University and they obtained written parental consent for all youth players prior to data collection.

Measures

Grit.

To measure the levels of grit participants had at the time of the testing, Larkin and the colleagues (2016) utilized the child adapted version of the Short Grit Scale, the Grit-S (Duckworth & Quinn, 2009). As mentioned in the Chapter 3, Grit-S is an eight-item self-report questionnaire that has established construct and predictive validity and test/retest reliability (Duckworth & Quinn, 2009). An example of items on this questionnaire is "Setbacks (delays and obstacles) don't discourage me. I bounce back from disappointments faster than most people", where the participants are required to indicate, on a 5- point Likert scale from 1 (not like me at all) to 5 (very much like me), the extent to which the statement represents them. The total (Grit-S) score is calculated from the average of all eight items, with lower values representing lower levels of grit. The internal reliability was $\alpha = 0.63$.

Considering the recent controversy about the uniformness of the grit construct in general (Credé, 2018; Credé et al., 2017) and sport specifically (Cormier et al., 2019, 2021; Tedesqui & Young, 2017, 2018), we conducted confirmatory factor analysis (CFA). The one factor model (only grit) had a suboptimal fit, while the model with two factors, interest and perseverance, was clearly

superior (see Section 1 in the Appendix D). However, even the two-factor model was merely a good fit. The culprit proved to be one of the questions in the perseverance of effort items ("Setbacks don't discourage me. I don't give up easily."), which had already been identified in other studies as the reason for poor fit (Dunn et al., 2021; Shields et al., 2018; Tedesqui & Young, 2017, 2018). After removing this item, the fit of the model was excellent and significantly better than when the item was present (see Section 1 in Appendix D). We consequently performed all analyses excluding this item, which was a procedure adopted in other studies as well (Dunn et al., 2021; Shields et al., 2018; Tedesqui & Young, 2017, 2018).

Practice.

In the original study, Larkin and the colleagues used an adapted version of the Participation History Questionnaire, PHQ (Ward et al., 2007), in order to gather data relating to the players' age (date of birth), as well as the amounts of soccer-related activities that players had undertaken from the current season (around the age of 14) back to the age of 8. Participants were asked to give their best estimate of the number of hours spent engaged in soccer-related activities at a specific age. In addition to that, they were asked to provide the best estimate of the number of hours per week and the number of months per year engaged in different soccer-related activity categories, including match play (i.e., competitive soccer matches), coach- led practice (i.e., soccer practice with a coach), individual practice (i.e., soccer activity by oneself), peer-led play (i.e., soccer activities with peers, including small-sided games), and indirect involvement (activities of non-physical nature, such as playing soccer computer games and watching soccer games). The reason why the retrospective recall was considered specifically from the age of 8 (and not earlier) is because from this age the games more closely represent match play conditions, with a 7 vs. 7 game on a quarter sized pitch, line markings, a goalkeeper and a referee within the Australian Football developmental pathway. In the same pathway, prior to 8 years of age, players only participate in 4 vs. 4 small sided games without a goalkeeper (Australia, 2013 - FFA National curriculum). For other measures used in the original study, which we do not utilize and report here, please see Larkin et al. (2016).

Procedure

At the start of their testing process, Larkin and colleagues (2016) had the participants completed the Grit-S questionnaire, which took participants about 5 to 10 min. After that was done, participants moved onto filling in the PHQ, which took them approximately 1 hr to complete. Larkin

and research assistant were available during the period participants were filling in the PHQ, in order to answer any questions and provide further explanations if those were needed. In the final part of the study, the participants completed the perceptual-cognitive tasks, however, since these are not the focus of this chapter they will not be discussed in detail (please see Larkin et al., 2016 for more information).

Data Analysis.

Given that we were interested in how grit (or its two components) influences accumulation of practice over the early career of football players, we employed the multilevel modelling approach which accounts for nested data, such as repeated measures within an individual. The main distinction between traditional regression analysis and multilevel modelling boils down to the estimation of error term. While the traditional analyses use observed scores as the best possible guess of the true score, multilevel models estimate the error term and use it further to put more importance on the cases where the error is small. Consequently, the estimates obtained via multilevel modelling are more precise than estimates obtained by regression analysis (Singer & Willett, 2003).

There are three effects of interest in this study. The first assumes an initial effect of grit which remains constant over the years (intercept, additive effect). The second effect assumes that grit's effect is constant every year – each year grittier players log in more practice time than their less gritty peers (cumulative snowball effect). Finally, the third effect (accelerated snowball effect) assumes that there is an acceleration of logged practice in the later stages of the development. The initial effect can be checked by adding grit to the intercept, the snowball effect by adding grit to the linear term (here of age) to create an interaction (age x grit), while the accelerated snowball is investigated by adding grit to the quadratic term of age (essentially making age^2 x grit interaction). Each of these steps can serve as model building strategy (Singer & Willett, 2003) and the models can be compared based on their fit. We provide this approach in the Appendix D (Section 2). Given that our goal is to check whether the effects are present (and not to find the best fitting model), here we use the final model (Figure 4.1D) which entails all three effects. In the first version of the model, the grit measure is a composite score (entails both CI and PE items together). In the second version of the model, we use CI and PE in the model instead of the composite grit measure. In both versions, we use the total practice as the measure of practice (see Appendix D, Section 4 for the mathematical equations of the two models).

Unlike previous studies, we not only have both CI and PE together in a single model, but we also compare their effects directly (see Table 4.3). Additionally, we provide a fine-grained analysis on the different types of activities (e.g. competition, coach-led training, self-led training, play with peers,

and indirect activities) using multivariate multilevel analysis where all five different practice types are estimated in a single model to account for their interrelations (see the Results and Discussion sections).

The analyses were conducted in the Bayesian framework (Kruschke, 2011) using brms package (Bürkner, 2017) in R. Each model featured default uninformative priors, while there were 4,000 warm-ups, 8,000 iterations within 4 chains. The Bayesian framework has been chosen because it is more robust regarding the issues with non-normality (Kruschke, 2011) and it offers a flexible environment where the individual coefficients can be easily compared to each other (which is necessary for the CI vs. PE comparison). We use 89% Credible Interval (CI), a range of values on the posterior probability distribution that includes 89% of the probability, for inference. If 0 is not included in the range, then the effect can be considered reliable or significant in traditional sense. The 89% CI are taken because they are considered as a more stable alternative to the 95% confidence intervals (Kruschke, 2011; McElreath, 2018) and has been increasingly popular in research using Bayesian statistics (Makowski et al., 2019; Vaci et al., 2019).

Results

Descriptive statistics

Elite youth players started soccer related activities early, with most of them around age of eight but some of them as early as five years old. Figure 4.2 shows that by the age of fourteen the players have already accumulated over 5000 hours of practice activities on average. Overall, on grit, the participants scored high (M = 3.7, SD = .50; on a 5-point scale), higher than normative samples (Duckworth et al., 2007). The players had somewhat higher scores on Perseverance of Effort (M = 4.2, SD = .55) than on Consistency of Interest (M = 3.3, SD = .66). The Appendix D provides more detailed descriptive statistics, including practice total for individual years as well as the correlations of practice with grit (and CI and PE) – see Appendix D, Section 5.

The shape of the practice curve over the years (linear vs. quadratic function)

Figure 4.1 demonstrates that in most practice types, as well as in the total practice (the sum of all practice types), players logged more practice in later years than they did in the early years. This resulted in an accelerated curve at later age in all practice types except play with peers, where the amount of engagement time remained constant over the years. We checked this observation formally by comparing the fits of models where there was only linear increase with the models where there was also a quadratic increase, with the quadratic term capturing the acceleration of practice logging in later years. In all instances, except for the play with peers, the quadratic models fit the data significantly better (see Appendix D, Section 2).

As the final check, given that quadratic functions are notorious for overfitting (Gula et al., 2021), we used a two lines method (Simonsohn, 2018) to determine whether there was indeed an inflection point which would divide the x-axis on two linear regressions. As shown in Appendix D (Section 3, Figure D2), in all instances, age 13, was taken as the most likely breaking point. Although the first initial regression/line is also increasing and has a positive and significant linear coefficient, the second one if often three times larger, illustrating the huge difference in the steepness after the breaking point.

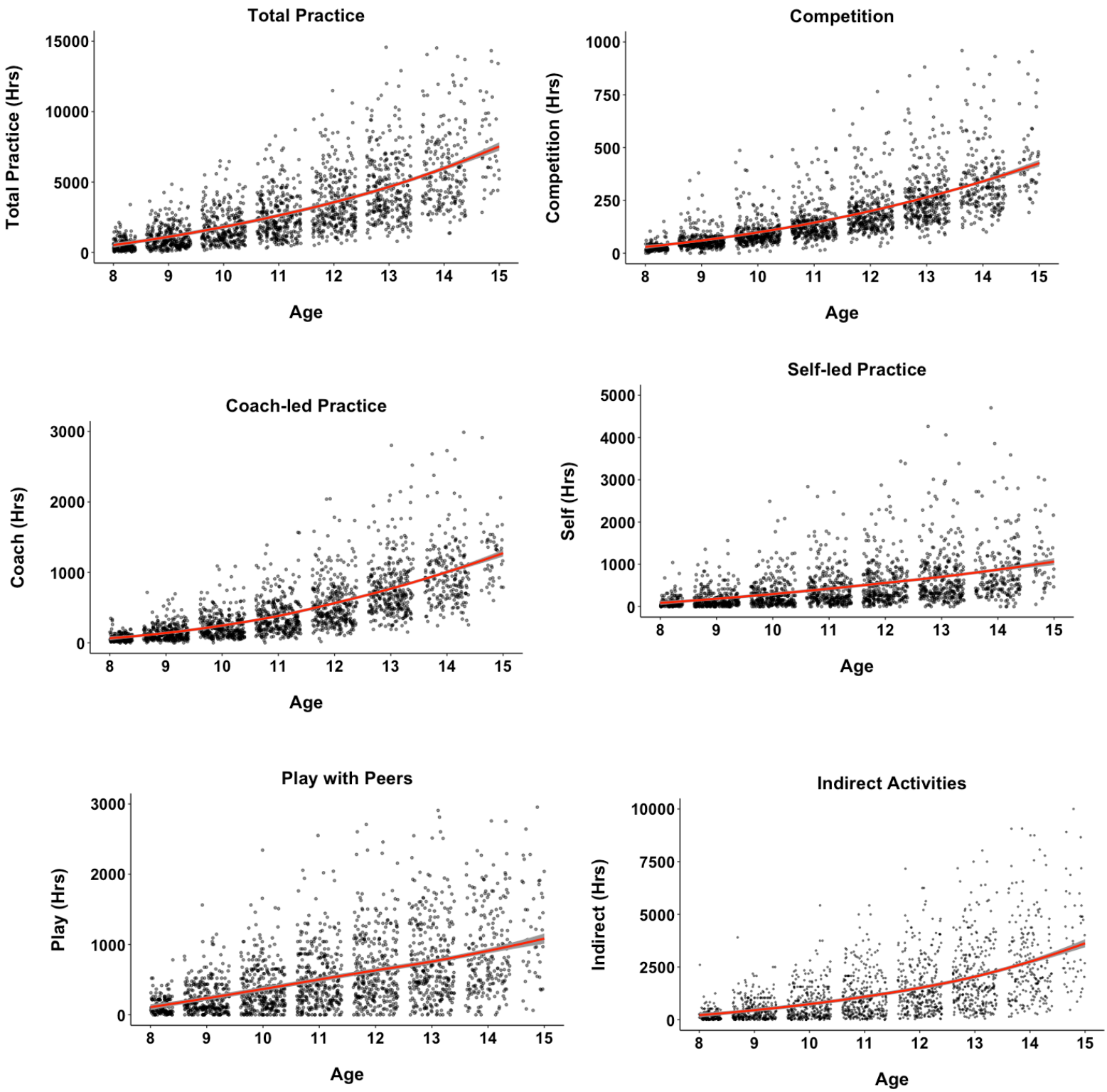


Figure 4.2. Accumulated practice (total and different types) over the years (8-15). The accumulation of practice is relatively constant until the age of 13 when it suddenly accelerates.

The effect of grit (and its components) on the total accumulated practice

Grit on total practice.

We first checked the initial additive, cumulative (snowball) and accelerated cumulative (accelerated snowball) effects of grit (measured as a composite) on the total accumulated practice, which includes all activities, over the years. The fixed effect was checked by adding grit to the intercept, the snowball effect by the interaction between age (linear term) and grit, while the accelerated snowball effect was investigated by the interaction of grit with the quadratic age term. In all instances, we used multilevel regression approach where the repeated measures over the years were nested within participants (see Methods).

Table 4.1 demonstrates that grit has both an additive and snowball effects on accumulated practice, but that its accelerated snowball effect is not significant. In other words, the grittier players start with a small but significant edge in the logged practice, which constantly increase over the years. The accelerated accumulation of the practice in the last two years is also affected positively by grit but the effect was not quite significant.

Table 4.1. *Grit's influence on accumulation of total practice.*

		Total Practice			
Effects	***Predictors***	*β*	*(Std. β)*	CI low	CI high
Intial (intercept)	Intercept	-19		-472	450
	Grit	**156**	(0.03)	34	278
Snowball (linear)	Age	-94	(0.19)	-410	256
	Age× Grit	**162**	(0.03)	74	250
Accelerated snowball (quadratic)	Age^2	**62**	(0.02)	42	84
	Age^2× Grit	1	(0.00)	-4	7
Model fit	Marginal R^2	0.55			
	Bayes R^2	0.99			

Note. Raw (β) and standardized (Std. β) estimates are presented. Age is centered at 8 (i.e., 0 in the model correponds to 8 years in dataset). Grit is not centered (e.g. the Interecept estimates assume the grit value of 0). Marginal R^2 includes only random effects parts of the model while the Bayes (also known as conditional) R^2 includes both, random and fixed effects. CI are 89% credible intervals. Coefficients in bold do not encmpass 0 within the 89% CI.

To illustrate the trends, we plot the model results using two hypothetical players with differing grit values. The high grit player has a grit value of 4.2, which is about a SD above the mean (3.7 + 0.5), while the low grit player has a grit value of 3.2, about a SD below the mean (3.7 - 0.5). As it can be seen in Figure 4.3, the difference in logged time between the more and less gritty players is small at the beginning. However, the grittier player constantly logs an additional amount of practice compared to his less gritty peer. In the end, the overall logged time is markedly different: at the age of 15, the high grit player has logged around 8000 hours, around 20% more than the low grit player, who accumulated around 6000 hours.

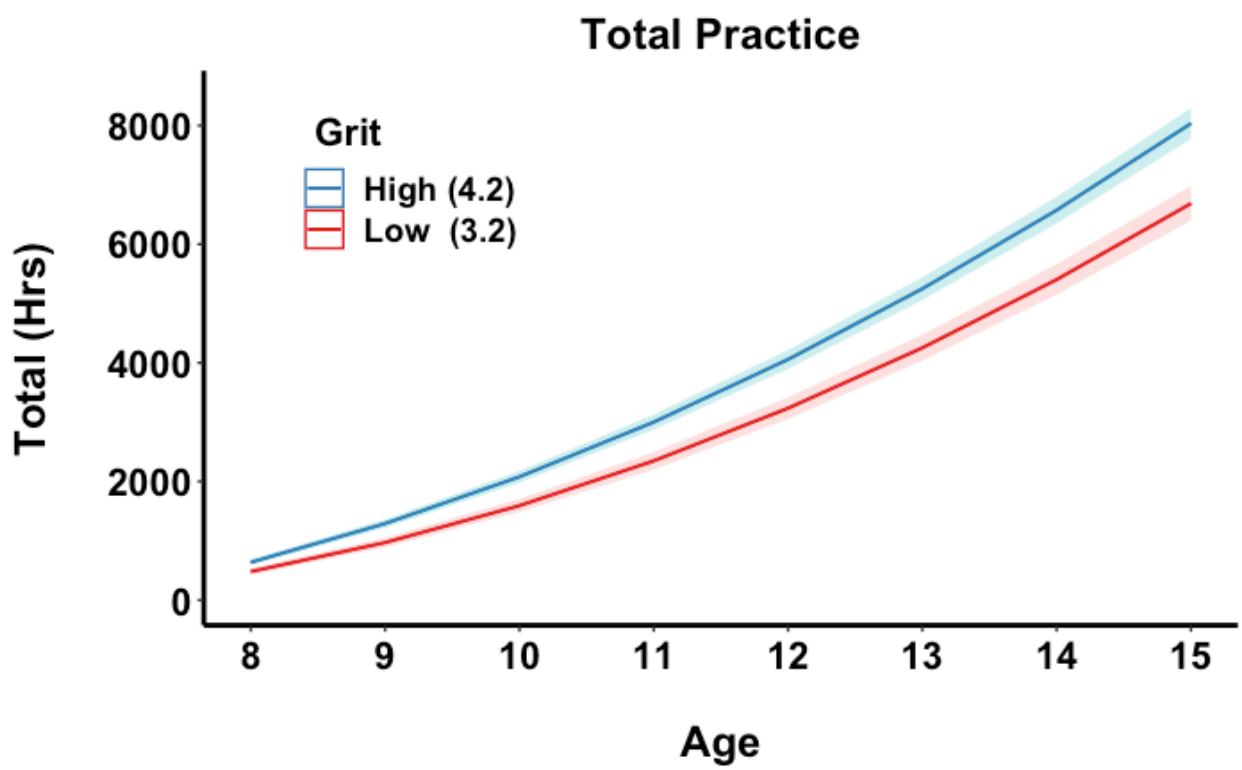


Figure 4.3. Model illustrating grit's influence on the total accumulated practice. Presented are accumulated practice times over the years for two hypothetical players, one with high grit score (+1 SD) and the other with low grit score (-1 SD).

CI and PE on total practice.

In the next step we replaced the (composite) grit score in the multilevel regression with its components, CI and PE. Table 4.2 shows that players with higher CI accumulated more practice overall at the beginning (additive effect) and then continued to accumulate more practice over the years (snowball effect). PE was not a significant predictor of the total amount of practice either at the beginning or in the follow up years. However, the situation was different in the last phase where the accelerated snowball effect was visible, that is, the players accumulated more practice per year in the last two years than in the previous years. Here the players with higher PE accumulated more practice hours in the last two years than their peers with lower PE scores. The CI, in contrast, was not a significant predictor of the accelerated acquisition of practice in the later stage.

Table 4.2. *The influence of grit's components, Consistency of Interest (CI) and Perseverance of Effort (PE), on the accumulated total practice.*

		Total Practice			
Effects	***Predictors***	*β*	*(Std. β)*	CI low	CI high
Intial (intercept)	Intercept	70		-460	548
	Consistency of Interest (CI)	**133**	(0.03)	**38**	**229**
	Perseverance of Effort (PE)	10	(0.00)	-102	126
Snowball (linear)	Age	-37	(0.18)	-402	321
	Age× CI	**150**	(0.04)	**81**	**216**
	Age× PE	8	(0.00)	-72	93
Accelerated snowball (quadratic)	Age^2	**49**	(0.02)	**26**	**72**
	Age^2× CI	-3	(0.00)	-8	1
	Age^2× PE	**7**	(0.01)	**1**	**12**
Model fit	Marginal R^2	0.56			
	Bayes R^2	0.99			

Note. Raw (β) and standardized (Std. β) estimates are presented. Age is centered at 8 (i.e., 0 in the model correponds to 8 years in dataset). Grit is not centered (e.g. the Interecept estimates assume the grit value of 0). Marginal R^2 includes only random effects parts of the model while the Bayes (also known as conditional) R^2 includes both, random and fixed effects. CI are 89% credible intervals. Coefficients in bold do not encmpass 0 within the 89% CI.

The different impact of the CI and PE on the total practice accumulated over the years is presented in Figure 4.4, where the regression results (Table 4.2) are visually presented. The difference between more and less 'consistently interested' players is already large at the early stages – at the age

of 10 more consistently interested player has logged around 2200 hours, around 41% more than their less consistently interested peer (they logged around 1300 hours). At the same age, the players who score high on PE do not necessarily have logged more practice than players who scored lower – around 25% difference, with more 'persistent' players logging around 1600 hours of total practice, while less 'persistent' players log around 1200 hours.

However, the trend changes in the later accelerated phase where suddenly PE has more impact on the separation (in the number of logged practice hours) between the players with the high and low PE scores. The more 'consistently interested' player, at the age of 15, logs around 8000 hours, around 20% more than less 'interested' peer (around 6400 hours); while the more 'persistent player', logs around 7100 hours, around 27% more than less 'persistent' player (around 5200 hours). In other words, the CI seems to impact the initial and subsequent linear increase, whereas the PE exerts more influence in the later, quadratic stage.

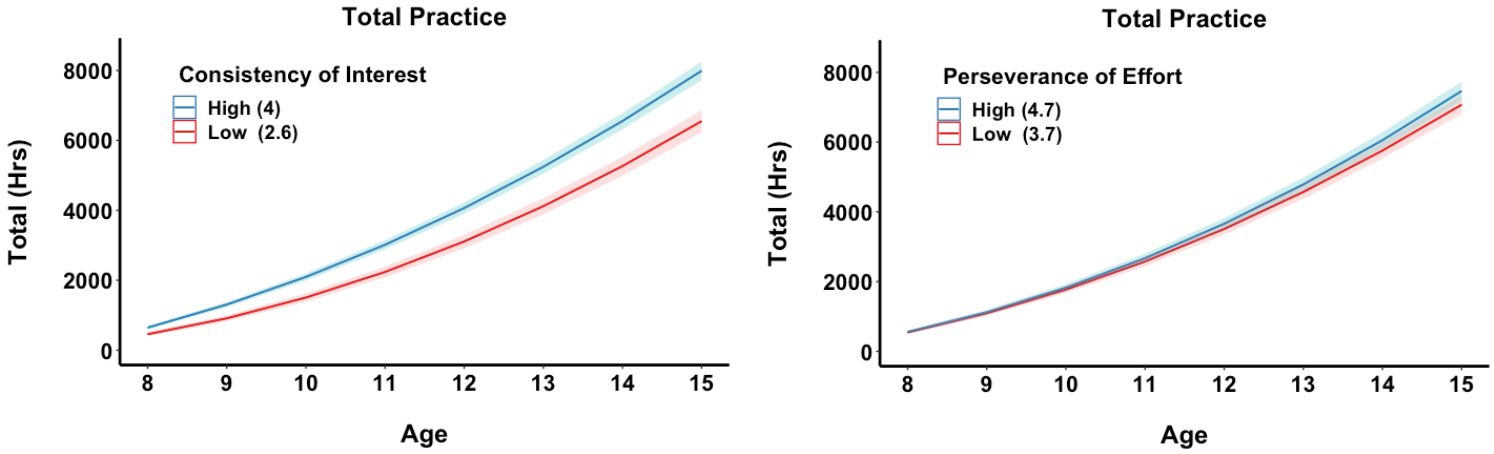


Figure 4.4. Model illustrating the influence of grit's components, Consistency of Interest (CI – left panel) and Perseverance of Effort (PE – right panel), on the accumulated total practice. Presented are accumulated practice hours over the years for two hypothetical players, one with high CI/PE score (+1 SD) and the other with low CI/PE score (-1 SD).

We can go a step further and formally assess whether the differences between CI and PE at different stages are statistically reliable. Table 4.3 demonstrates that there are no differences between

CI and PE when it comes to the initial additive effect. However, both snowball and accelerated effect are influenced significantly differently by CI and PE. The cumulative effect of practice is driven more by CI than PE, while the later burst of logged activity is more influenced by PE than CI. The pattern of result is not influenced by slightly different scales characteristics of CI and PE (e.g. higher mean of PE and higher SD of CI). When all values in the regression are standardized, the different pattern persisted (see z-value rows in Table 4.3).

Table 4.3 *The difference between Consistency of Interest (CI) and Perseverance of Effort (PE) on the accumulated total practice when it comes to the initial, snowball, and accelerated snowball effect.*

			Total Practice				
Effects	***Predictors***	***Estimate***	Consistency of Interest (CI)	Perseverance of Effort (PE)	Difference CI - PE	Credible Interval Low	High
Intial (intercept)	Consistency of Interest (CI) or Perseverance of Effort (PE)	raw	133	10	123	-49	287
		z-value	89	5	84	-21	189
Snowball (linear)	Age× CI or Age× PE	raw	150	8	**142**	20	261
		z-value	100	5	**95**	21	170
Accelerated snowball (quadratic)	Age^2× CI or Age^2× PE	raw	-3	7	**-10**	-18	-1.6
		z-value	-2	4	**-6**	-11	-0.98

Note. Raw (raw) and standardized (z-value) estimates of consistency of interest and perseverance of effort are presented. Differences in bold do not encmpass 0 within the 89% CI.

The effect of grit (and its components) on the different types of practice

Grit on different types of practice.

The next step involved checking the effect of grit on different types of practice activities. Here we use multivariate multilevel models where all five types of practice are estimated in a single model, which accounts for their inevitable inter-dependence. Table 4.4 demonstrates that there were no initial effects of grit on different practice activities, apart from coach-led practice. The grit's interaction with age (the linear term, cumulative snowball effect) is, however, significant in all instances except for the

competition. We find grit's snowball effect in all practice types where a difference of one point on the grit scale (around 1.5 SD) results in the difference between 5 and 61 logged hours per year for competition and indirect activities, respectively (see Age x Grit column in Table 4.4). Once a small difference (e.g. 31 hours in a year for coach-led practice) becomes a significant one over the course of 10 years (e.g. 310 hours more correspond to a full extra year of training).

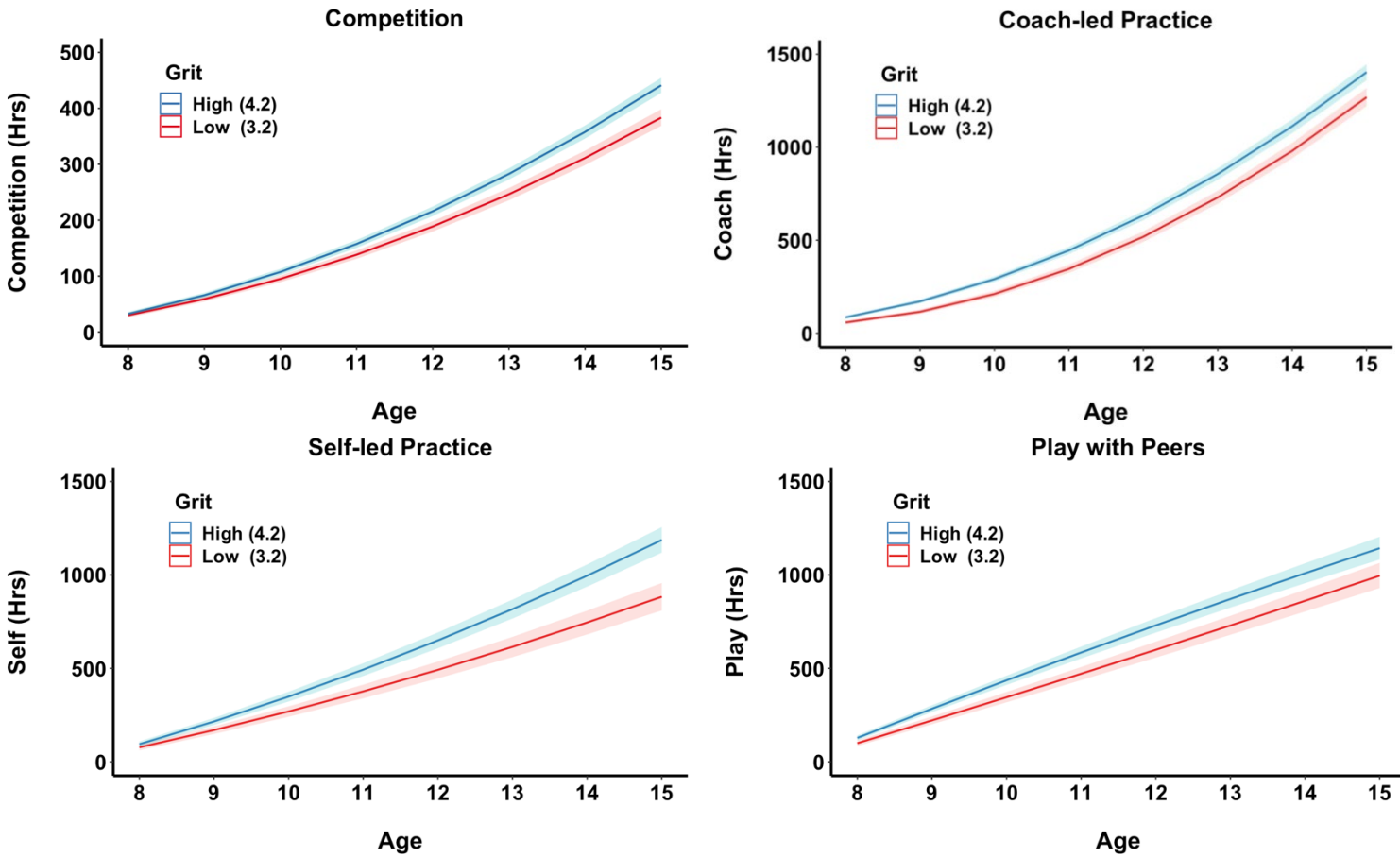
There were, however, also accelerated snowball effects of grit on practice in particular for indirect involvement, self-led practice, and competition (see Age^2 x Grit column in Table 1). Grittier players not only log more indirect soccer-related activities than less grittier peers, but that difference becomes bigger as the time passes in particular for competition, self-led practice, and indirect activities. In contrast, some practice activities, such as play with peers and coach-led practice, had a negatively accelerated effect. The increase in number of hours logged, for these two activities, in later years, was faster for less gritty than for grittier players.

Table 4.4. *Grit's influence on accumulation of different types of practice.*

		Competition				Coach-led Practice				Self-led Practice				Play with Peers				Indirect Activities			
Effects	***Predictors***	*β*	*(Std. β)*	CI low	CI high	*β*	*(Std. β)*	CI low	CI high	*β*	*(Std. β)*	CI low	CI high	*β*	*(Std. β)*	CI low	CI high	*β*	*(Std. β)*	CI low	CI high
Intial (intercept)	Intercept	23		-9	56	-31		-102	42	21		-106	147	8		-120	136	-35		-334	269
	Grit	2	(0.01)	-7	11	**28**	(0.01)	9	46	17	(0.02)	-16	51	28	(0.03)	-6	62	79	(0.03)	-2	158
Snowball (linear)	Age	13	(0.18)	-7	31	-58	(0.11)	-120	4	1	(0.18)	-87	90	4	(0.26)	-70	81	-66	(0.12)	-294	155
	Age× Grit	4	(0.01)	-1	9	**30**	(0.03)	14	46	**27**	(0.02)	4	51	**37**	(0.03)	16	56	**67**	(0.02)	8	127
Accelerated snowball (quadratic)	Age^2	**2**	(0.03)	0.1	3	**26**	(0.04)	21	31	-2	(0.01)	-9	4	**10**	(0.01)	4	16	**27**	(0.03)	12	42
	Age^2× Grit	**1**	(0.01)	0.1	1	**-2**	(-0.01)	-3	-1	**2**	(0.01)	0.3	4	**-3**	(-0.01)	-4	-1	4	(0.00)	-0.3	7
Model fit	Marginal R^2	0.55				0.55				0.55				0.55				0.55			
	Bayes R^2	0.99				0.99				0.99				0.99				0.99			

Note. Raw (β) and standardized (Std. β) estimates are presented. Age is centered at 8 (i.e., 0 in the model correponds to 8 years in dataset). Grit is not centered (e.g. the Interecept estimates assume the grit value of 0). Marginal R^2 includes only random effects parts of the model while the Bayes (also known as conditional) R^2 includes both, random and fixed effects. CI are 89% credible intervals. Coefficients in bold do not encmpass 0 within the 89% CI.

Figure 4.5 illustrates the results of the models by plotting hypothetical curves of high and low grit players. For example, for the indirect activities, the difference in number of hours logged, between the high and low grit players, is small at the beginning. At the age of 11, the grittier player has logged around 1100 hours, around 27% more than the low grit player (around 800 hours). At the age of 13, where the most likely breaking point is, grittier player logs around 2200 hours (an 100% increase compared to hours logged at the age of 11, +1100 hours,), while their less gritty peer logs around 1500 hours (+87% compared to number of hours at age 11, +700 hours), around 32% less. Finally, by the age of 15, the gritty player has logged around 3600 hours (an increase of 1400 hours compared to age 13, +64%) while their less gritty peer has logged around 2300 hours (+800 hours, +53%), therefore around 36% less than the gritty player. Overall increase for the player high in grit, from ages 11 to 15, was around 227% (+2500 hours), while for the less gritty players, it was around 187% (+1500 hours).



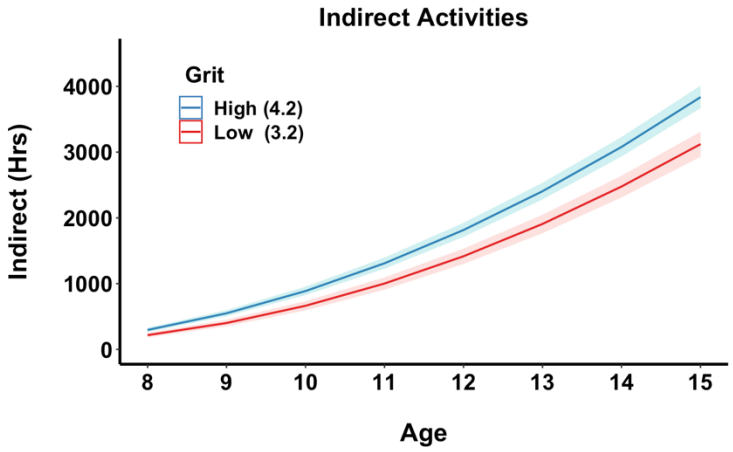


Figure 4.5. Model illustrating the influence of grit on the different practice types. Presented are accumulated practice times over the years for two hypothetical players, one with high grit score (+1 SD) and the other with low grit score (-1 SD).

Is grit more important for certain practice types?

Given that the models were estimated together in a Bayesian multivariate multilevel analysis, one can directly compare the posterior distributions of the intercept, linear, and quadratic terms and their interaction with grit for different individual types of practice. This way we can statistically determine whether grit has a significantly more initial additive effect (intercept), cumulative snowball (i.e. interaction with the linear term), and accelerated snowball effect (i.e. interaction with the quadratic term) in one type of practice than in the other type of practice. Table 4.5 demonstrates that the differences are rather small at the beginning (initial additive effect), especially when we account for widely differing scales by standardizing practice times.

The reliable difference when it comes to the snowball effect (e.g. between competition and coach-led practice on the one hand, and competition and play with peers, on the other) also becomes non-existent when the scales differences are taken into account. However, there are reliable differences between the effects of grit on the different practice types in the later stages. Grit, for example, influences more reliably the accelerated accumulation of competition hours in the later phase than it does for coach-led practice or play with peers. Similarly, grit impacts the accelerated snowball effect more significantly for the self-led practice than for the coach-led practice or play. Grit is more relevant for the later accumulation of indirect activities than it is for coach-led practice or play with peers.

Table 4.5. *Difference between interactions between age and grit (linear cumulative effect) and age squared and grit (quadratic accelerated effect) for different types of practice for raw values (Δ β) and for standardized practice values (Δ βz).*

		Initial Effect: Grit				Snowball: Age× Grit				Accelerated Snowball: Age^2× Grit			
Practice type 1	**- Practice type 2**	$\Delta\beta$	*SE*	$\Delta\beta_z$	SE_z	$\Delta\beta$	*SE*	$\Delta\beta_z$	SE_z	$\Delta\beta$	*SE*	$\Delta\beta_z$	SE_z
Competition	Coach-led	**-25.6**	11.7	-0.021	0.020	**-26.3**	**9.6**	-0.019	0.013	**2.7**	**0.7**	**0.0041**	0.0010
Competition	Self-led	-15.7	21.7	-0.009	0.026	-22.0	14.7	-0.049	0.035	-1.4	1.0	-0.0001	0.0027
Competition	Play	-21.4	25.6	-0.019	0.026	**-25.7**	**14.0**	-0.085	0.034	**2.8**	**1.0**	**0.0095**	0.0026
Competition	Indirect	-72.3	49.1	-0.018	0.021	-56.0	37.3	-0.041	0.036	-3.2	2.4	-0.0021	0.0026
Coach-led	Self-led	9.9	22.7	0.013	0.021	4.3	16.2	-0.003	0.035	**-4.0**	**1.2**	**-0.0074**	0.0026
Coach-led	Play	4.2	26.8	0.002	0.022	0.6	15.9	-0.040	0.034	0.1	1.2	0.0022	0.0025
Coach-led	Indirect	-46.7	48.7	0.003	0.018	-29.8	37.5	0.005	0.034	**-5.9**	**2.4**	**-0.0094**	0.0024
Self-led	Play	-5.7	25.1	-0.010	0.020	-3.7	14.5	-0.037	0.027	**4.1**	**1.2**	**0.0096**	0.0022
Self-led	Indirect	-56.6	48.1	-0.010	0.022	-34.0	36.4	0.008	0.032	-1.8	2.3	-0.0020	0.0023
Play	Indirect	-50.9	50.3	0.001	0.023	-30.3	36.8	0.044	0.032	**-5.9**	**2.5**	**-0.0117**	0.0024

Note. The Δ β represent the difference between the (raw values) coefficients for the initial effect (intercepts) and the interactions between age and grit (linear snowball effect) and age sqaured and grit (quadratic accelerated snowball effect) of the first and second practice types. Δ β_z indicate that the practice type values have been standardized. Bold coefficients do not encompass 0 within 89% CI.

CI and PE on different types of practice.

As with the total practice (see Table 4.2 and Figure 4.3), we also performed all the multivariate multilevel analysis on the different types of practice using Consistency of Interest (CI) or Perseverance of Effort (PE) instead of grit. Table 4.6 demonstrates that a similar pattern of results as for the total practice is noticeable for self-led practice, indirect involvement and plus play with peers – CI plays a bigger role in the earlier stages, while PE has a bigger role at later stages of early expertise development for activities under own control, especially those which are enjoyable (e.g. play with peers).

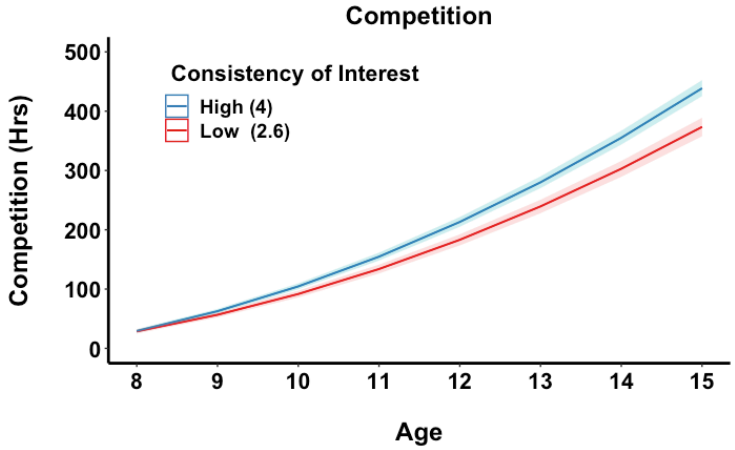
Table 4.6. *The influence of grit's components, Consistency of Interest (CI) and Perseverance of Effort (PE), on accumulation of different types of practice.*

		Competition				Coach-led Practice				Self-led Practice				Play with Peers				Indirect Activities			
Effects	***Predictors***	*β*	*(Std. β)*	CI low	CI high	*β*	*(Std. β)*	CI low	CI high	*β*	*(Std. β)*	CI low	CI high	*β*	*(Std. β)*	CI low	CI high	*β*	*(Std. β)*	CI low	CI high
Intial (intercept)	Intercept	19		-10	49	-23		-101	57	82		-63	227	-14		-157	125	13		-338	370
	Consistency of Interest (CI)	0	(0.00)	-5	6	**18**	(0.02)	3	33	**27**	(0.03)	0.2	54	25	(0.03)	-1	51	**64**	(0.03)	1	127
	Perseverance of Effort (PE)	2	(0.01)	-5	9	8	(0.01)	-10	26	-21	(-0.02)	-54	14	10	(0.01)	-22	42	7	(0.00)	-72	86
Snowball (linear)	Age	18	(0.18)	-4	39	-63	(0.11)	-131	9	24	(0.19)	-80	128	18	(0.26)	-65	104	-24	(0.12)	-281	236
	Age× CI	4	(0.02)	-0.4	7	**16**	(0.02)	2	29	**21**	(0.02)	3	40	**37**	(0.05)	22	52	**72**	(0.03)	24	118
	Age× PE	-1	(-0.00)	-5	4	15	(0.02)	-1	31	2	(0.00)	-21	26	-1	(-0.01)	-21	18	-10	(-0.00)	-69	49
Accelerated snowball (quadratic)	Age^2	**2**	(0.03)	0.2	4	26	(0.04)	20	31	-8	(0.01)	-15	-1	6	(-0.00)	-1	12	**24**	(0.03)	7	41
	Age^2× CI	**0.4**	(0.01)	0.1	0.8	**-1**	(-0.01)	-2	-0.2	0.2	(0.00)	-1	2	**-4**	(-0.01)	-5	-3	1	(0.00)	-2	5
	Age^2× PE	0.1	(0.00)	-0.3	0.5	-1	(-0.00)	-2	0.4	**3**	(0.01)	1	4	**2**	(0.01)	0.2	3	3	(0.00)	-1	7
Model fit	Marginal R^2	0.57				0.57				0.28				0.32				0.39			
	Bayes R^2	0.98				0.98				0.98				0.98				0.98			

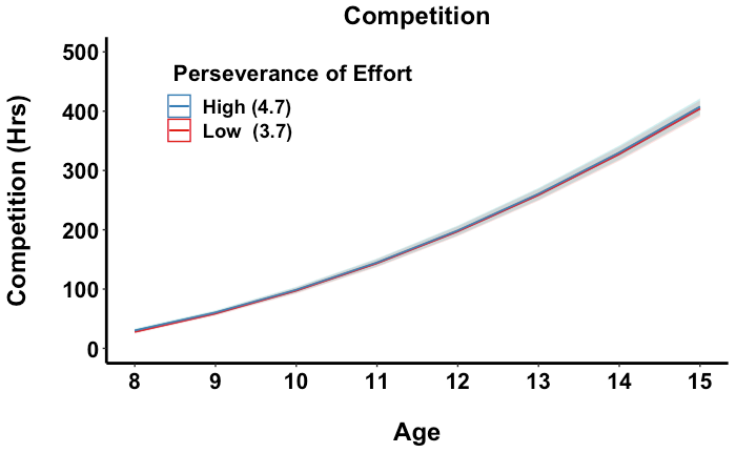
Note. Raw (β) and standardized (Std. β) estimates are presented. Age is centered at 8 (i.e., 0 in the model correponds to 8 years in dataset). Grit is not centered (e.g. the Interecept estimates assume the grit value of 0). Marginal R^2 includes only random effects parts of the model while the Bayes (also known as conditional) R^2 includes both, random and fixed effects. CI are 89% credible intervals. Coefficients in bold do not encmpass 0 within the 89% CI.

Figure 4.6 illustrates the model results by plotting the accumulated practice (for different types of practice) of hypothetical players with high and low CI/PE scores. For the indirect involvement, at the age of 10, as for the total practice, the difference in hours between more (~900 hours) and less 'interested' (~600 hours) players is bigger (around 30%) than the difference between more (~600 hours) and less 'persistent' (~500 hours) players (around 15% difference). At the age of 13, when the most likely breaking point is, the difference between more (~2500 hours) and less 'interested' (~1900 hours) players is around 25%, similarly, the difference between more (~2000) and less 'persistent' (~1500) players is also around 25%. Finally, at the age of 15, more 'interested' player (~3700) logged around 19% more hours than their less 'interested' peer (~3000), while more 'persistent' player (~3500) logged around 23% more hours than their less 'persistent' peer (~2700) - therefore the difference in hours between players becomes bigger in favour of PE at this stage. However, for coach-led practice the impacts of PE and CI are reversed – PE seem to have more of an impact on early development stages, while CI's role is more noticeable in later stages. Furthermore, consistency of interest seems to have more impact on competition in all of the recorded stages of early development.

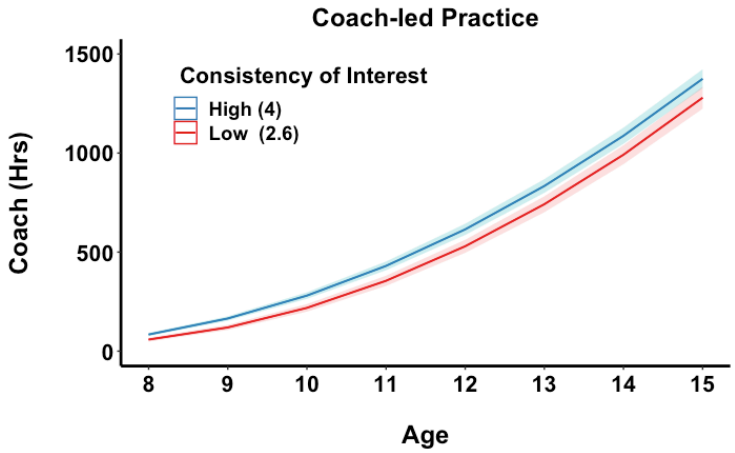
CONSISTENCY OF INTEREST

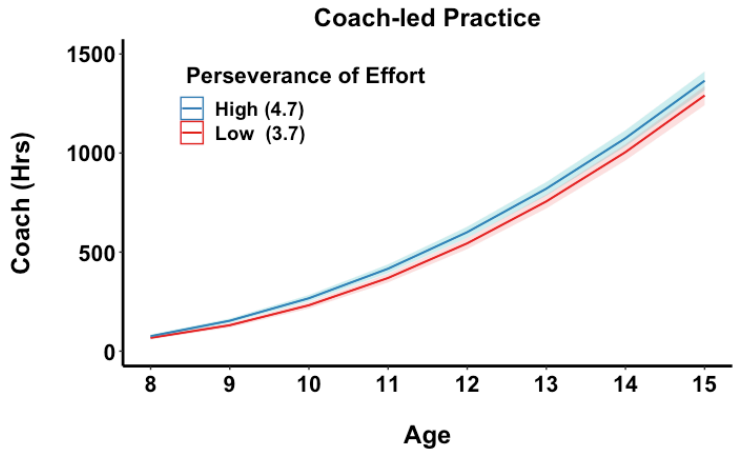


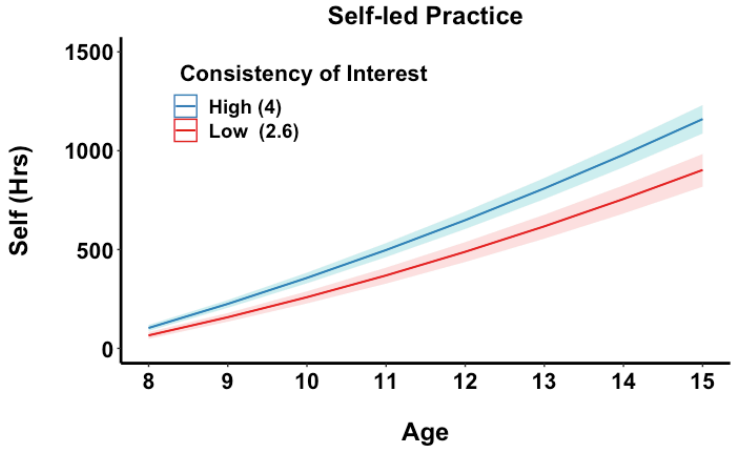
PERSEVERANCE OF EFFORT

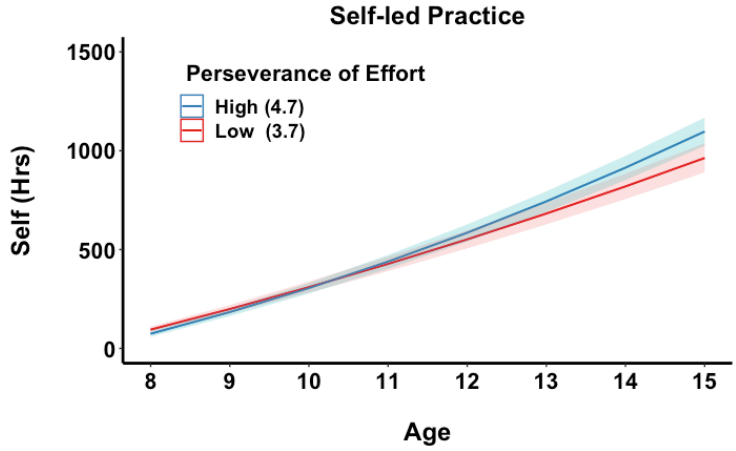


CONSISTENCY OF INTEREST **PERSEVERANCE OF EFFORT**









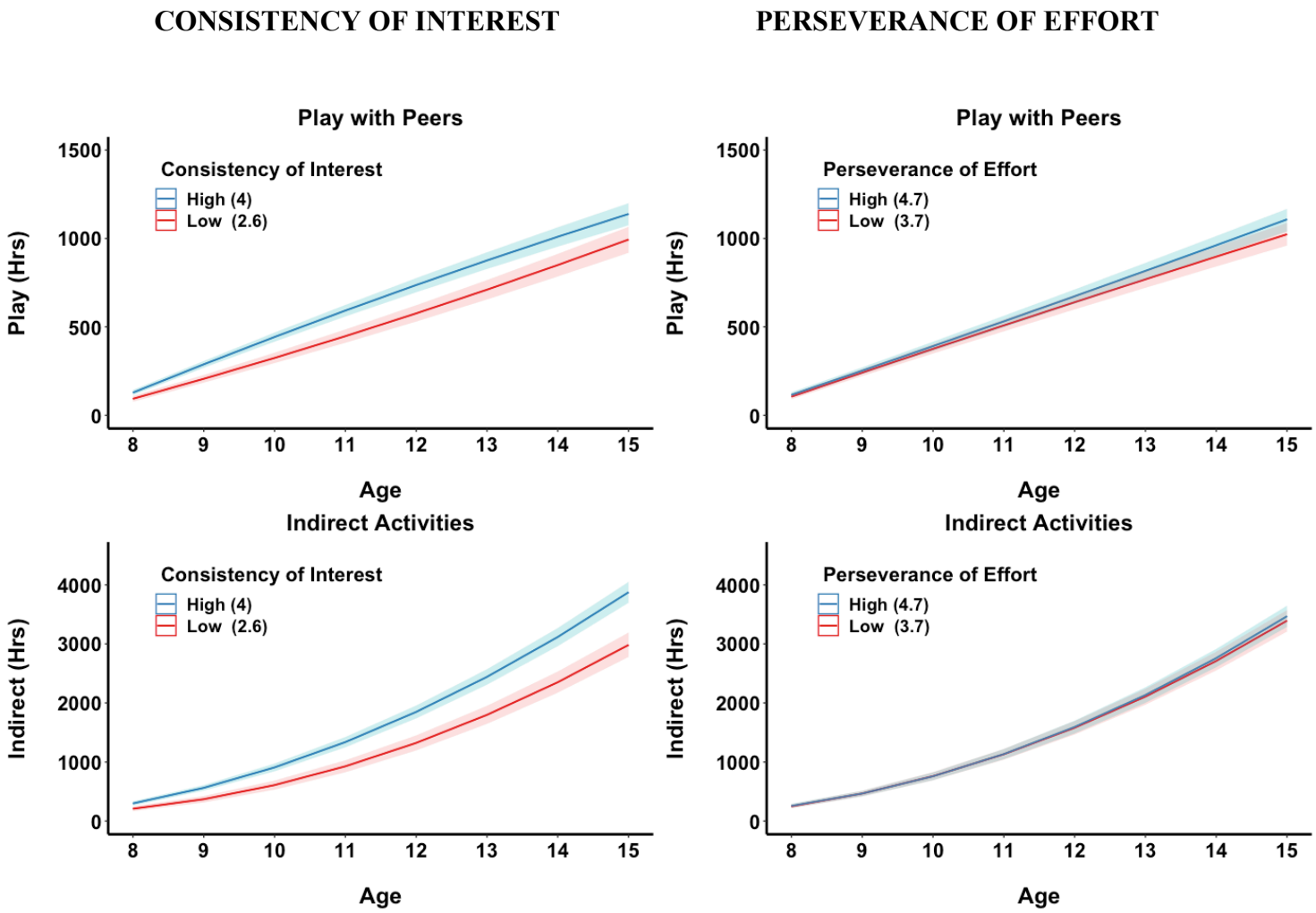


Figure 4.6. ***Model illustrating the influence of grit's components, Consistency of Interest and Perseverance of Effort, on the different practice types.*** Presented are accumulated practice times over the years for two hypothetical players, one with high CI/PE score (+1 SD) and the other with low CI/PE score (-1 SD).

We went a step further and directly compared the posterior distributions of consistency of interest (CI) and perseverance of effort (PE) for initial additive effect, snowball effect (linear interaction), and accelerated snowball effect (quadratic interaction). As shown in Table 4.7, the CI has indeed larger (and statistically reliable) impact on the linear increase on the play with peers and indirect activity than the PE. In contrast, the PE has a reliably bigger impact on the quadratic increase than the CI when it comes to self-led practice and play with peers.

Table 4.7. *The difference between the impact of Consistency of Interest (CI) and Perseverance of Effort (PE) on the initial additive effect, snowball effect, and accelerated snowball effect for different types of practice*

Consistency of Interest (CI) - Perseverance of effort (PE) for	Initial effect CI - PE				Age× CI - Age× PE				Age^2× CI - Age2× PE			
	$\Delta\beta$	*SE*	$\Delta\beta_z$	SE_z	$\Delta\beta$	*SE*	$\Delta\beta_z$	SE_z	$\Delta\beta$	*SE*	$\Delta\beta_z$	SE_z
Competition	-1.6	6.3	-0.006	0.026	4.2	4.4	0.017	0.018	0.3	0.4	0.002	0.002
Coach-led	10.0	16.5	0.015	0.021	0.1	15.1	0.004	0.019	-0.3	1.2	-0.001	0.001
Self-led	47.7	30.7	0.052	0.034	19.4	21.0	0.021	0.024	**-2.7**	1.5	**-0.0026**	0.0016
Play with Peers	15.1	29.2	0.020	0.033	**37.9**	17.7	**0.046**	0.020	**-5.3**	1.3	**-0.006**	0.002
Indirect Activities	57.6	70.3	0.025	0.028	81.8	52.9	**0.035**	0.021	-1.5	3.6	-0.001	0.001

Note. The $\Delta\beta$ represent the difference between the (raw values) coefficients for the consistency of interest (CI) and preseverance of effort (PE). $\Delta\beta_z$ indicate that the CI and PE , as well as the practice values, have been standardized. Bold coefficients do not encompass 0 within 89% credible interval (CI).

Discussion

How is practice accumulated in elite youth soccer players?

We demonstrated that elite youth soccer athletes, for age range 8 to 12, log constantly, similar amount of practice activities – in other words, there is a cumulative snowball effect in practice hours, as per our hypothesis. However, age of 13 seems to be the most likely breaking point of this growth, after which there is a sudden increase in engagement in domain-related activities which produces an accelerated accumulation of practice over the remaining two-three years measured in our study (e.g. curvilinear trajectory, see Figure 2). This is in line with our hypothesis, as well as Côté's (1999; Côté et al., 2001; Côté & Hay, 2002; Côté & Vierimaa, 2014) Developmental Model of Sport Participation (DMSP), which points out age 13 as the cut-off between first two phases of sport expert development: the sampling years (between ages 6-13) and the specializing years (between ages 13-15). According to DMSP (Côté, 1999) these two phases differ, among other things, in: levels of involvement with different sport-related activities (and different sports); importance of deliberate play versus deliberate practice; and extent of control over the engagement with sport-related activities that youth athletes have. In this model it is stated that, in elite children athletes, with temporal progression, levels of engagement, as well as the amount of self-initiation to engage, increase and that importance of deliberate practice overtakes the importance of deliberate play. The growth in number of hours our

sample of elite players logged, during the early stages of development, as well as the type of the growth that we registered (linear first and then accelerated) are in line with the expected outcomes in first two stages of DMSP.

Is grit related to this pattern?

Yes. As hypothesized, we demonstrated that differences at the beginning are small and constant throughout the years thus resulting in the snowball effect (in other words, in linear – cumulative effect). Grittier elite athletes, even at this young age, constantly log more practice time (than their less gritty peers) which, over years, leads to the end result of a significant difference in the amount of hours spent engaging in soccer-related activities.

The personality trait of grit, and its components CI and PE, affect this practice acquisition process at all stages. Grittier elite athletes have a slight edge in the amount of accumulated practice at the beginning (initial additive effect). They, however, constantly log more practice time (than their less gritty peers) which, over the years, leads to a situation where an initial minor difference in the amount of time spent engaging in soccer-related activities snowballs into a much larger difference (Figure 4.3). Grit, as a composite measure, does not quite influence the later increases in the engagement, but its two components, CI and PE, effect the accelerated accumulation. Their effect is, however, markedly different. The players who are consistently more interested accumulate more practice at the beginning and over the follow up years (Figure 4.4). The CI, however, is not a driving force behind the accelerated accumulation in the later stages. In contrast, persistent effort does not impact the early stages of the practice accumulation. The players who more persistently exert effort benefit from it only in the later stages, after age of 12 (Figure 4.4).

Grit's role in accumulation of different practice activitites in elite youth soccer players

This is particularly the case for practice activities that are under the players' own control (such as self-led practice and indirect activities), for which we demonstrated that grit is especially important (when compared to the other practice types). In DMSP, Côté (1999) underlines the importance of leadership role within families of elite children-athletes when it comes to engagement in sport related activities, as well as how that role changes over the years of early development. According to this model, the leading role switches from elite athletes' parents, in the very first stage of development, to

the elite athletes themselves around the age of 13. At this age, according to DMSP, elite athletes start committing to one or two sports (compared to many in the prior phase) and are becoming more focused on sport specific skill development (through practice) instead of centring their sport engagement around fun and enjoyment, like they did in the earlier phase. In other words, after the age of 12, the players themselves are taking engagement in sport-related activities under their own control and are deciding what to focus their efforts on, and how to spend their time, by themselves. Even though Côté (1999), and the other colleagues that followed his original (Côté et al., 2001; Côté & Hay, 2002; Côté & Vierimaa, 2014; Ward et al., 2007) were not necessarily interested in grit and its role in the engagement in activities necessary for expertise development, our findings are indicating its importance as one of the potential factors that play a role in the development of experts and their skills.

Out of the practice activities that Larkin and colleagues (2016) collected data about, self-led practice and indirect involvement are the two that can be classified as the activities under own control. Self-led practice is an effortful, not exactly enjoyable activity that differs from what is classically considered deliberate practice (Ericsson et al., 2018) due to the lack of supervision and feedback (from a coach). Therefore, in the context of deliberate practice framework (Ericsson, 2008; Ericsson, Krampe, & Tesch-Roemer, 1993), it might not be considered as beneficial for performance as some other types of practices (such as coach-led practice for example) Nonetheless, given the effort it requires, and that it is self-initiated by its nature, it seems clear that girt should influence how much players log this type of practice – as only gritty players would push themselves through it completely on their own.

On the other hand, indirect involvement is obviously not an effortful activity. It reflects ones interest and intent of becoming serious about the sport, which includes watching more matches on TV and playing soccer-related games. It is possible that because of the increasing complexity of practice and competition, as players get older, their interest in sport itself increases as well, thus resulting in them seeking out more sport-related content to learn from and look up to (e.g., trying to mimic Messi's latest trick shot, looking up to Ronaldo and his on and off court behaviour). Furthermore, sporting video games are targeted for children at their early teenage years (FIFA states that their target audience is age 13+) which may also contribute to the larger increase in indirect involvement as, with increased interest in the sport, players start spending more time playing soccer video games as well.

Even though we found similar, but weaker, relationship between grit and competition, the relationship with play with peers and coach-led practice was negative. In other words, grittier youth elite athletes have greater accelerated growth in logged hours earlier (for these two types of practice

activities), but that growth slows down later on when compared to their less gritty peers. This finding, when it comes to play with peers, also fits well with the propositions of DMSP (Côté, 1999)– especially the ones relating to deliberate play. Côté (1999) propositioned that during the sampling years (between ages 6-13) sole focus of engagement in sport is for fun and enjoyment, with deliberate play being of far greater importance than deliberate practice. However, this changes during the specializing years (between ages of 13-15), during which elite youth athletes become more serious about their sporting engagement starting to focus more on sport specific skill development and less on just having fun enjoyable time. During this period, Côté states, that deliberate practice increases in importance, slowly overtaking deliberate play. This pattern can clearly be seen in number of hours logged in play with peers within our sample. It should be noted that for the third stage of development (between ages 15-18), DMSP states that deliberate practice completely takes over deliberate play and is much more important. Due to the age range of our sample, we unfortunately were not able to check that empirically as well – but, given the trends in our data, one could expect even stronger negative relationship with grit for play with peers.

The weak negative relationship between grit and coach-lad practice might be initially surprising, especially given the fact that this type of practice is the closest to what might be considered deliberate practice (within deliberate practice framework) (Ericsson, Krampe, & Tesch-Roemer, 1993). However, it is possible that ceiling effect plays some role in the observed data patterns. Like mentioned before, our sample consists of the most elite soccer players in Australia, at their age range, that we further divided into groups based on their grit levels. In other words, it consist of people who already undergo the most strict and rigorous training regimes, spending a lot of their time (outside of school) engaging in various soccer-related activities (including coach-led practice). Given that there is only limited amount of hours in a day, and that the players themselves cannot decide when nor how often they will have coach-led practice, it is possible that the grittier, among the elite group of players, start attending all possible coach-led sessions earlier on than their less gritty peers, thus hitting the maximum amount of possible practice hours (led by a coach) and having less room for an increase in those hours later on (the numbers of these hours only increases once the coaches offer more coach-led sessions during a week or start working one on one with the players). This would further lead to grittier players having to restore to engaging in different types of soccer related activities that are under their control (such as self-led practice and indirect involvement) in order to work on and improve their skills.

The role of grit's components, CI or PE, the process of practice accumulation

By using both grit's components within the same multilevel model, we were able to establish their differing patterns of influence on the process of practice acquisition. CI was a stronger than perseverance of efforts, especially at the beginning and the earlier stages of development – when linear increase in the practice hours is happening (or, in other words, cumulative snowball effect). However, for the accelerated snowball effect, in later stages of early development, the trend was reversed – only the PE had a significant effect on the sudden increase in soccer activities.

These trends are also somewhat in line with Côté's Developmental model of sport participation (Côté, 1999; Côté et al., 2001; Côté & Hay, 2002; Côté & Vierimaa, 2014; Ward et al., 2007). Like we mentioned prior, the sampling years are the period when elite youth athletes are focused on enjoyment, having fun, exploring numerous different sports and, overall, developing an interest in sport (and sport engagement). The specializing years, on the other hand, are the period when the elite youth athletes are focusing more on a specific sport, their skills and are starting to engage with more complex and demanding forms of practice (compared to the previous developmental stage).

Therefore, it would not be unreasonable to assume a relation between CI and sport engagement at earlier stages of development (when the players are still developing their interests and motivation to continuously participate), as well as increasing importance of PE with the increasing complexity of demands both in and out of practice (and competition). If this assumption is valid, the investment period, which is often when the complexity of practice and competition further increase to a much higher level, although not captured by our sample, would be expected to be even more impacted by factors related to persevering efforts despite increase in struggles and setbacks. This seems to be indeed the case in other sport-related studies (Cormier et al., 2021; Tedesqui & Young, 2018), as well as in a large meta-analysis in academic settings (Credé et al., 2017), where the PE is by far better predictor of success. Future research should investigate relationship between sport engagement and individual grit facets in greater detail, on more diverse samples, including those with larger age spans as well as bigger differences in expertise level.

Our study is unique in that it is the first study that has followed the suggestion by Credé (2017) to investigate CI and PE within the same model. In rare instances where the grit's components were investigated, normally two separate models, one for CI and another PE, were postulated (Cazayoux & DeBeliso, 2019; Tedesqui & Young, 2018). However, even though a lot of them just report on the correlations, some of them specifically claim greater importance of either of the grit facets over the

other (sometimes even completely disregarding one of them) without actually comparing them statistically against one another (e. g. Cazayoux & DeBeliso, 2019; Tedesqui & Young, 2017, 2018; Ueno et al., 2018). Future studies should make sure to actually compare the two facets directly against one another statistically (and not just rely on measures significance and correlation), before making claims on their importance (or trends) to ensure furthering our understanding of grit, its facets, and impacts they have, both in sport and non-sport contexts.

Shortcomings

As in introduction, it is worth discussing different definitions of deliberate practice and what those entail in sport. Currently, in sport expertise literature, there is a lack of consensus of what deliberate practice is. According to DPF propositions (Ericsson, Krampe, & Tesch-Roemer, 1993), in order for any practice to be considered deliberate, it has to be effortful, conducted solitary, under supervision, with regular feedback, with the intention to improve one's performance. These requirements are especially problematic for group sports, such as soccer, as the practice activities, that resemble conditions of competition, are not done alone. Additionally, the feedback given to each of the players is given in differing amounts and at different timings (which prompted a whole separate line of research on how to optimize feedback giving process, for review see Hendry et al., 2015).

Furthermore, one of critiques of this approach (DPF) in the sport domain (regardless of it being individual or group) is the finding on the (lack of) effort that sport practice requires, when compared to traditional deliberate practice, as many studies have found that athletes consider sport related activities quite enjoyable (for review see Ford et al., 2015). This have led to researchers grouping practice activates into completely different categories and either focusing on the ones that are closest to definition of deliberate practice, as considered by DPF, or including all sport related activities that can be measured (as we did in our study). Baker and colleagues (2020) have recently proposed two critical conditions of defining deliberate practice in sport: 1) *Deliberate design* (deliberate selection and development of activities to improve performance) and 2) *Deliberate engagement* (which they define as athletes' concentration, as well as conscious cognitive effort to make refinements throughout the iterations of different practice activities). In other words, their definition of deliberate practice in sport is highly individualized and implies that no particular type of practice activity can be considered deliberate practice in absolute terms. Even though, deliberate practice in sport, if defined like this, would allow for comparison between different sports (once could

even compare individual versus group sports), it would make athletes' recall of the relevant sport-related activities much harder (as different activities would be deemed as relevant for development of different players throughout their sporting careers, thus different activities will constitute deliberate practice for different players). Therefore, in the future, there should be a focus on how to make recall of relevant sport activities less burdensome for the participants while applying the most up to date understandings of deliberate practice in sport (Baker et al., 2020) or a focus on how to pick out the most relevant activities, upon recalling them using similar methods that are currently in the usage.

Furthermore, it is noteworthy to mention that in our study grit was measured towards the end and therefore may be a reflection of how successful players are – better players are more interested because they get positive feedback, therefore they keep logging more practice time (which made them better in the first place). More adequate measure of grit would be to keep evaluating it concurrently every year and see how it changes depending on success and the amount of practice logged. In other words, it is worth checking if grit is a stable trait or not. Criticos and colleagues' (2020) findings provide us with some indication as they showed changes in grit, in different directions, throughout the six weeks long competitive season of track and field student-athlete throwers. However, given the number of participants (N = 9), as well as the temporal length of measuring grit, further studies are needed in order to understand volatility of grit and its impacts not only on the amount and types of practice one undergoes, while developing their expertise, but also on the performance itself, directly and through the practice.

Finally, given the cross-sectional design of our studies, as well as the homogenous nature of our sample, one should be cautious when generalizing our findings. We refrain from making interpretations that imply directionality between grit (and its facets) and engagement in sport related activities (and sport performance), but do encourage further, more controlled, examination into their relation and how they influence development of sport expertise.

Conclusion

One should not find it surprising that individuals who are more interested in a domain, and are also more willing to exert greater amount of effort, accumulate more hours engaging in domain-related activities. It has been shown time and time again that grit, or other psychological traits such as conscientiousness, can distinguish between expert and non-experts across multiple domains, sports and

non-sports related. Uniqueness of grit goes a step further as it has also been shown (see Chapter 3: Grit – Deliberate practice mediation on performance) that it differentiates well even amongst the elite (youth) athletes that are already competing at the highest levels (for their age group). Grit's effects on practice and performance (directly and indirectly through practice) have been theoretically predicted (Duckworth et al., 2011) and empirically shown (see Chapter 3: Grit – Deliberate practice mediation on performance). Gritty players spend more time in domain-related activities, developing their skills through more or less enjoyable practice activities, which in turn leads to development of mental structures needed for (exceptional) expert performance. Athletes high in grit constantly and consistently log more practice time than their less persistent peers so that differences, that may not be large at the beginning, snowball and become more noticeable over time; to the point that by the time they reach early teenage years, accumulated practice hours, under the influence of girt, differentiate even between the very best athletes in the country.

Our findings indicate the importance of personality factors for development of expertise, especially within elite samples where other factors may play a smaller role given that, at this level, athletes are similar in terms of talent and physical abilities. This study highlights the potential grit has, as additional factor, for understanding talent identification and development of expertise.

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Data and materials availability

The data and the code used for the analyses can be retrieved from here.

Chapter 5: Aging curves of sport expertise

Abstract

Researchers interested in changes which occur as people age are faced with a number of methodological problems, starting with the immense time scale they are trying to capture, which renders laboratory experiments useless and longitudinal studies rather rare. Fortunately, some people take part in particular activities and pastimes throughout (the entirety of) their lives, and often these activities are systematically recorded. In this study, we use the wealth of data collected by the National Basketball Association (NBA) to describe the aging curves of elite basketball players. We have developed a new approach rooted in the Bayesian tradition in order to understand the factors behind the development and deterioration of complex motor skills. The new model uses Bayesian structural modelling to extract two latent factors, those of development and aging. The interaction of these factors provides insight into the rates of development and deterioration of skill over the course of a player's life. We show, for example, that elite athletes have different levels of decline in the later stages of their career, which is dependent on their skill acquisition phase. The model goes beyond the description of the aging function as it can accommodate aging curves of subgroups (e.g., different positions played in the game), as well as other relevant factors (e.g., the number of minutes on court per game) that might play a role in skill changes. The flexibility and general nature of the new model makes it a perfect candidate for use across different domains in lifespan psychology.

Key Words: Bayesian modelling, Big data, Aging, Motor expertise, Skill development, Lifespan psychology, Basketball

Introduction

Describing the changes in motor and cognitive skills over the human lifespan is an important topic in psychology. For example, developmental psychology is interested in continuous changes in cognitive and physical domains with age (Grusec, 1992), research into aging looks at how older adults deal with the unavoidable decline of general and domain-specific abilities (Salthouse, 2004), while expertise researchers are interested in the development and retention of a particular skill over the course of a person's life (Vaci et al., 2015). The investigation of changes affecting complex skills over the course of the human lifespan poses several problems. The timescale of such changes, as well as the complexity of the skills in question, render laboratory experiments impracticable. Similarly, longitudinal studies are difficult to conduct and are consequently rather scarce. Most studies rely on cross-sectional data which suffer from a number of problems (Hedden & Gabrieli, 2004)). Here, we exploit the existence of historical records of a complex motor skill, basketball play, to demonstrate changes in the skill levels of elite athletes. We analyse a sample of over five decades' worth of data from the National Basketball Association (NBA) using a new way of dealing with such data which is based on Bayesian structural modelling. We extract latent factors of development and aging and show how they differ depending on other external factors, such as the particular position occupied by a player during the game or a player's activity level (e.g., number of minutes and games played).

Age-related changes

Age-related changes are commonly assumed to bring a consistent decrease over the course of the human lifetime. Physiological and biological indicators such as muscle strength, endurance, contraction time, and the number of fibres in a muscle all increase throughout childhood, reaching their peak in early adulthood around the age of 25. The decrease is initially slow until about the age of 50, after which there is a rapid decrease in basic motor indicators (Booth et al., 1994; Faulkner et al., 2007; Goodpaster et al., 2006; Rogers & Evans, 1993; Thelen, 2003). Similarly, general cognitive abilities such as processing speed and working memory decline as otherwise healthy adults age (Salthouse, 2010, 2016; Verhaeghen & Salthouse, 1997). Just like with the motor indicators, negative age-related changes in general cognitive abilities start in people's 20s or 30s and are continuous and qualitatively similar throughout adulthood (Salthouse, 2016; Verhaeghen & Salthouse, 1997).

On the other hand, there are processes that offset the natural decline of general abilities. They include processes that depend on exercise and accumulated knowledge. The size of the vocabulary is a good example of such a process; another is the motoric skill of rolling cigars, where knowledge and

skill logarithmically increase with experience and age (Crossman, 1959; Keuleers et al., 2015; McCabe et al., 2010). The knowledge of language is a good example of a domain that never decreases over time, where people always learn new words, but rarely forget the previously learned ones (see Ramscar et al., 2014). The power-law increase in the case of vocabulary size is illustrated using a big-data approach by Keuleers and colleagues (2015). Similarly, the decline in the case of chess performance, which strongly depends on knowledge, is much shallower than decline in games or sports that rely on speed of processing (see Vaci et al., 2015). However, motor skills, even basic ones, can also be influenced by the systematic implementation of different types of exercises (Buford et al., 2010; Faulkner et al., 2007; Rogers & Evans, 1993). The question, then, is what happens with complex real-life motor and cognitive skills? These skills inevitably rely on general abilities, which undergo normative age-related decline. However, they also depend on experience and acquired knowledge, where little or no decline should be expected with age (Salthouse & Maurer, 1996). In other words, even though people experience a decline in the general abilities underpinning their skills, the accumulated knowledge should preserve their skill and slow down the actual decline.

Currently there is a lack of evidence concerning basic age-related function in real-life skills. Often, researchers do not have the data to model the performance measures as people age. In those rare cases when they have some data, there are usually not enough data points to capture the intricacy of the nonlinear behaviour of the age-related function. Here we present a way of using archival data to model the age-related changes in a complex real-life motor skill. We use professional basketball players' performance to model age-related changes. The domains of competitive game performance are the ideal examples of tasks that depend on both general and domain-specific abilities, where motor speed and power, as well as experience and knowledge, come together to define the level of performance (Bilalić, 2017; Starkes & Ericsson, 2003). Competitive games and sports provide an excellent opportunity for researchers to utilize a well-defined measure of performance and to investigate age-related changes in greater depth (Roring & Charness, 2007; Starkes & Ericsson, 2003; Vaci & Bilalić, 2017).

Here, we will first illustrate different ways in which practitioners have investigated the basic form of the age-related function in the case of real-life performance, and comment on the potential shortcomings of this common approach to dealing with big data. We proceed by presenting a new way of dealing with the data, which is based on Bayesian latent variable modelling (Vanderkerckhove, 2014). Finally, we demonstrate how researchers can use the newly developed Bayesian model, which we call *B-Ianus*. The first letter of the model's name denotes the Bayesian analytical philosophy that

governs the model estimation and its use, while 'Ianus' refers to the Roman god of beginnings, transitions, duality, passages, and endings. This god is often depicted with two faces, one looking to the past, and another looking to the future. In a way similar to its divine counterpart, our model does the same thing. By modelling two phases of age-related changes, development and aging, we investigate the interactions between them. In other words, once we reach the peak of performance we are asking the question of whether we can predict the future decline (aging) of our performance by knowing the preceding increase to the peak (development).

Modelling age-related changes

The main goal in lifespan psychology is to examine the general principles of development throughout the human lifespan, that is, to describe the form of age-related changes. Lifespan researchers have three goals: (1) generating knowledge of the inter-individual shape of the age function, (2) investigating whether the overall function differs between groups and individuals, and (3) understanding how more basic processes, the building blocks of age-related changes, influence these changes (Baltes, 1987; Baltes et al., 1977, 1999; Baltes & Baltes, 1990; Lerner, 1984). One of the dominant views in lifespan psychology is the theory of gain-loss relation (Baltes, 1987). This theory states that development at all points in life is a joint expression of features of growth (gain) and decline (loss). In other words, the developmental progression across the lifetime always displays adaptive properties, as well as declining ones. The relation between the gains and losses changes systematically over the lifetime. Childhood is characterized by allocation of resources towards the gains, where most of the increases in performance are expected to occur. The middle life period tends to be focused on maintaining a stable level of gains and losses, while in old age resources are directed towards the management of loss. When observing a real-life skill performance, the continuous interaction between the two overarching forces of gains and losses, which underlie this particular skill, often produces a nonlinear function over the years. In the following paragraphs, we provide an overview of modelling approaches that are frequently used to investigate these age-related changes, and we also indicate their limitations when analysing nonlinear behaviour of data.

To capture the nonlinear changes that occur during life, researchers often use polynomial regression, where age is transformed by the power functions (usually quadratic transformations). Polynomial regressions result in a nonlinear fit of the relationship between age and performance, which sheds more light on the form of the age-related changes (Goal 1 in lifespan psychology). In lifespan psychology, a second-order polynomial or quadratic function is often the relation of choice

when modelling age-dependent changes. These studies indicate that performance follows two phases of development with one transition point. For example, practitioners of speed-dependent sports, such as baseball, peak at the age of about 27 years on most measures of performance, and then start to decline relatively quickly (Allen, 2015; Bradbury, 2009; Brander et al., 2014; Dendir, 2016; Hollings et al., 2014; Laivaux et al., 2014; Schulz et al., 1994). Similarly, studies investigating cognitive skills such as chess showed that players improve quickly and reach the peak of performance in their late 30s (Roring & Charness, 2007; Vaci et al., 2014, 2015; Vaci & Bilalić, 2017). After this peak, chess performance starts to decline as people age.

We have recently demonstrated that the third-order polynomial or cubic function fits the data better in cognitive domains (Vaci et al., 2015). The cubic function adds a third phase of development in addition to development and decline. The peak performance is indeed followed by a decline, but the decline is not constant. The cubic function reveals a potential third phase of age-related development, where players stabilize in their performance and preserve it in the face of increased age (Vaci et al., 2015). In comparison to the quadratic relationship, the cubic function adds theoretically relevant implications concerning additional aging stages. It could also represent a significant theoretical and practical difference between the general processes (e.g. memory and reasoning) and domain-specific abilities (e.g. decision making in chess) in how they fluctuate across the lifetime.

However, both quadratic and cubic polynomial functions suffer from multiple drawbacks when they are used for analysing real-life performance. One problem is that individual polynomial coefficients are highly correlated. In situations in which researchers are interested in the underlying factors that influence age-related changes (Goal 3 above), it is not just the basic form of the function, but also the interaction between variables of interest with polynomial coefficients, that can result in strong overfitting of the data. In addition to this, the polynomial functions are symmetric around the point of inflections (maximal and minimal value of the function). When applying them to the behavioural and psychological data, for example in sports, a sharper decrease of the function after the peak of performance does not necessarily mean a sharper decline. It might simply indicate that this player increased much more quickly and dramatically in comparison with other people in the dataset. In other words, the subgroup analysis, one of the main interests of lifespan psychology (Goal 2 above), is problematic. The cubic function alleviates this problem to some extent by adding a third phase and the prolonged tail of the function, which inflects the decrease and indicates that this player is not experiencing a dramatic decline. In other words, it adds more flexibility and degrees of freedom in the

model, which can subsequently adapt better to the data. However, every polynomial regression suffers from this problem to the same extent.

One way around the problems inherent in polynomial regression is to use exponential functions. Just like the polynomial function, exponential functions provide us with an understanding of the basic form of changes over the course of life. However, they are more flexible than the polynomial function when fitting sudden changes of performance around the peak value. For example, instead of using a single function, Schroots (2012) utilized double logarithmic functions to describe age-related changes in the functional capacity of people. The first function describes the development before the peak, while the second function fits the decrease after the peak. Similarly, Simonton (1999, 2015) used a double-exponential function to describe the creative potential and changes in the output of ideas throughout a person's life.

Both models are preferable to the common polynomial models because they adjust the age-related function for the group and individuals much more accurately. In other words, the exponential function allows us to test and compare the behaviour of cognitive processes between the groups, as well as between the processes themselves. For example, the model of career trajectories and landmarks showed different rates in the creative potential of practitioners in different fields, indicating that novelists generate original ideas more slowly, and take longer to develop them, than poets do (see Simonton, 1989).

These models were also used to illustrate the differences between the lifespan changes in fluid and crystallized abilities (Schroots, 2012). Fluid intelligence follows a two-step function with one inflection point: that is, people increase in fluid abilities until their mid-20s, when they reach the peak, which is followed by constant decline as people age. In the case of crystallized abilities, lifelong changes progress through three stages with two inflection points. People slowly build up crystallized abilities until their late 30s, when they reach the peak. This is followed by maintenance of the abilities, which stay at the same level until old age, when people's abilities slowly start to decline.

However, these models still have a problem with taking into account the building blocks of age-related changes (Goal 3), that is, the different factors that influence lifelong function. Additional variables cannot be interacted with exponential coefficients during the model fitting. A possible way around this problem, namely a two-step analysis, where exponential coefficients are estimated in the first step and regressed jointly with the factors of interest in the second step, suffers from *generated regressor bias* (Pagan, 1984). In other words, using generated values from regression to draw valid

inferences in the second step can be problematic, as we are using aggregated results that are sensitive even to small biases in the data. When the resulting value from the first regression suffers from sampling bias, the regression analysis in the second step results in biased estimates and inflated effect sizes and test statistics (Boehm et al., 2018).

Finally, the researchers can use nonlinear data driven methods such as Generalized Additive Models (GAM; see Wood, 2006). The GAM is a data-driven method designed to estimate the nonlinear relation between the covariates and the dependent variable. A generalized additive model is nothing other than a generalized linear model with a linear predictor over a sum of smooth functions of covariates. Therefore, the main goal of this analysis is to estimate the space of functions that can represent the nonlinear shape of the data (see van Rij et al., 2020). In contrast to the standard linear model, in GAM we do not have to specify the function (polynomial terms, exponential equation, etc.), as it iteratively optimizes the smooth function (basis) and proposes an optimal structure between the dependent and independent variable. The main problem with the nonlinear methods is that the results of the GAM model cannot be interpreted in the standard linear regression terminology, where the results tell us about the change in the dependent for one unit increase or decrease in the independent variable. The GAM provides information about the wiggliness of the regression line (summarization of all individual functions), and whether the function is significantly different from zero. As in the case of most data-driven and nonlinear methods, the visualization is a necessary tool when interpreting the results, while we cannot quantify the information behind the estimated parameters.

Here we primarily use exponential functions to model the changes with age seen in expert performance in basketball. We model the age-related changes separately before and after the peak. We do, however, also provide additional analysis where we calculate the inflection point, the exact age when the increase in performance starts decreasing, using the Heaviside functions (Bracewell & Bracewell, 1986). In addition to only modelling the age-related changes, we propose a structural model constructed using a Bayesian latent cognitive variable modelling approach, which offers more information on the research questions proposed in the domain of lifespan psychology. We show how this model can be used on natural and large datasets to investigate age-related changes, as well as the different factors that influence these changes. Finally, we quantify the relationship between two factors and show how development (pre-peak increase) interacts with aging (post-peak decline).

Method

Dataset and measures of basketball skill

Unlike many real-life domains, in competitive games and sports it is possible to quantify the skill of players using performance measures (Franks & Goodman, 1986). In the case of this study, we used large datasets that measure basketball performance (*Basketball Statistics and History*, n.d.). This type of dataset, which collects demographic and performance level variables for players who compete at a professional level, is usually maintained by official sport federations. Since there are multiple ways of quantifying basketball performance, we have chosen the three measures that are most commonly used in today's basketball performance analyses: win shares (WS), value over replacement player (VORP), and player efficiency rating (PER; for more information, see (Kubatko et al., 2007). WS is an estimate of players' contributions (to the team) in terms of wins: it attempts to allot shares in the credit for a team's success to the individuals on that team (Kubatko, n.d.; Oliver, 2004) WS is widely used, as it is one of the only measures that takes into account both the defensive and the offensive contributions of players to a team's win (while other measures rely more on offense-related statistics). WS measure also takes into account the time the player spent on the court as well as the pace of the game during player's time on the court. VORP is an estimate of each player's overall contribution to the team, measured against what a theoretical replacement would provide (the replacement being either a player given a minimum salary or a player who is not a regular part of the team's rotation, Barzilai & Ilardi, 2008; Myers, n.d.). It is an estimate of the number of points a player is producing above/below a replacement player per 100 team possessions in a season. Even though standardized for a specific season (thus allowing players that played during the same season to be compared) it relies heavily on offense-related statistics, and hence is not a very good defence measurement tool. Player efficiency rating (PER) is a measure of how productive and efficient a player is during the time spent on the court (*Calculating PER*, n.d.; Hollinger, 2002)

Out of the three most commonly used measures, PER is the only one that takes into account how much time a player has spent on the court playing. Similarly to WS, it also takes into account the pace/speed of the game during that play. PER, like VORP, relies mostly on offense-related measures and does not represent a good measurement tool of the defensive qualities of players. However, PER is a standardized measure enabling comparisons not only between players participating in the same season but also between players from different periods of the sport's history.

It is clear that all three measures have their own advantages and disadvantages. Given that the topic of this paper is the modelling of the aging function of motor expertise, we have chosen to showcase, in the main text, the analysis conducted on WS measures because it is the only one of the three that takes into account a broader range of abilities (e.g., defence and offence). However, since WS, unlike the other two measures, is lacking in standardization and does not take into account the pace of the game and the time spent of court, we have also conducted analyses on PER and VORP, and these can be found in the Appendix E.

We illustrate our B-Ianus model on the WS in the main text and provide the same analyses for the other two measures in the Appendix E. The details and descriptive statistics on the complete data, including cross-validation on the polynomial regressions, and all following investigations, are described in the online materials together with accompanying R codes (here). We structured our analyses around the three goals of lifespan psychology: 1) describing the changes in performance over the course of the careers of NBA players, 2) the different career trajectories of different groups, in this case the position they play in the game, and 3) investigating how other factors, in this case the playing time, influence the age-related function. The first analysis, on the form of age-related changes, we conduct using the whole sample, which contains 50 years' and 2845 players' worth of data. The second two analyses, on the subgroups and activity (minutes per game played), are performed on a randomly chosen sample of 400 basketball players[18]. All analyses are carried out as a methodological illustration of the model, which can be employed in different domains. In this particular case, player position and time spent on the court were among the available variables. In other domains, other variables may be available which may be more pertinent than those used here.

Goal 1: The form of the age-related changes

In the first step of our investigation, we compared different exponential functions that can explain age-related changes in the case of basketball performance. The illustration of the raw data can

18 The analyses presented here are a primer of how the B-Ianus model can be used. Analysing all data would require computational resources that the authors currently do not have at their disposal. To calculate the model on the 400 players we utilized Amazon AMI services that run a 3.0Ghz Intel Xeon Scalable processor with 32GB of memory. Using this service, the estimation of the parameters was running for approximately 12 hours per model. The high computational cost is the main limitation of the proposed model.

be seen in Figure 5.1, with the general age-related changes (Figure E1) and age-related changes moderated by players' activity (total minutes per game played). To be able to estimate the complete form of the lifespan function, we separated the age-related changes into the pre-peak increase and the post-peak decrease and modelled them as two different processes. For each of the two parts, we examined various exponential functions that can explain age-related changes (see Table 5.1). Firstly, we included the power law function behind age-related increase and decrease in performance, as previous studies showed that this function explains the majority of activity-related changes in performance (Newell & Rosenbloom, 1981; Ritter & Schooler, 2001). Secondly, we included exponential growth curve as a potential underlying function, which proved useful in previous studies (Schroots, 2012; Simonton, 1989, 1991, 1997). The third function that we examined was logistic growth, which is a good way of capturing the accumulation of knowledge (Keuleers et al., 2015). Finally, we included linear changes in the model because these should indicate a potential constant increase to the peak and decrease after it (Roring & Charness, 2007; Salthouse, 2010, 2016).

Table 5.1. *Mathematical functions used to model age-related pre-peak increase and post-peak decrease of performance in basketball*

Function	Equation
Power law	$Performance_{pi} = \alpha * age_i^{\beta_p}$
Exponential growth	$Performance_{pi} = \alpha * \exp(\beta_p * age_i)$
Logistic growth	$Performance_{pi} = \dfrac{\delta_p}{1 + a * \exp(\beta_p * age_i)}$
Linear function	$Performance_{pi} = \alpha + \beta_p * age_i$

Note: The parameters in different models refer to the same age-related process. *Performance* refers to the rating of an individual player (*p*) at a time point (*i*). The α parameter estimates the starting number of performance points, the β parameter estimates the rate of the change, while the δ parameter estimates the upper limit or maximal level of performance.

The power law and logistic growth function indicate that age-related increase in performance slows as players reach the peak of their performance. In other words, the accumulation of skill is rapid at the beginning of the skill acquisition period, when every exercise brings new gains. As players get older, the increase in performance slows down and approaches the upper plateau asymptotically. The

main difference between these two functions is in the beginning of the skill acquisition period, where the logistic function predicts a slower acquisition of skill. In comparison with logistic and power law functions, the exponential function does not assume that the speed of skill acquisition decreases at the peak, but rather that it continues in the same manner. Finally, the linear function assumes that acquisition of skill follows a continuous increase until the peak level of performance. The same interpretation of exponential functions applies to the age-related decrease in the second part of the lifespan when the age-related changes become more negative.

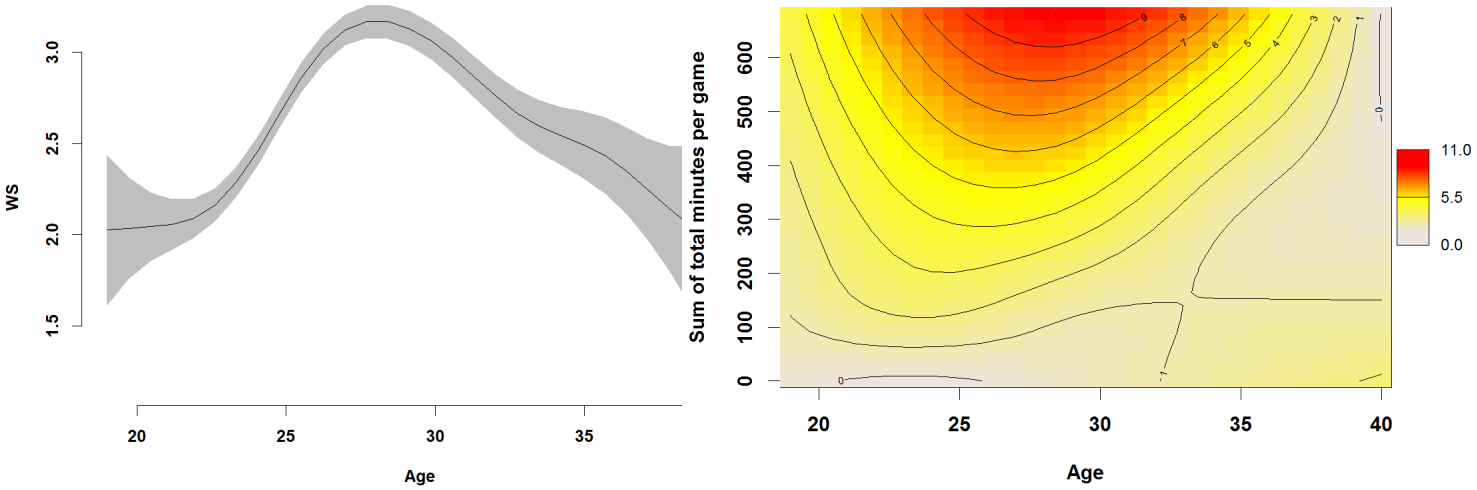

Figure 5.1. The Illustration of the raw data for win share (WS) performance across players' ages. The left panel illustrates nonlinear age-related changes in WS performance. The line indicates change in the mean WS performance across ages, whereas the shaded area shows 95% confidence intervals for the mean. The right panel illustrates the relation between the summed minutes per game individuals played during their lifetimes and their age-related changes in WS performance. The heat map indicates region of higher (red) and low (white) performance, as measured by WS and how this changes over age (*x*-axis) and total minutes per game played (*y*-axis)

We used Bayesian hierarchical modelling where the exponential functions were fitted separately for the pre-peak increase and post-peak decrease for every player in the dataset, as well as the age when the increases in real-life performance transition to consistent decrease. Following the lifespan theory, we do not assume that all individual processes that underlie real life performance decline at the estimated age, nor that all players decline at the same time. However, this is the moment

when the product of individual processes results in negative changes. We employed the ad hoc division of the age-related function to test the shape of the functions, and the model-based estimation of the inflection point to test the age when this transition between two functions occurs. To estimate the age when the transition between two functions occurs, we used step or Heaviside functions (Bracewell & Bracewell, 1986), which govern the conditional influence of the parameters in the model (see Inflection point section in the online materials). In the case of our model, the Heaviside function defines and estimates the age at which the pre-peak increase changes to post-peak decrease. This type of model is often referred to as a broken stick model (Flora, 2008; Hall et al., 2003). The simple broken-stick model, which calculates the pre- and post-peak slopes as well as the inflection point, was estimated on the sample data (400 random players) with 50,000 samples as the adaptation phase, 10,000 burn-in samples, and 5000 samples with the thin factor of 5.

To test the shape of the functions, we choose age 27 as the value at which the pre-peak increase turns towards the post-peak decrease. This value was based on estimates from previous studies (Benedict, 2017; Faulkner et al., 2008; Laivaux et al., 2014; Schulz et al., 1994; Wakim & Jin, 2014), while the aggregated performance across players becomes negative at 27 years, and the results from Heaviside functions show that inflection point falls within this age range. Although ad hoc division of the peak value can result in individual player biases to the overall functions, this approach decreased the complexity of the overall model, as it was not necessary to calculate the peak for every player in the dataset. For the shape of the functions, we ran 5000 samples as adaptation phase, 8000 burn-in samples, and 5000 samples with the thin factor of 5.

To investigate how well the mathematical functions fit the observed data, we used Deviance Information Criterion (DIC), as the analogue to the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). All of these measures indicate the relative quality of a statistical model for a given dataset. DIC is particularly suited to Bayesian model estimation where the results have been obtained by Markov chain Monte Carlo (MCMC) simulations. As well as measuring how well the model fits the data, the information criterion penalizes for the number of parameters used. When comparing two models with equal fit to the data, the more complex model is going to have a higher (i.e. worse) DIC measure than the less complex one.

Age of inflection

To estimate the age of inflection, we calculated global intercept and individual slopes for the age variable, while the age of inflection was adjusted for every player in the data. The age was centred to 0, to make the estimate of the cut-off point easily interpretable, and we fitted models with linear and exponential functions (see Inflection point section in the online materials). The results show that in the case of all three measures the change of the net performance occurs at a similar age. Players increase in performance up to 28 or 29 years and start declining from that point on, while the individual inflection points range from 24 years to 33 years for all three performance measures. In other words, the function that models the increase in performance is active until 28 (including the age of 27) to 29 (including the age of 28) years, when the slope that governs the decrease becomes active. The results from our model confirm findings from previous studies that show that the peak should be expected at around 27 or 28 years.

Shape of the function

The results show that in the case of a pre-peak increase, exponential and power-law functions result in the lowest deviance information criteria when compared with other used functions (see Pre-peak in Table 5.2). In the case of WS the pre-peak increase follows an exponential function, where compared to linear change the rate of the increase in players' skill increases more rapidly. The VORP initial increase follows a power-law function while PER is best described by a linear increase (see Table E1 in Appendix E). For the post-peak decrease, the results show that the power law function has the lowest DIC measure across all three different measures of performance (see Post-peak period in Table 5.2). The results indicate that basketball players decrease in skill quickly after the peak of performance, but the rate of the decline is not constant and slows down in older age.

Table 5.2: *Deviance information criterion for exponential functions used to model the age-related changes in WS separately for the pre-peak increase and post-peak decrease*.

	WS	
	Pre-peak	Post-peak
Power law	51,118	34,974
Exponential	50,911	44,277
Logistic	56,360	NA
Linear	51,515	35,345

Note: The NA (not available estimates) indicates that models with specified functions for the pre-peak increase or post-peak decrease could not be estimated.

In addition to comparing the different functions that can explain the age-related changes in performance, we also investigated the necessity of adjusting the random structure of the models. We compared the models with and without random adjustments for intercept and slope of the final function used. The results indicate that the chosen slope adjustment for each player in the dataset is well founded, while the intercept adjustment does not seem to be necessary. However, once we adjust the slope for every player in the data, the general slope of the function loses statistical significance. Even though we are not primarily interested in *p*-values and interpretation of significance, this is a potentially interesting result that may indicate a high degree of variability in the increases and decreases in performance over a player's career (see Table 5.3 and Table E2 in Appendix E). This suggests that some players, in fact, do not decline as they age or that the additional increase in the first part of the career is limited to players who are already highly skilled on entering the league. Overall, the results indicate that age-related changes isolated from other potentially impactful variables do not have large explanatory power for the players' performance in basketball.

Table5. 3. *Estimates of the intercept and the slope WS, given separately for the pre-peak increase and post-peak decrease.*

		Function	Parameters	
			Intercept	Slope
			Mean (95% CI)	Mean (95% CI)
WS	Pre-peak	Exponential	1.34 (1.27 – 1.40)	.000 (-.00091 – .0020)
	Post-peak	Power law	2.00 (1.96 – 2.16)	-.012 (-.022 – -.0018)

In the next step of the analysis, we combined the two functions that provide the best fit to the age-related changes, in a joint model that aims to investigate how different variables influence these changes, and potentially answers the question of increased variability in them. Finally, we calculate correlation between two phases, development and aging, to understand and produce a complete function of performance over players' careers.

Bayesian approach

The Bayesian statistical approach is based on the idea that probability can be defined as a degree of knowledge about a particular hypothesis (Gelman et al., 2014; Kruschke, 2011; Lee & Wagenmakers, 2014). The probability is expressed as the prior belief or probability of an idea or hypothesis, and it is updated when we observe the new evidence coming from the collected data, resulting in posterior probability. In other words, the probability of a hypothesis is an orderly opinion expressed as a probability distribution, and inferences coming from the data (likelihood) offer revision of that opinion in the light of relevant information. In the Bayesian approach, we can easily use these probability distributions to represent knowledge and uncertainty about variables of interest. More importantly, this knowledge can be processed, summarized, updated and manipulated using the laws of probability theory (Lee, 2004, 2008).

One of the prominent ways in which the Bayesian approach can be employed is to build models that relate psychological processes to the observed data (Lee, 2004; Lee & Wagenmakers, 2014). This is not identical to the data analysis approach, in which practitioners use statistical tests,

such as analysis of variance, to test the theoretical assumption. Instead, the goal is to create a more detailed statistical model of a particular aspect of cognitive functioning or behaviour and relate this model to the data. The memory retention or diffusion models are good examples of such an analysis, where the estimated parameters are describing the decay rate of information and the drift rate (accumulation of information) over time (Ratcliff & McKoon, 2008). These parameters represent the aspects of the assumed cognitive or theoretical process, which can then be isolated and investigated in more depth. This is one of the main reasons why we decided to use the Bayesian approach to the data modelling. Leaving aside the often-reported benefits of Bayesian analysis, we primarily used this environment because the proposed B-Ianus model requires high-dimensional integration with no known analytical solution. In other words, we do not have mathematical optimizers for the likelihood functions with which the B-Ianus model operates. This is mainly due to the necessity of investigating the interaction of lifelong changes with potentially interesting covariates. In this case, Bayesian modelling that relies on numerical integration methods such as Markov chain Monte Carlo methods (MCMC; Robert & Casella, 1999) can estimate the parameters of the proposed model by sampling the values of the parameters from simulated posterior distributions.

Bayesian latent cognitive variable modelling

In this study, we combined age-related modelling procedures with the factor analysis to build a more informative model of age-related changes in real-life skills. In the first part of the modelling process, we used exponential functions to investigate age-related changes in performance in basketball (as already introduced in the Age-related functions subsection). In present study, we show how the age-related functions can be interacted with variables of interest using latent variables, which results in a cognitive latent variable model – CLVM (Vanderkerckhove, 2014). Therefore, we combine an exponential modelling of the age-related changes with individual differences in performance (Cronbach, 1957). The model we propose is built on three different levels: random effects, manifest predictors, and latent predictors.

The first level of the model represents a random effect structure for the parameters of interest in the model. This is a set of parameters that are assumed to be drawn from some superordinate distribution (Baayen et al., 2008; Radanovic & Vaci, 2013). For example, the sampled participants in the experimental setting are just a small fraction of the whole population which varies, for example, in

their basketball skill. In the case of this study, we adjusted the β parameter (slope) of the increase and decrease function for every player in the database. By doing that, we modelled the rate of growth and decline of performance for every player over the course of their career. The individual slopes are defined as β_{1p} (pre-peak) and β_{2p} (post-peak) in the Figure 5.2.

The second level of the model comprises the manifest predictors – all the measures that can explain variability in the dependent variable. There are multiple ways in which researchers can model these predictors, from analysis of variance or regression approach, where we usually assume linear structure between dependent and independent variables, to non-linear regression analysis (e.g. GAMs) and cognitive models (e.g. diffusion models). We used previously explored exponential functions that capture age-related changes in measures of performance (WS, VORP, and PER), but we also included the playing position of the player and how many minutes per game were played during a player's pre-peak and post-peak career period. The manifest predictors are illustrated with the shaded nodes in Figure 5.2.

The third level in a model comprises the latent factors that offer us a joint explanation of the covariance between the set of observed variables. In other words, the latent factors are not observed but are estimated from the covariance matrix of the observed variables. Even though this approach is often used in the psychology of personality and intelligence, estimation and assumptions of the potential latent structure are rarely used in age models (but see Oberauer et al., 2000). In the case of our model, we included two latent factors that correspond to the skill acquisition and aging period. Unlike previous models in the domain of age-related changes, latent factors offer the possibility of modelling age-related changes in performance together with other possibly interesting variables (Goal 3). Latent factors are notated as ϕ nodes in Figure 5.2.

Before going into the results, we will explain the basis of the model step by step (for a detailed introduction to latent variable modelling, CLVM, see Vanderkerckhove, 2014). For the data level we used exponential functions that model the age-related changes, as well as the positions of the players and total number of minutes played during the pre-peak and post-peak period. In the next step, we specified two latent factors of age-related changes, pre-peak development and post-peak aging. In essence, we used the confirmatory model approach in the factorial analysis. The factorial analysis is usually represented in the linear equation system $Y = \Lambda * \Phi + \mathrm{E}$, where Φ is the matrix of person-specific factor scores, Λ is a matrix of factor loadings, and E is a matrix of independent, zero-centred, normally distributed errors. Because the latent factors do not have the scale of measurement and are, therefore, completely theoretical, we need to define which manifest variables are allowed to be related

to the latent variable. The usual approach is to relate the first group of manifest variables to the first latent factor and the second group to the second latent factor, usually known as a simple structure or congeneric factor model (Anderson & Gerbing, 1988; Meredith, 1993).

Two different versions of the model were tested. The first version had the cut-off age for the pre-peak and post-peak manually defined by the authors. In the second version this inflection point is automatically calculated using Heaviside functions (see B-Ianus Model 1 and Model 2 in Model section of online materials). Besides a difference in defining the inflection point across the age, the two models differ slightly in the overall structure. Model 1 has two separately defined likelihoods, one for the pre-peak increase and one for post-peak decrease. Model 2 has only one defined likelihood for the age-related changes in performance. This difference between specification of the likelihoods results in different complexity, when it comes to estimation and retrieval of parameters. Model 2 with automatic estimation of inflection point has higher complexity, as it has an additional parameter (the inflection point) and slope parameters that are jointly estimated. In combination with latent structure, the model has a problem converging and retrieving the possible parameter values in feasible number of MCMC runs. In contrast, Model 1 with separate likelihoods converges on the highest probable value of parameters in the same number of runs.

In the case of both models the rate of increase was loaded onto the first factor, while the rate of decrease was loaded onto the second factor. The players' position and total minutes played per games were loaded onto both factors. We aggregated these variables for every player into the pre-peak and post-peak values, choosing 27 years as a cut-off value. Additionally, the loading values (λ node in Figure 5.2) for the slopes of the pre-peak increase and post-peak decrease functions (β parameters) were fixed on a value of 1 for each factor: in this way, the measurement of a latent factor was defined as the rate of performance change before and after the peak. Consequently, this allowed us to investigate how the position played and the minutes contributed to each game correlate with the change in performance with age for basketball players. The positive β values in the developmental latent factor mean that the players improve more dramatically, while positive β values in the aging factor mean that the players decrease in skill at a slower rate. Finally, we specified the correlation structure between the two latent factors and investigated how the rate of pre-peak increase influences the post-peak decrease of performance in elite NBA players (lifespan interaction, illustrated as a ρ parameter in Figure 5.2).

The complete overview of the model is illustrated in Figure 5.2. Starting from the bottom of the graph, we can see that the change in performance is modelled as an exponential function for the

pre-peak increase and the post-peak decrease. These functions were adjusted for every measure of performance, that is, for, WS, VORP, and PER. The β (rate of change) is estimated for every player in the database. Therefore, they are drawn from the superordinate distributions that tell us about the individual differences in these parameters. On the second level, the expertise-related activity expressed as the total number of games played, together with the β parameter, is loaded onto the latent factors (skill acquisition and aging). The $\lambda_{1,2}$ and $weight_{1,2}$ parameters are loadings of the rate of change and the player's position or total minutes per game on the latent factors, where the λ parameters are constrained to 1. Therefore, the measurement scale of the latent factors is inferred from the slope of the age-related changes. This allows us to investigate all other auxiliary variables that can influence age-related changes in performance, such as intelligence, motivation, and personality dimensions (Bilalić, McLeod, et al., 2007; Bilalić, McLeon, et al., 2007; Burgoyne et al., 2016; Charness et al., 2005; de Bruin et al., 2007; Ericsson et al., 1993). In other words, the model offers the possibility of investigating the building blocks of age-related changes in real-life performance. Finally, we investigated the interactions between the two latent factors by including a correlational structure between pre-peak increase and post-peak decrease. This parameter offers the possibility of estimating the relationship between the skill acquisition function and the aging function. The same model is illustrated more graphically in Figure E1.

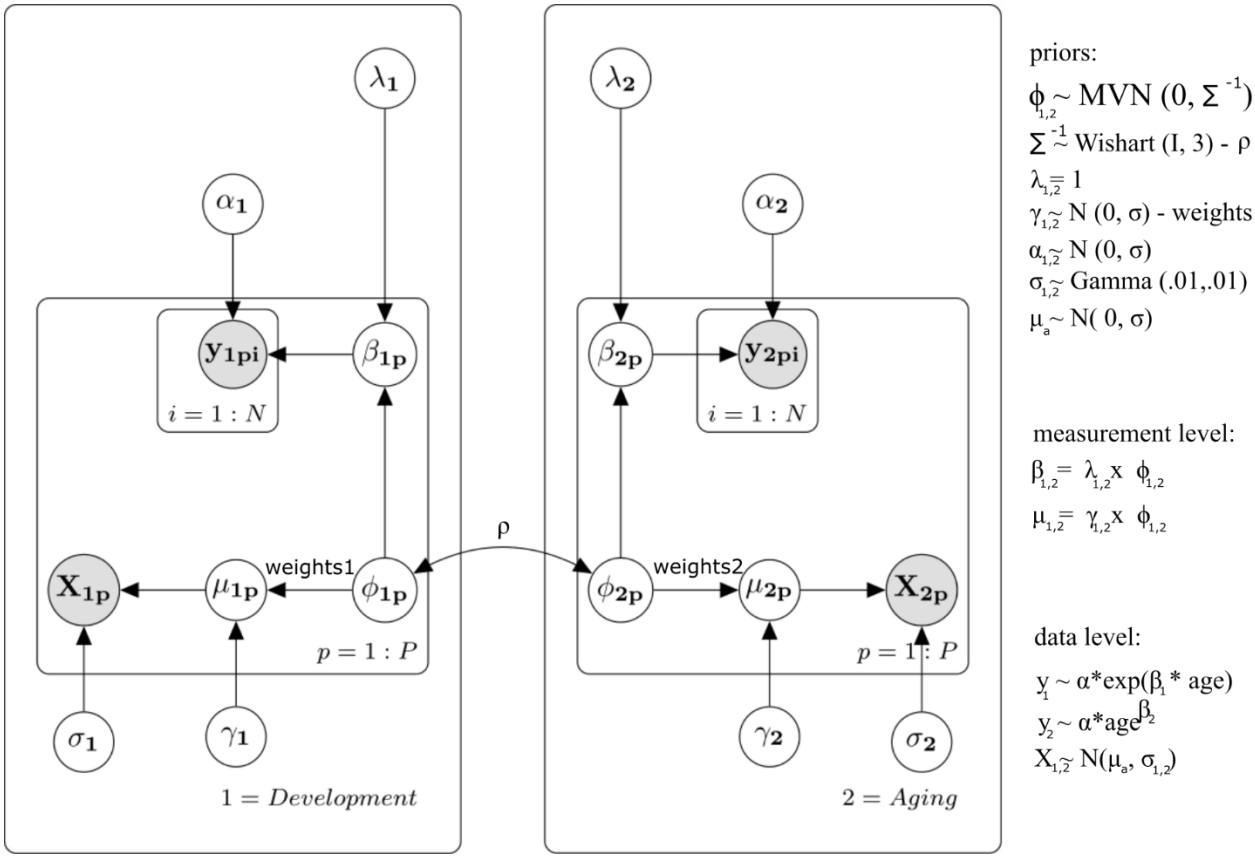

Figure 5.2. The graphic representation of the B-Ianus model of age-related changes in sports (Model 1). Plates 1 and 2 indicate pre-peak increases and post-peak decreases in the performance that were modelled separately. The *p* plate shows independent repetitions over participants, while *i* shows independent repetitions over trials. The α_1 and β_1 parameters represent the increase in performance, while the α_2 and β_2 parameters model the decrease of the performance across age. The β_1 and β_2 parameters are loaded onto the development (ϕ_1) and aging (ϕ_2) factors, by setting the λ_1 and λ_2 constraints. The covariates, minutes per game and position (X_{1p} and X_{2p}) in our case, are loaded onto the respective latent factors through *weights (γ)* parameters. Finally, the B-Ianus model also estimates the relation between the development factor and the aging factor, which is performed through the *ρ* parameter.

Estimation of the model

The full model that includes all relations and underlying latent factors was only calculated on the random sample of 400 people. We also transformed the relation between performance measures and age to an approximate linear relation. This improved model optimization and decreased the time

required to sample the posterior distribution of the parameters. In particular, in the case of the power law relationship we logarithmically transformed both performance measure and age, while in the case of the exponential relationship only performance measure was transformed with the logarithmic transformation. The final estimates can be easily transformed to original values by using exponential transformations on the predictions of the model. To estimate the model, we used the Amazon AMI service, utilizing its cloud computing capabilities and reducing the time necessary for sampling out the complex posterior distribution as in the case of this model. For each batch, we used 50,000 samples to adapt the model, 10,000 burn-in samples, and 10,000 samples with the thin factor of 3 steps.

Results

Goal 1 – Basic form of the age-related function (continued)

The intercept and the slope (the α and β parameters, respectively; see Figure 5.3 for the slopes) are estimated similarly to the separate models for the development and aging functions (see Goal 1 above). The results indicate that people vary in the degree of change during the pre-peak and post-peak, where a more positive parameter indicates greater development and a more positive aging function, that is, less decline. The histogram plots show the possible value of parameters for the age-related changes and interactions. In the case of WS (see Figure 5.3) and VORP (see Figure E6 in the Appendix E), the development slope is centred slightly above zero with a prolonged tail on the positive values of the parameter. This shows that most players do improve during the first period of their career, while some players show a marked development, indicated by the large positive parameters. The negative values for the pre-peak slope indicate that decline in performance can also occur during the pre-peak phase. This is prominent in the case of the PER measure (see Figure E2 in the Appendix E) that seems to decline in the case of most players, indicated by the large negative values.

In the case of the aging function, results show that most of the players decline in all measures, as the highest density of the distribution is covering negative values of parameters.

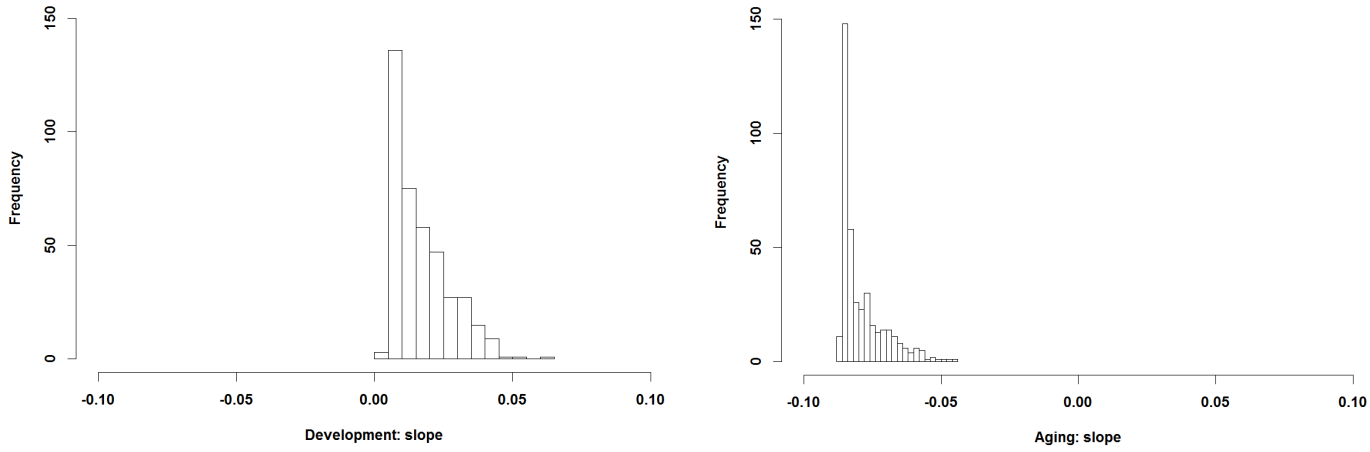

Figure 5.3. Estimated parameters for pre-peak (development) and post-peak (aging) changes (slope of the function used). The figures show the possible values of parameters for slope during the pre-peak and post-peak changes when we approximate the exponential and power-law changes with the linear function. The intercept of the functions were not adjusted for the individual players, thus, they are equally estimated as in the case of previous analysis (see shape of the function) and not presented here.

Interaction of pre-peak and post-peak changes

As well as investigating the pre-peak and post-peak changes, the B-Ianus model also estimates how these two periods interact with each other for each player in the dataset. In the case of all measures of performance, the results show that the rate of the increase during the development phase correlates with the rate of decline in the aging phase (Figure 5.4). In other words, the players that have a stronger and positive pre-peak increase display a shallower and slower decline in later life, while the players with the strongest developmental phase barely decline in their performance at all. The additional measures also indicate similar interaction (see Figures E3 and E7 in the Appendix E).

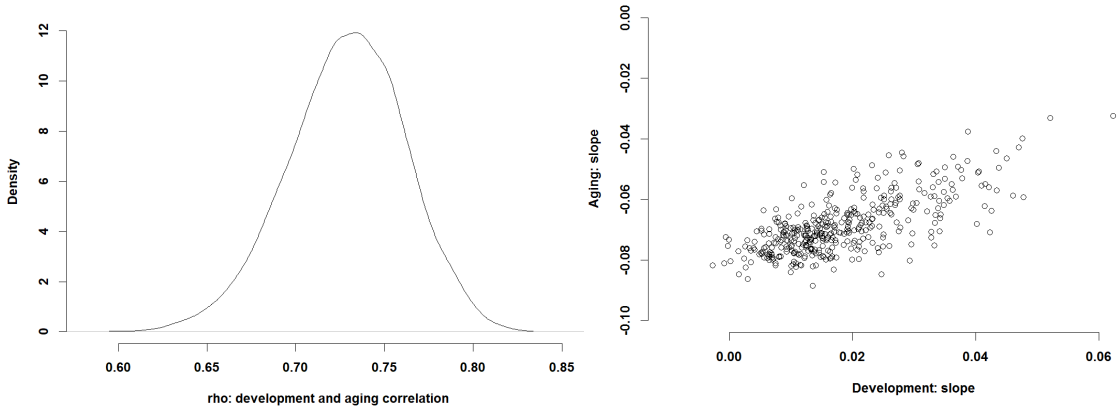

Figure 5.4. The interaction between the slope of the pre-peak increase and the slope of the post-peak decrease for the 400 random players in the database. (Left). illustrates the size of the correlation between the pre-peak and post-peak slopes. (Right) shows values for pre-peak increase and post-peak decrease for random 400 players in the dataset. The x-axis shows slope size for the pre-peak change, while the y-axis illustrate slope size for the post-peak change. The positive values indicate a stronger increase and shallower decline while negative or smaller values show a shallower increase to the peak and stronger decline after it. The figures show the possible values of slope parameters for the pre-peak and post-peak functions when we approximate the exponential and power-law relationship with the linear function. The slopes are estimated in log-linear and log-log space.

Goal 2: Group analysis

The B-Ianus model also offers the possibility of investigating whether overall age-related function differs between groups and individuals (the second goal of lifespan psychology). Here we have included the position of the player as the numeric covariate in the model. The position of the player, together with the slope of the pre-peak and post-peak function, was regressed onto the latent factors. We used five main positions: PG - point guard, SG - shooting guard, SF - small forward, PF - power forward and C - center. In this way, we investigated the potential interaction between the position of the players and the size of their slope during age-related changes. The results show that player position does not change the slope of the increase or decrease during the pre-peak and post-peak changes for the WS, nor does it change for other measures (see Figure 5.5 and E4 and E8 for other measures).

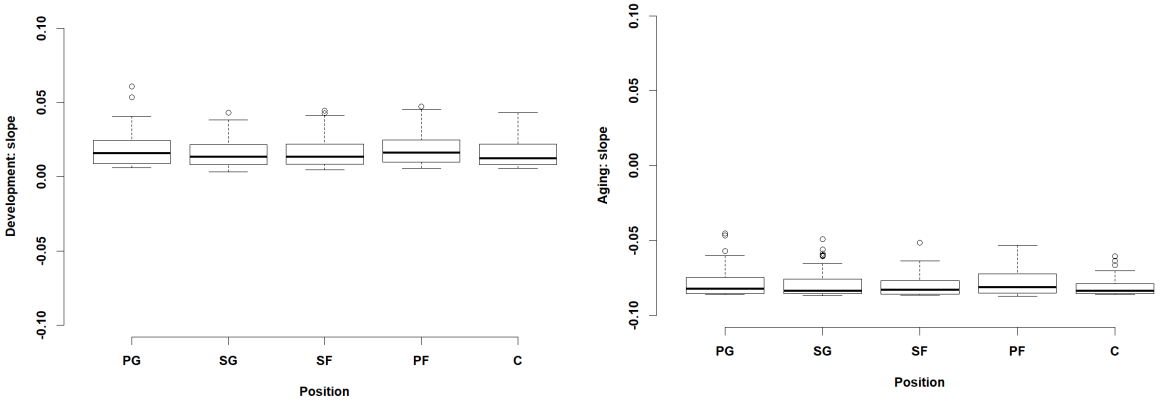

Figure 5.5: Difference in the size of the slope for the win shares based on the different positions in basketball: PG - point guard, SG - shooting guard, SF - small forward, PF - power forward and C - center. The y-axis illustrates the size of the slope for the pre-peak and post-peak change, while the x-axis shows different positions in basketball. The figures show the possible values of parameters for the slope of the pre-peak (left) and post-peak functions (right) when we approximate the exponential and power-law relationship with the linear one. The slope in this case represent this relation in log-linear and log-log space.

Goal 3: Building blocks of real-life performance

In the final step, we investigated potential building blocks of the performance and variables, which can influence the changes in performance (the third goal of lifespan psychology). We used the total minutes per game that players contributed during the pre-peak and post-peak changes (for a similar measure, the total number of played games during the career, see the Appendix E). The results show that, during the pre-peak increase, contributing more minutes per game has a positive interaction with the slope. That is, the players who increase in performance during the first part of their careers also play more minutes per games. Similarly, players that play more minutes per game tend to decrease less in their performance in comparison with the people contributing fewer minutes per game (see Figure 5.6, as well as, Figures E5 and E9, in the Appendix E, for other measures of performance).

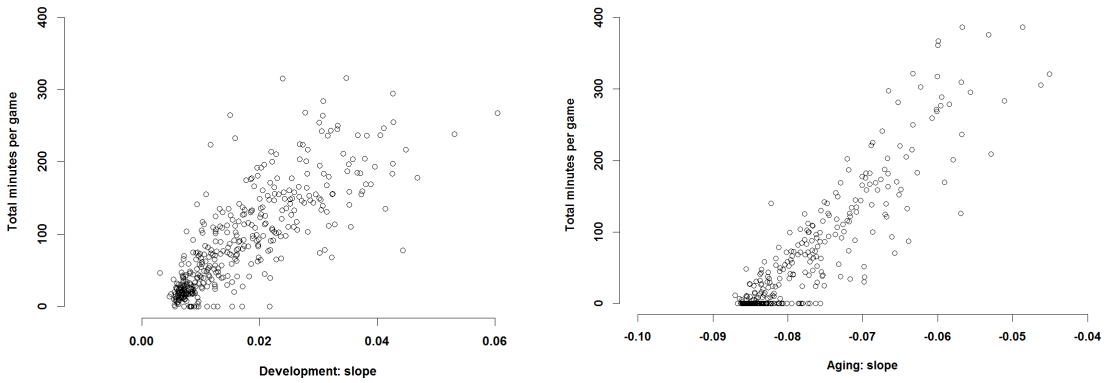

Figure 5.6: Interaction of the pre-peak and post-peak slope for WS performance with the total minutes per game contributed by players during their careers. The y-axis illustrates the total number of minutes per games players contribute during the pre-peak (left) and post-peak period (right), while the slope for the functions estimated on the pre-peak and post-peak changes is illustrated on the x-axis. The positive values of the slope indicate stronger positive change during the pre-peak period and lesser decline during the post-peak period, and vice versa.

Discussion and Conclusion

The relationship between performance and cognitive functioning, on the one hand, and age, on the other, has a long history of investigation. These changes have been investigated from different perspectives, ranging from skill acquisition studies which focus on age-related improvements that take place in early life (Donner & Hardy, 2015; Gaschler et al., 2014; Heathcote et al., 2000; Tenison & Andersn, 2016) to aging studies which focus on decline in cognitive performance that occurs in later life (Bugg et al., 2006; Lindenberger & Ghisletta, 2009; Salthouse, 2001, 2010). Even though studies in these domains provided an invaluable amount of evidence relating to age-related changes, an understanding of the general age-related function of real-life performance, as well as the factors that change this function, has proved elusive. We believe that this is due to two main reasons: the difficulty of obtaining large sample sizes of measurement in real-life domains, and the complexity of modelling nonlinear changes in the aging function.

In this study, we provide a potential solution to those problems by proposing a methodological and statistical environment in which practitioners can investigate age-related changes in greater detail by modelling natural datasets of real-life performance in sports. We use Bayesian cognitive latent

variable modelling (Vanderkerckhove, 2014) to investigate age-related changes across the complete lifespan and quantify the interactions between age-related improvements and declines in basketball performance. Besides including the complete career performance, we also demonstrate how the age-related changes which occur over the course of a basketball player's career can be jointly investigated with other variables of interest, such as the player's playing position and the levels of activity.

In comparison with previously proposed models, such as the Janus model or the model of career trajectories and landmarks (Schroots, 2012; Simonton, 1991, 1997), the B-Ianus model offers an estimation of additional parameters, which are of interest for the investigation of different theoretical proposals. Firstly, researchers can investigate the optimal underlying function that explains age-related changes in performance, and can use these functions to model the changes. In other words, the B-Ianus model allows practitioners to use different age-related functions (e.g. power law, exponential, linear), while previous models use the pre-specified double exponential or double logistic curve. Secondly, it is possible to adjust the random structure of the model: that is, we can estimate the individual differences of the parameters which are used to describe age-related changes. In this way, practitioners can calculate individual peaks (maxima) or the rate of performance change for individual people or different groups of individuals. Adjustment of the random structure and individual differences is particularly useful when dealing with complex data, as it solves problems with the aggregation of the data (Heathcote et al., 2000).

Another advantage is that the random adjustments help to alleviate problems with the outliers, as these values are shrinking towards the mean of distribution for a particular parameter (Baayen et al., 2008; Radanovic & Vaci, 2013). The model also allows the inclusion of time-invariant variables and the investigation of their relationship with age-related changes over the course of the career. Ultimately, B-Ianus enables us to also investigate the interaction between the rates of pre-peak increase and post-peak decrease. The model estimates the potential relationship between the growth rate in the first function and the rate of decrease in the second, given any other variable that can influence and change this relationship. The quantification of this parameter proved elusive in the case of the most modelling endeavours. In the case of polynomials, the individual parameters are (by the mathematical definition of polynomial) correlated, even though this does not have to be the case with the data. Contrary to this, exponential functions require two-step procedures, where in the first step researchers estimate the pre-peak and post-peak functions and in the second step they calculate the correlation between these estimates. Finally, nonlinear models, such as GAMs, even though they calculate the optimal nonlinear function, provide this information only on the visual level by interpreting the fit of

the model (as illustrated in Figure 5.1). In practical terms, the B-Ianus model quantifies the relationship presented in Figure 5.1, in the case when we divide the age-related progression into pre-peak increase and post-peak decrease.

Using the B-Ianus model, we showed how the three goals of lifespan psychology can be investigated in more detail. In the case of the basic form of the age-related function (Goal 1), we demonstrated that three frequently-used measurements of basketball performance (WS, PER, and VORP) differ during the first part of the career, in which some of them change exponentially, linearly or in a power-law fashion. It is likely that different developmental patterns observed on these measures reflect differing cognitive processes (e.g., Heathcote et al., 2000; Newell & Rosenbloom, 1981), especially when taking into account the fact that measurements aim to quantify different aspects of performance. Contrary to the pre-peak development, the decrease after the peak, for all three measurements, follows a power-law function. People decrease rapidly immediately after reaching their peak, but, as they age, this decrease in performance lessens and slows down. The B-Ianus model also indicated that there are no differences in the changes of performance over the career between the different positions that players usually play. The rate of increase and decrease, the slopes of the functions, do not change based on the playing position. In this way, we investigated the second goal of lifespan psychology – changes in the aging function based on subgroup analysis.

However, adding these types of covariates can also tell us more about the aging function, especially if we can identify people who drop out at an earlier or later stage of their career. Including this information in the model can potentially give more information regarding whether the decrease in the post-peak decline is influenced by the drop-out rates, where stabilization of the decline is there just because of the higher-performing individuals. In addition, the B-Ianus model also showed that the number of minutes played per game correlates with the slope of the pre-peak and post-peak functions, thereby meeting the goal of lifespan psychology, that is, revealing the potential building blocks of real-life performance. The players who show greater development in the first part of their careers seem to contribute more minutes per games in comparison with their slower-developing teammates. The same result is obtained in the case of the second part of the career, as players who contribute more minutes per game display a shallower age-related function. In this particular instance, it is not possible to claim with certainty that activity improves the skill acquisition process or that it preserves the negative age-related changes. The amount of time spent on the court is dependent on how well players perform. Obviously, those who perform better at later stages of their career will be played more by their coaches than their less well-performing peers.

One of the most intriguing results in the current study is the B-Ianus parameter that estimates the interplay between pre-peak and post-peak changes. The results on all three measurements of performance show that players showing greater development during the first part of their careers display shallower declines in performance as they age. This indicates potentially preserving effects of the skill acquisition phase, in which players who excel in the domain collect more knowledge and skill. On the one hand, basketball is a speed- and strength-dependent sport (Latin et al., 1994), in which greater declines in performance are expected (Faulkner et al., 2007; Goodpaster et al., 2006; Rogers & Evans, 1993; Thelen, 2003) given the general finding of more decline in physical domains compared to cognitive domains (Fair, 2007). On the other hand, we are investigating a complex real-life skill where people acquire a vast amount of knowledge and continue to do so in the later stages of their careers (e.g. in the case of vocabulary). In basketball, that knowledge is of a kinetic nature and may involve one's own and one's opponents' movements, as well as team-specific patterns (Bilalić, 2017). Once the decline in performance begins, related to diminishing physical abilities, more knowledgeable or more able players may utilize their knowledge to preserve their current performance in the face of aging. It is possible that other factors, such as physical ability, personality, motivation, or even general genetic makeup which enabled certain players to acquire knowledge and skill more quickly, may act as mediators of this correlation. In any case, the result runs counter to a large body of evidence that demonstrates that age is not kinder to more able people (Blum & Jarvik, 1974; Vaci et al., 2015).

The B-Ianus model and the way it is estimated can be used in different domains of real-life performance, but also in domains in which researchers need to model nonlinear changes over time. In the case of this study, we showed how researchers can use it on the natural datasets collected in the basketball domain. The flexible nature of the Bayesian framework, that underlies B-Ianus, allows the application of this model to any other domain.

Chapter 6: Conclusion

The purpose of this thesis is to further existing knowledge of cognitive and conative underpinnings of sport expertise. To do so, I have conducted a series of studies looking into (impacts of) cognitive and conative factors (on expertise) in early skill development and throughout the lifespan. I utilized several methodological approaches, as well as complex statistical analyses (alongside traditionally used ones), to provide multifactorial perspective on sport expertise. In the following paragraphs, I will provide direct answers to questions I raised in Chapter 1: Introduction , summarizing all of the findings, and discuss the original contributions to the pool of knowledge this thesis is making as well as its shortcomings and my suggestions for future research directions.

Summary of findings

Chapter 2: Anticipation in Handball

Findings, once again, emphasize the importance of kinetic knowledge for expert performance, as well as for retainment of expert abilities throughout the lifetime. Domain-specific kinetic knowledge underpins the differences in performances between athletes of different skill level, as well as strategies they use to approach and solve problematic situation in the domain of expertise. However, to understand the most relevant parts of movement sequences for expert abilities, and their kinetic knowledge in general, it is important to have a consensus on the strategies for choosing and analysing different parts of movement sequences, as well choosing and analysing different measures of reactions of experts (and novices) to those parts of movement sequences. This is addressed and discussed in greater detail in Chapter 2: Anticipation in handball, but below I provide the answers to the relevant questions.

What is the best strategy for choosing occlusion points?

When choosing occlusion points one should combine analysis of typical (relevant) movements (within a movement sequence) with analysis of expert accuracy and reaction times. This will help pinpoint the time windows which contain not only the most relevant information, but also provide the experts with enough time to adequately react. An adequate reaction requires the players to match the perceived movement with previously stored movement patterns (domain-specific kinetic knowledge), make a decision on the best possible response to that (out of all possible responses) and execute appropriate movement sequences.

When the cuts ought to be made – how long video segments should last?

There should be no universal "rule" regarding the length of movement sequences presented to the participants and therefore number of overall cuts in the video. The decisions should be made on case by case basis, based upon previously conducted analysis of typical movement sequences, for the sport (and specific situation itself), and their relevancy for successful movement execution. When cutting and choosing the length of the video one should make sure that the whole (relevant) portion of the movement sequence is presented, instead of cutting mid-way through it. Subsequent cut should then incorporate additional (relevant) kinetic information.

What is the importance of meaningful occlusion points?

As demonstrated in Chapter 2: Anticipation in handball, only meaningful occlusion points, chosen based upon (previous) analysis of relevant movements, can provide us with insightful findings and have the potential to be further utilized in practice (to teach athletes' themselves what to actively pay attention to or, alternatively, what they need to hide/manipulate if trying to deceive the opponent). The usage of occlusion points chosen using different strategies may have played a role in previous inconsistent and non-significant findings, especially when comparing consequent time windows that are, theoretically supposed to, incorporate more (relevant) information (Alsharji, 2014; Loffing et al., 2014; Loffing & Hagemann, 2014). Only carefully chosen occlusion points allow insights into how different patterns of movement impact expert ability to anticipate.

How to better utilize outcome measures to further our understanding of expert abilities and their performance?

It is of importance to not treat outcome variables as independent and analyse them (only) separately – they should be taken into account together when interpreting the results. Focusing only on one or the other can result in overestimation/underestimation of expert performance. As demonstrated with the analysis done in Chapter 2: Anticipation in handball, and further supported by similar analysis conducted in different sport domains (Farrow et al., 2005; Mann et al., 2007), accuracy measures should be complemented with reaction time measures to further our understanding of athletes' abilities. Accuracy measures alone, although necessary, provide us with only a part of "the picture" – they inform us which kinetic information is relevant for expert anticipatory abilities. However, as discussed in Chapter 1: Introduction, the most accurate predictions are made only once the movement sequence has been completed and the ball has left shooter's hand (in other words, there is no other influence on the ball's trajectory), which does not leave enough time for the opponent to react and defend against it. Reaction time measures come into play here – they provide us with the information of how early an expert needs to react in order to be able to execute an appropriate response in a timely manner. Combining that information with accuracy information helps pinpoint the exact parts of movement sequence that enable for the most accurate anticipation possible, given the restrictions, with enough time for response. Furthermore, even when accuracy measures improve significantly in novices alongside experts (though not at the same rate), like it was the case in this study, reaction time measures are still able to distinguish between the two as novices' reaction time is not sufficient for timely responses (despite adequate levels of accuracy).

Chapter 3: Grit - Deliberate practice mediation on performance

Furthermore, results in this study point out the importance of a personality trait (conative factor) on expertise. On the sample of elite youth soccer athletes, grit not only had bigger overall impact on performance than practice did, but also explained performance outcomes above and beyond practice. This indicates that, especially in elite samples (where classical factors such as practice and talent indication may explain only a small chunk of performance due to the lack of variability), other conative factors should be considered as potential contributors to overall expertise. Below are the answers to the questions that address that (for more in depth discussion, please refer to Chapter 3: Grit - Deliberate practice mediation on performance).

Can non-ability factors (grit) influence expert skill/performance (especially for elite athletes)?

As shown in Chapter 3: Grit - Deliberate practice mediation on performance, conative, non-ability, factor grit has a positive influence on (high level) performance, amongst a sample of elite youth soccer players.

Is the influence direct or indirect? And can it go above and beyond influence of practice

Influence of grit on performance is both direct and indirect, mediated through practice. In other words, not only does grit influence the performance of elite youth athletes, but goes above and beyond the influence practice has on performance. Furthermore, in this highly skilled sample, grit's influence on performance was greater than that of practice.

How big of an influence there is and does it differentiate between skill levels?

Grit's total influence (indirect + direct) on performance is sizeable - increase of one standard deviation in grit score leads to almost half a standard deviation better performance score. Furthermore, grit is able to differentiate between skill levels, even among the most elite of youth players.

Which "types" of practice does it influence the most and through which does it have an effect on performance?

As discussed in Chapter 1: Introduction there is no consensus on what constitutes deliberate practice in sport, so different researchers approach this by measuring engagement with all sport-related activities and then group them together, based on different criteria for analysis. In this thesis, sporting activities were grouped together based on how structured they are, resulting in two categories: Structured activities – consisting of Coach-led practice (which is arguably the closest thing to deliberate practice in this context) and Competition; and Unstructured activities – consisting of Self-led practice, Play with peers and Indirect involvement (for more on them please see Chapter 3: Grit - Deliberate practice mediation on performance and Chapter 4: Snowball effect of grit on (deliberate) practice). Even though grit had a strong positive relationship with both groups of activities, it exerted

influence on performance only through more demanding and challenging group of activities (Hendry et al., 2019), Structured practice.

How does a non-ability factor influence expertise (directly)?

Despite the fact that answer to this question, unfortunately, remains out of scope of this thesis, in Chapter 3: Grit - Deliberate practice mediation on performance I proposed some possible explanations. Most likely being that grit exerts its direct influence on performance through some other metacognitive processes, which have been previously shown to differentiate between athletes' of different skill (Jonker et al., 2012).

Are there any differences between impacts of consistency of interest (CI) or perseverance of effort (PE)?

Even though CI has overall stronger correlations with both practice and performance than PE does, when formally compared to each other, either within the same models or by comparing models containing only one of them against the other, there is no difference between their impacts.

Chapter 4: Snowball effect of grit on (deliberate) practice

In Chapter 4: Snowball effect of grit on (deliberate) practice I demonstrated one of the mechanisms behind the process of acquisition of practice, which is considered one of the main determinants of expertise development (Baker & Farrow, 2015). Conative factor grit is able to differentiate the amount of accumulated practice hours even among the best elite youth athletes. Small difference in the starting amount of practice, between gritty and less gritty players, soon snowballs into a large one as they progress with their development. Furthermore, the results tie into Developmental Model of Sport Participation (Côté, 1999; Côté & Vierimaa, 2014) providing not only further verification of the model, but also a potential driver behind the model predicted behaviours. These findings once again emphasize the importance of incorporating, and investigating, conative factors and their relationship to both practice and performance, as they might contribute to better understanding of developmental phases in sporting expertise and contribute to improvement of talent identification. Below are the

answers to relevant questions this chapters covers (for more in depth discussion, please see Chapter 4: Snowball effect of grit on (deliberate) practice).

How is practice accumulated in elite youth athletes? In other words, what is the process of practice acquisition?

As demonstrated in Chapter 4: Snowball effect of grit on (deliberate) practice, during the first few years of their development elite youth soccer athletes accumulate a constant amount of domain-related practice. However, that changes after the age of 12, when a sudden increase in engagement (in domain related activities) produces an accelerated accumulation of practice hours over the remaining two-three years measured in this study.

Is grit related to the pattern of practice acquisition?

Grit has a substantial effect on practice acquisition process at all stages of elite youth athletes' development (measured in this thesis). Grittier athletes have a slight edge in the amount of accumulated practice from the start (initial additive effect). Furthermore, they consistently keep logging more practice hours over the years, leading to small initial differences snowballing into much larger differences at later age. This is especially the case for practice activities that are under the control of players themselves (such as self-led practice and indirect involvement).

Are there any differences between impacts of consistency of interest (CI) or perseverance of effort (PE)?

Even though both grit components affect the accelerated accumulation of practice hours, the pattern of their influence on the process of practice acquisition is different. Overall, CI seems to have stronger impacts than PE, but it is especially so during the earlier stages of development when linear increase is happening. In other words, among the two, CI seems to be the driving factor underlying cumulative snowball effects. That is not the case in the later stages of early development, the trend is reversed – only PE has a significant effect on the sudden increase in engagement with soccer related activities. In other words, among the two, PE seems to be the driving factor underlying accelerated snowball effects.

Chapter 5: Aging curves of sport expertise

Finally, in Chapter 5: Aging curves of sport expertise, I focus on age-related changes in (different measures of) performance recorded over the duration of careers of NBA athletes. Findings indicate that the rate of skill acquisition relates to the rate said skills are maintained and the rate of their decline. In other words, it seems that the kinetic knowledge, experts acquire through practice and play, is one of the factors responsible for prolonged maintenance and slowed down deterioration of athletes' performance. Answers to relevant questions can be found below (refer to Chapter 5: Aging curves of sport expertise for more in depth discussion of them as well as detailed description and discussion of the model used for the analysis).

What is the basic shape (form) of the age-related function in sport?

Shape of the aging function pre-peak (prior to age of 27) changes depending on which measure was used to model the aging function, although all of them are showing (different rates of) growth. Given that the measures of performance were chosen so that they capture different aspects of expert athletes' performance and skill, it is possible that the difference in rates of growth stem from these measures capturing different cognitive and kinetic processes. Shape of the aging function post-peak (after age of 27), regardless of measure used, followed a power-law function. People decrease rapidly immediately after reaching their peak, but as they age, this decrease in performance lessens and slows down. Furthermore, the model indicated a relationship between the two slopes – the stepper increase in pre-peak period, the slower and shallower decrease in the post-peak period.

Does the function differ between specific groups and individuals?

As shown in Chapter 5: Aging curves of sport expertise, the model indicated that there are no differences in the (age-related) changes in performance players display over the span of expert athletes' careers, when grouping them together based on the position they play. The rates of increase and decrease stay the same as the reported overall rate of change, regardless of players' position.

How are more basic processes, the building blocks of age-related changes, influencing these (age-related) changes?

The relationship between number of minutes played, one of the determinants of a players displayed performance, and the slopes of pre-peak and post-peak functions has been investigated and a correlation was found. The players for whom a more pronounced development was recorded in the pre-peak part of their careers seemed to be contributing more minutes per game than their teammates that displayed slower rates of improvement. Similarly, in the post-peak part of their career, those who contributed more minutes of play per game displayed a shallower age-related function. However, it should be pointed out that this relationship is not causal in its nature, therefore it is not possible to claim with confidence that it is the activity itself (amount of time spent playing in the official matches) which improves the process of skill acquisition or reduces the negative age-related changes post-peak. Often, the amount of time a player spends on the court is dependent on how well they perform to being with, so the better performing players will inevitably play more than worse performing peers, regardless of which stage of development they find themselves in.

Original contribution

Overall, this thesis adds onto the existing body of research that emphasizes the importance of kinetic knowledge, and its acquisition, for experts' outstanding performances. However, it furthers that pool of knowledge by pointing out required methodological and analytical improvements for bettering the understanding of phenomenon that is anticipation. In doing so, I was the first (to my knowledge) to utilize a multilevel model (mixed-effect regression) analysis, alongside (traditional) ANOVA for comparison, to demonstrate greater sensitivity of these statistical tools and their better fit for data typically gathered in this field of research. In hopes of paving a way to further usage of multilevel modelling in research on anticipatory skills in sport, I provided access to the code used for data analysis for others to use.

Furthermore, I highlighted the importance of conative factors for expertise and necessity of incorporating them to better our understanding of expert performance and expertise development. This is especially the case when conducting research on the elite athletes only, as other factors deemed important for expertise (such as practice and talent) are uniform among them – yet there are still clear

differences even among the very best of youth players. Findings on grit are somewhat aligned with previous research in sport and non-sport domain, however, as discussed in Chapter 1: Introduction, given the novelty of this topic in the domain of sport, complete consistency among all of the findings is not to be expected. When it comes to performance, the most important contributions of this thesis are the findings of the direct and indirect influence (through practice) of grit on performance which, on a homogenous, highly skilled sample, is sizeable (and bigger than influence of practice). In terms of practice, grit was shown to be a driver behind the differing amounts of sporting engagement, even among the elite youth athletes, resulting in snowballing differences further in the development. To my knowledge, I was the first to try to connect and complement Côté's model of sport engagement during expertise development with the conative factor grit. In both of these studies I am among early adopters of Structural Equation Modelling (SEM) for creating different models of impact(s) grit has on practice and performance and trying to find the best fitting one. On top of that, by using SEM, I formally statistically compared influences of Perseverance of effort and Consistency of interest against one another (within the same model) to understand the importance each of these grit subscales has for both, practice and performance, which, to my knowledge, has not been done before.

Finally, this thesis contributes to understanding of fluctuations in performance experienced by elite athletes during the span of their professional careers. Not only was this the first attempt in applying a novel Bayesian model to analyse real-life performance data in sport context, but is also first attempt to model, and thus understand, age-related changes in performance of elite athletes through the entirety of their careers, instead of focusing on either acquisition or decline periods, separately. To encourage further usage of complex models, such as this one, I provided the code necessary for running it on own data.

In order to support the open science movement, all of the data, codes used for running analyses on the data and analyses outputs (plus stimuli for the anticipation study) are all provided on the Open Science Framework website (links to the materials relevant for each of the chapters can be found in the chapters themselves).

Shortcomings and Future research directions

As discussed in Chapter 1: Introduction, the currently on-going pandemic, as well as technical and cyber difficulties, have severely impacted the course of this thesis. Outlined strategies for choosing meaningful parts of movement sequences for research, and analysis, of anticipation in sport (Chapter 2: Anticipation in handball) need further experimental corroboration that I was not able to conduct. To further validate the importance of chosen time windows (and therefore the strategy for choosing them), future research ought to employ usage of eye movement recordings to enquire into what experts are looking at prior to and when anticipating; as well as utilization of spatial occlusion techniques and liquid-crystal occluding goggles to investigate impacts of lack of this (kinetic) information on expert performance both in real life and laboratory setting. Furthermore, future collaborations on creating publically available data sets of similar (validated) analyses of relevant movement sequences (in different situations and different sports as well), to be used for choosing meaningful stimuli, would be beneficial for furthering our understanding of experts' abilities.

When it comes to conative factors, although superior, longitudinal approach to measurement (of grit, practice and performance) was out of the scope of this thesis. Future research could benefit from measuring conative factors multiple times throughout the duration of expertise development to understand their volatility and (potentially) different impacts they have on both practice and performance during different stages (of development). Furthermore, if possible, it would be beneficial if future research tracked down elite youth soccer players, which were originally part of the study, measured the outcome of their development (such as, but not limited to: are they still competing and, if so, at what level, what is level of their performance now, how much do they practice) and related that to the current findings in order to model the predictors of their expert performance. As mentioned in the summary of findings section, further research into mechanisms through which grit has a direct effect on performance remained outside of the scope of this thesis, therefore future research should look into moderating effect different metacognitive processes have on grit-performance relationship. On top of that, grit scale used ended up being not only quite controversial, but also problematic, so, for future research, utilization of appropriate statistical tools (such as SEM) and adaptation of the instrument is advised to ensure meaningfulness of the findings (for some current recommendations of how to improve grit scale please see Tynan, 2021).

Finally, future research should further validate the model used for modelling age-related changes in sport performance by applying it not only to different groups of players (such as WNBA, EuroLeague players) but also to different sports where similar data is available. Furthermore, potential inclusion of less successful athletes (competing at lower levels, such as NBA G league), or athletes that dropped out at different periods of their career (be it due to injuries or other circumstances) would further our understanding of how exactly expert kinetic knowledge helps them maintain and retain their cognitive and motoric abilities.

This thesis highlights the importance of choosing meaningful movement sequences for understanding performance, as well as the importance conative factors have for said performance and its predictors (practice), and how those influences change during early development and throughout the lifetime. These findings have the potential to extend its importance beyond the theoretical and laboratory settings, as by understanding how cognitive and conative factors impact expertise, and how their impacts vary throughout the experts' life, we can provide sport managers, recruiters and coaches with improved models for identification of potential future experts; we can help prepare, both athletes as well as sporting stuff supporting them (coaches, sport performance analysts, sport psychologists, et cetera) for potential fluctuations and setbacks that are to be expected during the span of expertise development (and, eventually, how to deal with them); and we can participate in the creation of most adequate (as possible) training regimes that are able to not only help experts acquire domain-related knowledge in the most efficient way, but are also capable of keeping them consistently motivated to engage with the domain (and maintain acquired skills), despite the effort required to do so.

Appendices

Chapter 2: Anticipation in Handball - Appendix A

Classical ANOVA analyses on reaction and accuracy

Table A1. *The results of ANOVA on the reaction time.*

Within Subjects Effects

	Sum of Squares	df	Mean Square	F	p	η^2_p
Occlusion	1.228	2	0.614	21.63	< .001	0.546
Occlusion ✻ Group	0.692	2	0.346	12.19	< .001	0.404
Residual	1.022	36	0.028			

Between Subjects Effects

	Sum of Squares	df	Mean Square	F	p	η^2_p
Group	2.898	1	2.898	3.765	0.068	0.173
Residual	13.856	18	0.770			

Note. Type III Sum of Squares

Table A2. *The results of ANOVA on the accuracy.*

Within Subjects Effects

	Sum of Squares	df	Mean Square	F	p	η^2_p
Occlusion	0.471	2	0.235	102.11	< .001	0.850
Occlusion ✻ Group	0.088	2	0.044	19.05	< .001	0.514
Residual	0.083	36	0.002			

Between Subjects Effects

	Sum of Squares	df	Mean Square	F	p	η^2_p
Group	0.173	1	0.173	31.93	< .001	0.639
Residual	0.098	18	0.005			

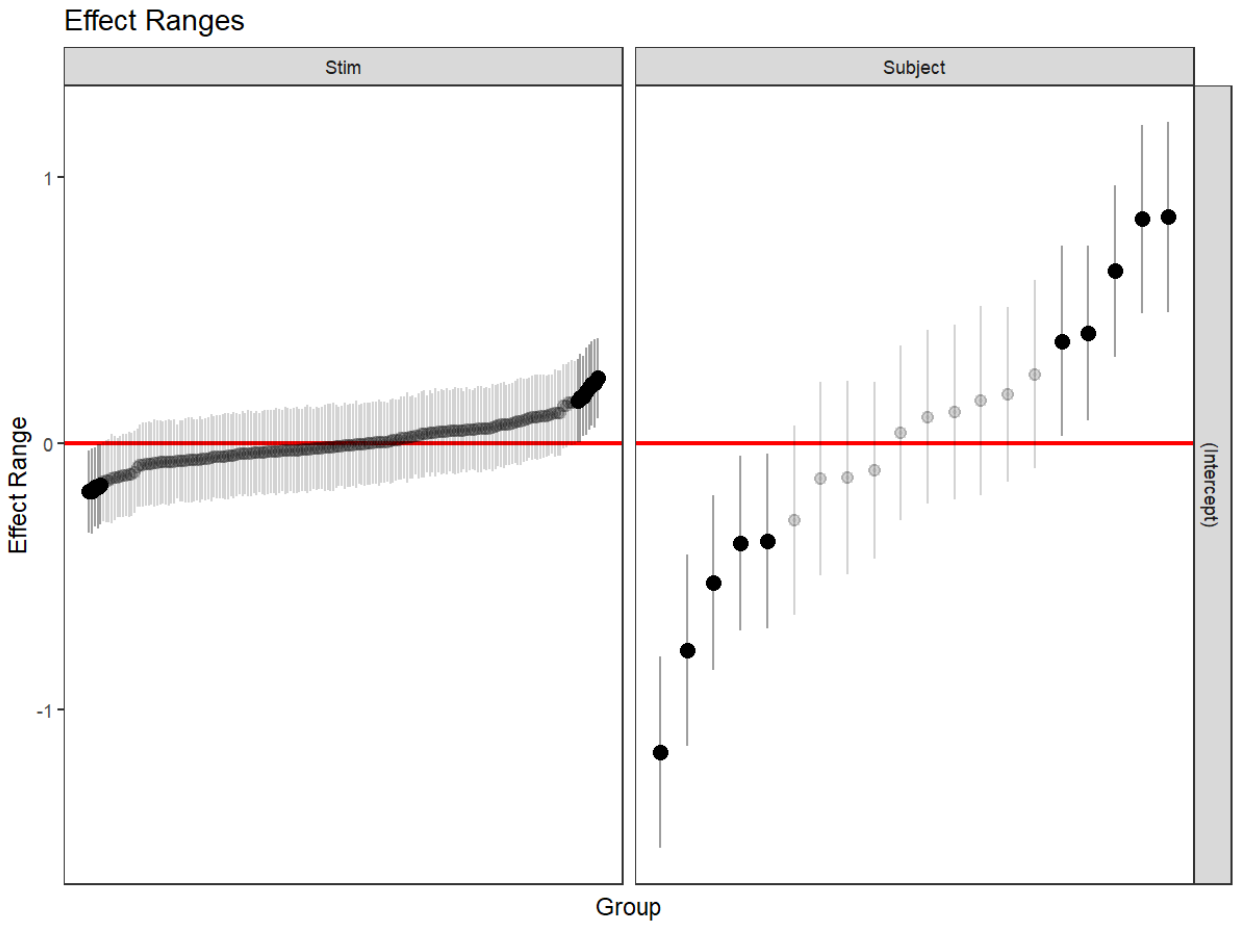

Figure B1 Random adjustments of the intercept in the case of reaction time analysis. Left: random adjustments of the intercept for stimuli (videos); Right: random adjustments of the intercept for participants in the experiment. Red line indicates global estimate of the intercept, while individual estimate illustrates how much the intercept is adjusted for each level of the factor.

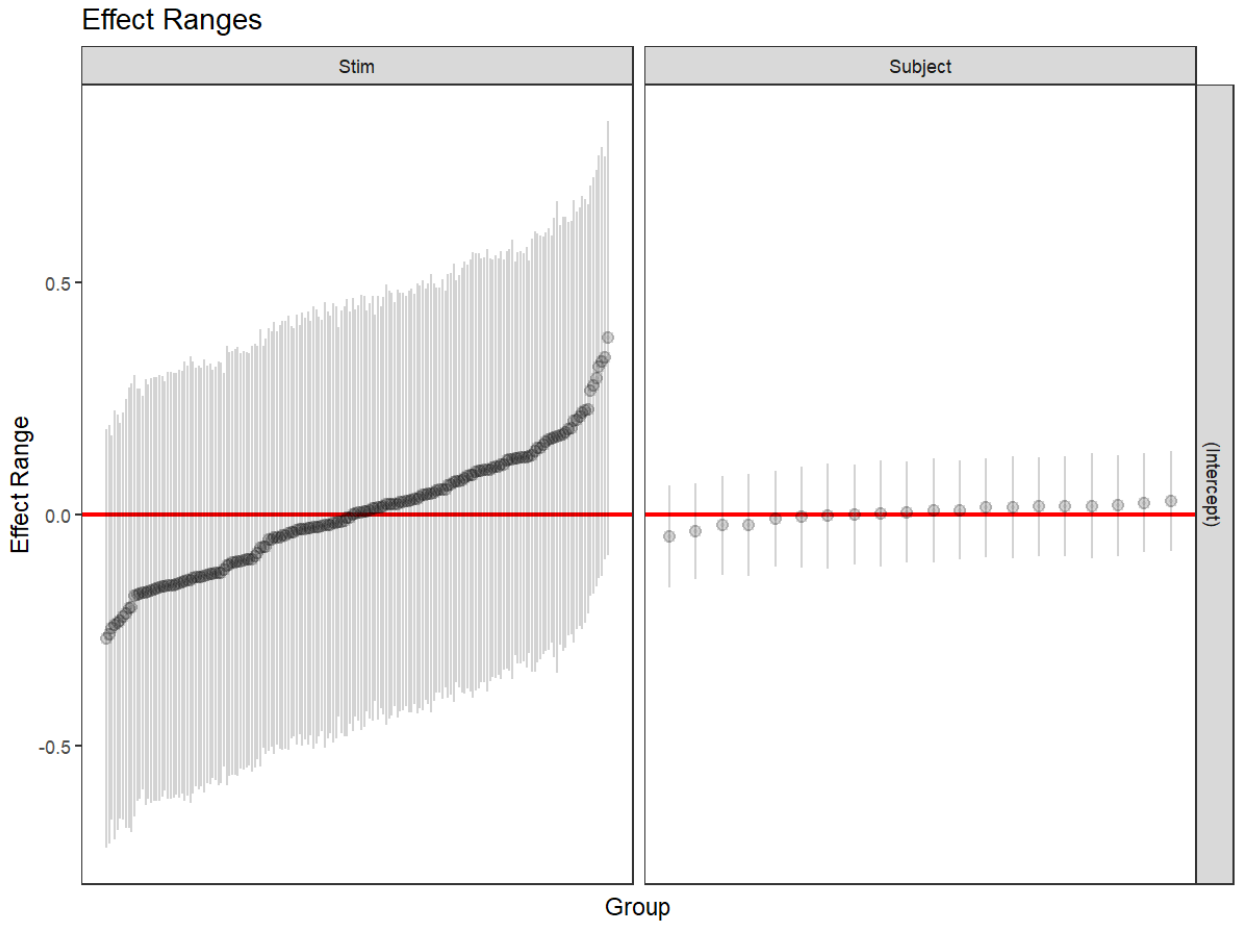

Figure B2. Random adjustments of the intercept in the case of accuracy analysis. Left: random adjustments of the intercept for stimuli (videos); Right: random adjustments of the intercept for participants in the experiment. Red line indicates global estimate of the intercept, while individual estimate illustrates how much the intercept is adjusted for each level of the factor. (Note that the range of y-axis here is much smaller than for RT.)

Chapter 3: Grit - Deliberate practice mediation on performance - Appendix C

Section 1: Confirmatory Factor Analysis for Grit Scale

We used the short Grit scale, which has eight items, four for each of the two grit's components: Consistency of Interest (CI) and Perseverance of Effort (PE).

The four items for CI are:

Q1. New Ideas Distract Me from Previous Ones

Q3. I Have Been Obsessed with A Project for a Short Time but Lost Interest

Q5. I Often Set a Goal but Later Choose to Pursue a Different One

Q6. I have difficulty Maintaining Interest in a Projects Longer than a Few Months

The four items for PE are:

Q2. Setbacks Don't Discourage Me

Q4. I am Hard Worker

Q7. I Finish Whatever I Begin

Q8. I am Diligent

We performed a confirmatory factor analysis on the grit scale in the statistical program R with lavaan package (Rosseel, 2012). First we constructed a one-factor model where all the items load onto a single (grit) construct (Figure C1 A). This model had a bad fit (see the box Model fit in Figure C1 A). The two-factor model, where one half of the items were loading on the CI and the other half of the items on the PE, had a much better fir (Figure C1 B). The formal test of the model fit indicated that the two-factor model had a significantly better fit ($\chi 2 = 838$, df = 1, $p < .001$). The two-factor model was,

however, not describing the data particularly well (see Model fit box in Figure C1 B). The main problem appeared to be Q2, which had a poor loading on PE (only .25). Once Q2 was left out and only other three items were forming the PE component, the revised model improved (Figure C1 C). The revised two-factor model (Figure C1 C) had a significantly better fit than the original two-factor model with Q2 (Figure SM1B) – $\chi2 = 38$, df = 6, $p < .001$. We have consequently used the revised two-factor model in our main analyses.

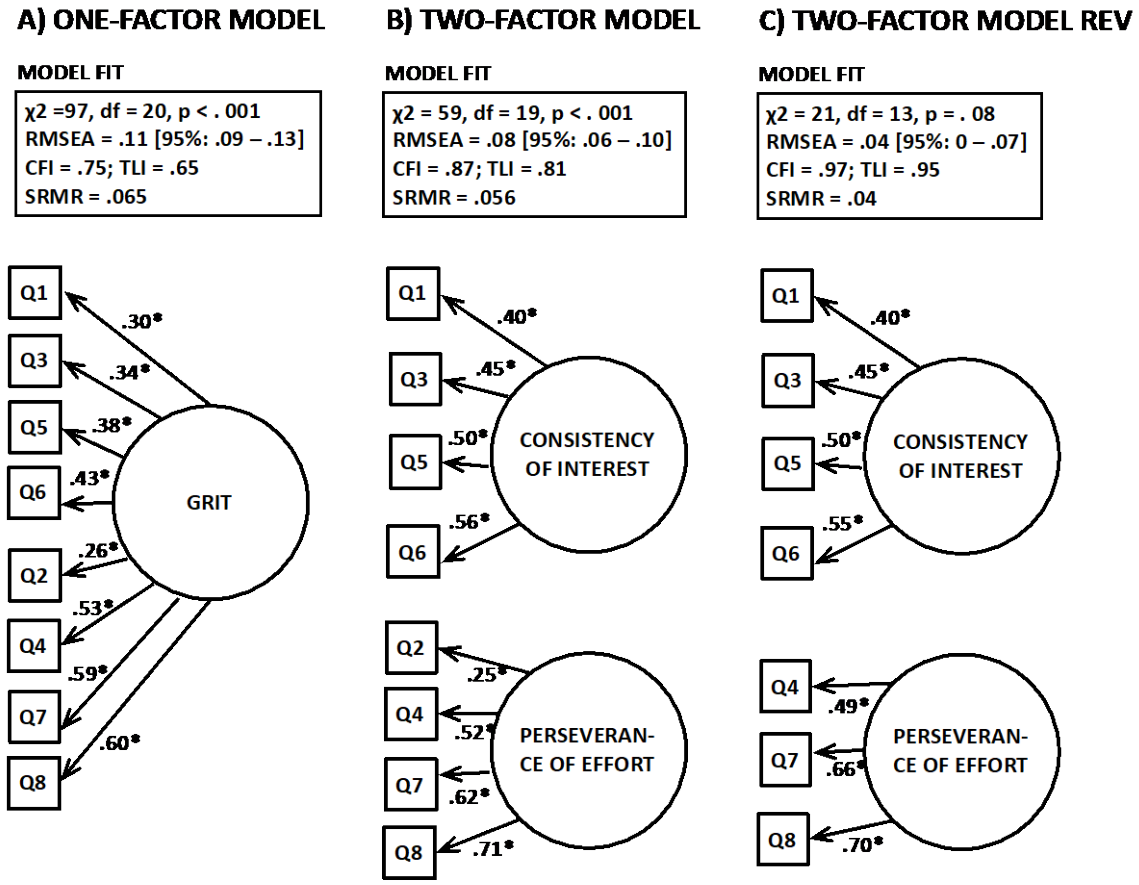

Figure C1CFA on Grit Scale. A) One-factor model where all items load on the single construct. B) Two-factor model where CI and PE components are identified separately. C) Revised two-factor model without Q2 in PE

Section 0:2 Confirmatory Factor Analysis for Practice Activities

The five practice activities were also subjected to the CFA. The first model where all practice activities load onto a single practice factor had a bad fit (One-Factor Model in Figure C2 A). When the assumed distinction between structured and unstructured practice was introduced, the two-factor model fit the data significantly better ($\chi 2 = 40$, df = 1, $p < .001$).

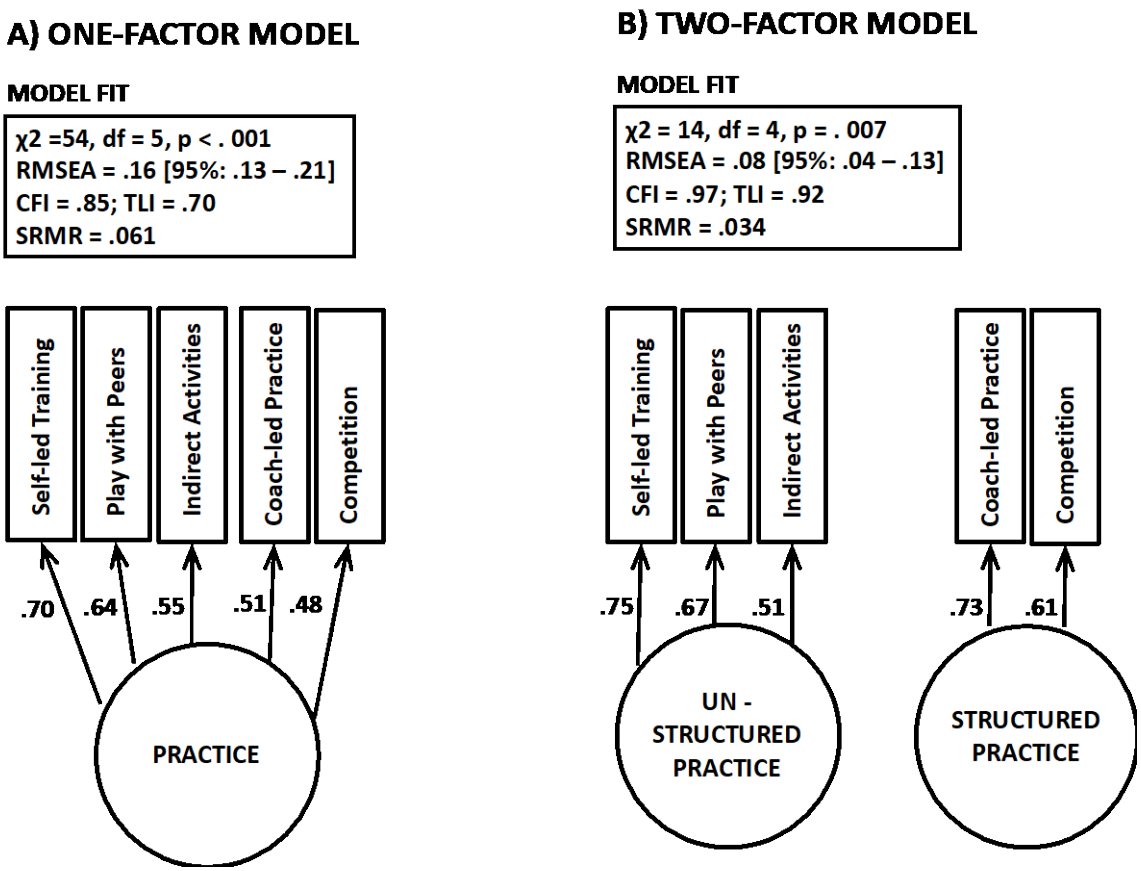

Figure C2. CFA on practice activities. A) One-factor model where all items load on the single construct. B) Two-factor model where structured and unstructured practice activities are identified separately.

Section 3:Main SEM Analyses

The SEM analyses presented in the main text were conducted in R with lavaan program (Rosseel, 2012) using case-wise (or 'full information') maximum likelihood estimation.

Table C1 provides the coefficients with SE for the model which features Coach-led (team) practice activities – see Model 1A and Figure 3.2 in the main text.

Table C1. *Model 1A – Practice represented as Coach-led (group) practice with Grit.*

Latent Variables:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
Interest =~						
Q1.NwIdsDsMFPO	1.000				0.359	0.425
Q3.IHvBOAPSTLI	1.335	0.286	4.668	0.000	0.479	0.464
Q5.IOfSGBLCPDO	1.328	0.300	4.431	0.000	0.477	0.466
Q6.IhvdfMIPLFM	1.683	0.354	4.747	0.000	0.604	0.563
Perseverance =~						
Q4.IamHardWrkr	1.000				0.328	0.494
Q7.IFnshWhtvrB	1.549	0.256	6.060	0.000	0.508	0.652
Q8.IamDiligent	1.532	0.236	6.494	0.000	0.503	0.707
Grit =~						
Interest	1.000				0.924	0.924
Perseverance	0.567	0.219	2.585	0.010	0.574	0.574
PER =~						
DM_Total	1.000				2.249	0.477
SP_Total	3.090	0.980	3.153	0.002	6.950	0.600
PRACTICE_str =~						
Trainng_cch_lg	1.000				0.232	1.000

Regressions:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
PER ~						
Grit (c)	2.477	1.270	1.951	0.051	0.365	0.365
PRACTICE_s (b)	2.115	1.009	2.096	0.036	0.218	0.218
PRACTICE_str ~						
Grit (a)	0.228	0.084	2.706	0.007	0.326	0.326

The alternative model (Model 1B and Figure 3.3 in the main text), with CI and PE as separate constructs, is estimated using the same parameters as the previous model. Table C2 provides the coefficients with SE for the model.

Table C2. *Model 1B – Practice represented as Coach-led (group) practice with CI and PE.*

Latent Variables:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
Interest =~						
Q1.NwIdsDsMFPO	1.000				0.358	0.423
Q3.IHvBOAPSTLI	1.343	0.288	4.658	0.000	0.481	0.465
Q5.IOfSGBLCPDO	1.332	0.301	4.424	0.000	0.477	0.466
Q6.IhvdfMIPLFM	1.691	0.357	4.738	0.000	0.605	0.563
Perseverance =~						
Q4.IamHardWrkr	1.000				0.327	0.493
Q7.IFnshWhtvrB	1.552	0.256	6.058	0.000	0.508	0.652
Q8.IamDiligent	1.537	0.237	6.490	0.000	0.503	0.707
PER =~						
DM_Total	1.000				2.262	0.480
SP_Total	3.056	0.965	3.168	0.002	6.915	0.597
PRACTICE_str =~						
Trainng_cch_lg	1.000				0.232	1.000

Regressions:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
PER ~						
Interest (c)	1.678	1.016	1.652	0.099	0.265	0.265
Persevrnc (c1)	0.660	0.938	0.704	0.482	0.095	0.095
PRACTICE_ (b)	2.332	0.997	2.338	0.019	0.239	0.239
PRACTICE_str ~						
Interest (a)	0.200	0.075	2.649	0.008	0.307	0.307
Persevrnc (a1)	0.004	0.071	0.063	0.950	0.006	0.006

Covariances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
Interest ~~						
Perseverance	0.062	0.017	3.662	0.000	0.529	0.529

The second model, which was created using the same parameters as the first, added another structured practice activity, Competition, to Model 1. The results of the second model (Model 2A, Figure 3.4 in the main text) can be found in Table C3.

Table C3. *Model 2A – Practice represented as Coach-led (group) practice + Competition with Grit.*

Latent Variables:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
Interest =~						
Q1.NwIdsDsMFPO	1.000				0.367	0.434
Q3.IHvBOAPSTLI	1.308	0.274	4.780	0.000	0.480	0.464
Q5.IOfSGBLCPDO	1.252	0.281	4.458	0.000	0.459	0.450
Q6.IhvdfMIPLFM	1.639	0.337	4.867	0.000	0.601	0.560
Perseverance =~						
Q4.IamHardWrkr	1.000				0.325	0.490
Q7.IFnshWhtvrB	1.565	0.259	6.032	0.000	0.509	0.654
Q8.IamDiligent	1.541	0.238	6.486	0.000	0.501	0.705
Grit =~						
Interest	1.000				1.005	1.005
Perseverance	0.462	0.179	2.584	0.010	0.524	0.524
PER =~						
DM_Total	1.000				2.229	0.473
SP_Total	3.115	0.968	3.219	0.001	6.943	0.601
PRACTICE_str =~						
Trainng_cch_lg	1.000				0.161	0.693
Competition_lg	0.854	0.183	4.671	0.000	0.137	0.666

Regressions:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
PER ~						
Grit (c)	1.524	1.062	1.435	0.151	0.252	0.252
PRACTICE_s (b)	4.558	2.003	2.276	0.023	0.329	0.329
PRACTICE_str ~						
Grit (a)	0.195	0.074	2.625	0.009	0.446	0.446

The coefficients with SE for the model alternative model (Model 2B and Figure 3.5 in the main text) with CI and PE as separate constructs can be found in Table C4 provides.

Table C4. *Model 2B – Practice represented as Coach-led (group) practice + Competition with CI and PE.*

Latent Variables:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
Interest =~						
Q1.NwIdsDsMFPO	1.000				0.365	0.433
Q3.IHvBOAPSTLI	1.317	0.276	4.779	0.000	0.481	0.466
Q5.IOfSGBLCPDO	1.254	0.282	4.455	0.000	0.458	0.449
Q6.IhvdfMIPLFM	1.644	0.338	4.864	0.000	0.601	0.560
Perseverance =~						
Q4.IamHardWrkr	1.000				0.325	0.490
Q7.IFnshWhtvrB	1.563	0.259	6.044	0.000	0.508	0.653
Q8.IamDiligent	1.543	0.238	6.489	0.000	0.502	0.706
PER =~						
DM_Total	1.000				2.253	0.478
SP_Total	3.050	0.933	3.269	0.001	6.872	0.595
PRACTICE_str =~						
Trainng_cch_lg	1.000				0.159	0.686
Competition_lg	0.871	0.187	4.667	0.000	0.139	0.672

Regressions:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
PER ~						
Interest (c)	1.000	1.069	0.936	0.349	0.162	0.162
Persevrnc (c1)	0.788	0.955	0.825	0.409	0.114	0.114
PRACTICE_ (b)	4.859	2.048	2.373	0.018	0.344	0.344
PRACTICE_str ~						
Interest (a)	0.214	0.066	3.238	0.001	0.490	0.490
Persevrnc (a1)	-0.028	0.059	-0.481	0.631	-0.057	-0.057

Covariances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
Interest ~~						
Perseverance	0.062	0.017	3.714	0.000	0.526	0.526

Finally, the last model had all the activities divided into two groups: Structured (Coach-led practice and Competition) and Unstructured (Self-led practice, Play with peers, and Indirect involvement). The results of the third model are presented in Table C5 for the model with girt (Model 3A, Figure 3.6) and Table C6 for the model with CI and PE (Model 3B, Figure 3.7).

Table C5. *Model 3A – Practice represented as Structured (Coach-led (group) practice and Competition) and Unstructured practice (Self-led practice, Peer play, and Indirect involvement) with Grit.*

Latent Variables:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
Interest =~						
Q1.NwIdsDsMFPO	1.000				0.350	0.415
Q3.IHvBOAPSTLI	1.303	0.278	4.677	0.000	0.456	0.442
Q5.IOfSGBLCPDO	1.308	0.292	4.482	0.000	0.458	0.449
Q6.IhvdfMIPLFM	1.808	0.374	4.832	0.000	0.633	0.591
Perseverance =~						
Q4.IamHardWrkr	1.000				0.324	0.489
Q7.IFnshWhtvrB	1.566	0.259	6.053	0.000	0.508	0.653
Q8.IamDiligent	1.546	0.238	6.493	0.000	0.502	0.707
Grit =~						
Interest	1.000				0.978	0.978
Perseverance	0.505	0.172	2.933	0.003	0.533	0.533
PER =~						
DM_Total	1.000				2.238	0.475
SP_Total	3.088	0.946	3.264	0.001	6.913	0.598
PRACTICE_str =~						
Competition_lg	1.000				0.133	0.647
Trainng_cch_lg	1.243	0.176	7.056	0.000	0.166	0.714
PRACTICE_unstr =~						
Training_sl_lg	1.000				0.312	0.747
Play_log	0.809	0.090	8.983	0.000	0.252	0.659
Indirect_log	0.696	0.091	7.625	0.000	0.217	0.545

Regressions:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
PER ~						
Grit (c)	1.798	1.153	1.560	0.119	0.275	0.275
PRACTICE_ (b)	6.176	2.922	2.114	0.035	0.368	0.368
PRACTICE_ (b1)	-0.563	1.033	-0.545	0.586	-0.078	-0.078
PRACTICE_str ~						
Grit (a)	0.170	0.057	2.949	0.003	0.436	0.436
PRACTICE_unstr ~						
Grit (a1)	0.388	0.136	2.842	0.004	0.426	0.426

Covariances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.PRACTICE_str ~~						
.PRACTICE_unstr	0.018	0.004	4.417	0.000	0.519	0.519

Table C6. *Model 3B – Practice represented as Structured (Coach-led (group) practice and Competition) and Unstructured practice (Self-led practice, Peer play, and Indirect involvement) with CI and PE.*

Latent Variables:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
Interest =~						
Q1.NwIdsDsMFPO	1.000				0.350	0.414
Q3.IHvBOAPSTLI	1.311	0.280	4.682	0.000	0.459	0.444
Q5.IOfSGBLCPDO	1.308	0.293	4.466	0.000	0.457	0.448
Q6.IhvdfMIPLFM	1.809	0.376	4.808	0.000	0.633	0.590
Perseverance =~						
Q4.IamHardWrkr	1.000				0.324	0.489
Q7.IFnshWhtvrB	1.567	0.259	6.055	0.000	0.508	0.653
Q8.IamDiligent	1.549	0.238	6.497	0.000	0.502	0.707
PER =~						
DM_Total	1.000				2.262	0.480
SP_Total	3.027	0.915	3.307	0.001	6.847	0.593
PRACTICE_str =~						
Competition_lg	1.000				0.134	0.650
Trainng_cch_lg	1.231	0.174	7.065	0.000	0.165	0.710
PRACTICE_unstr =~						
Training_sl_lg	1.000				0.312	0.748
Play_log	0.809	0.090	8.967	0.000	0.252	0.659
Indirect_log	0.696	0.091	7.612	0.000	0.217	0.545

Regressions:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
PER ~						
Interest (c)	1.112	1.112	1.000	0.317	0.172	0.172
Persevrnc (c1)	0.816	0.957	0.852	0.394	0.117	0.117
PRACTICE_ (b)	6.474	2.983	2.170	0.030	0.383	0.383
PRACTICE_ (b1)	-0.493	1.022	-0.482	0.630	-0.068	-0.068
PRACTICE_str ~						
Interest (a)	0.179	0.058	3.100	0.002	0.467	0.467
Persevrnc (a2)	-0.020	0.049	-0.408	0.683	-0.049	-0.049
PRACTICE_unstr ~						
Interest (a1)	0.367	0.122	3.006	0.003	0.412	0.412
Persevrnc (a3)	0.009	0.103	0.091	0.928	0.010	0.010

Covariances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.PRACTICE_str ~~						
.PRACTICE_unstr	0.018	0.004	4.635	0.000	0.522	0.522
Interest ~~						
Perseverance	0.059	0.016	3.629	0.000	0.521	0.521

Alternative Main Analysis – Path analysis with composites

The SEM analyses presented in the main text include the measurement error of the latent constructs. Here we demonstrate what happens when this measurement error is not taken into account as it is often the case in studies involving grit.

For the illustration, we used the first model with CI and PE (Model 1B, Figure 3.3 in the main text). First, we constructed the CI and PE constructs by averaging the score on the items for these two constructs (excluding Q2 for PE). The performance/skill was constructed using the composite of the decision making and situational probability. Practice was the accumulated Coach-led training estimate. These constructs were then subjected to the same structural model as with the SEM. The difference is that this path analysis does not include the measurement error associated with the constructs. In other words, it assumes that the constructs have been perfectly measured.

Figure C3 depicts the standardized coefficients of this model. As can be seen, the CI coefficients are considerably higher than in the main SEM analysis (see Figure 3.3 in the main text). The SEs are also smaller, which, in combination with larger coefficients, led to the relations with CI becoming statistically significant. Most importantly, the CI is now not only clearly better direct and indirect predictor of skill than PE, but also reliably so. The direct influence of CI (.42 vs. .07) is now significantly larger than that of PE, as is the mediation through practice (.14 vs. -.04), as well as the total effect on skill (.56 vs. .03).

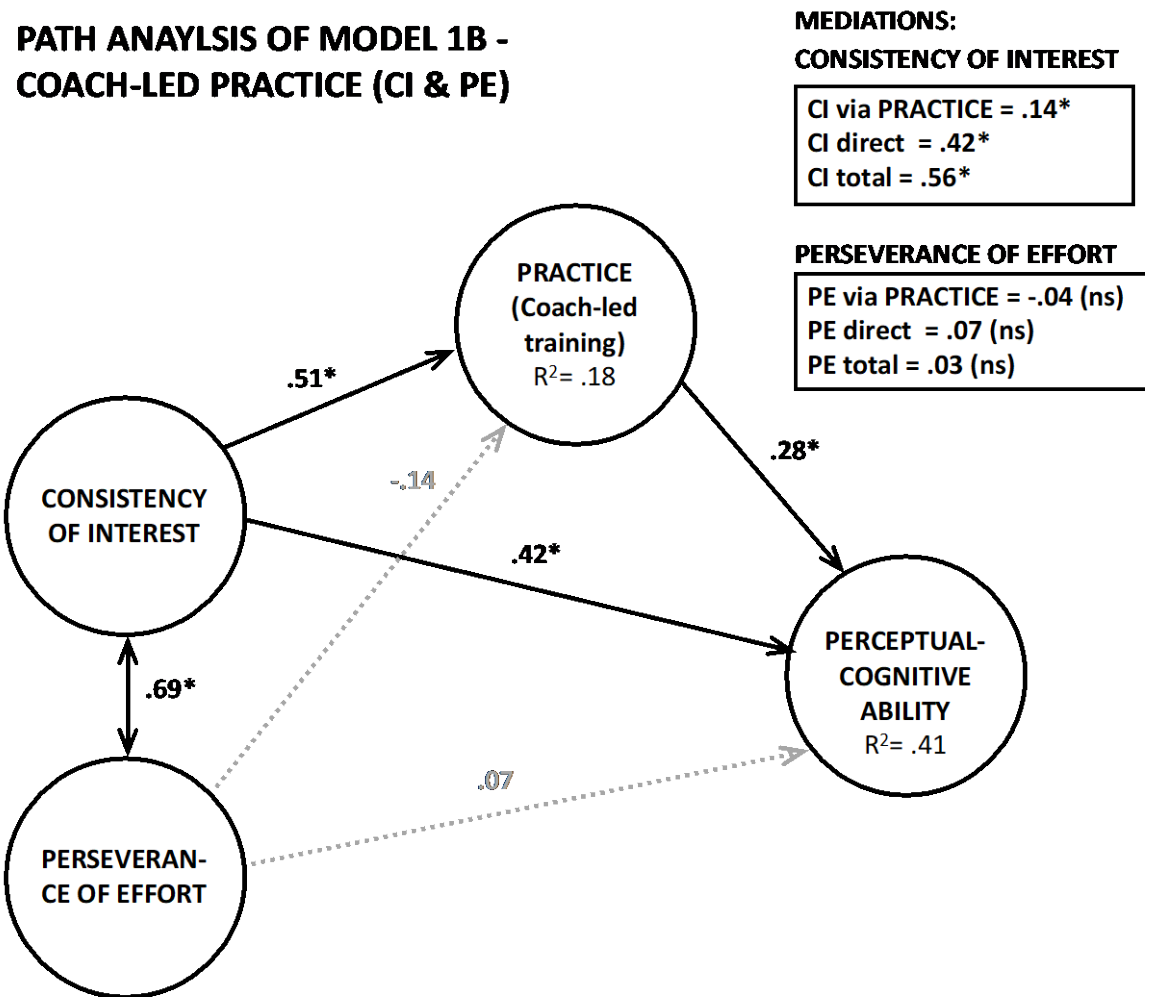

Figure C3. Path analysis on composite score for Model 1B (Coach-led training with CI and PE). The analysis does not include measurement error of the individual manifest variable as the SEM analysis in the main text does (see Figure 3.3). Consequently, the CI coefficient and their SEs are considerably larger, which leads to significant relations with other constructs as well as differences to PE.

Chapter 4: Snowball effect of grit on (deliberate) practice - Appendix D

Section 1: Confirmatory Factor Analysis for Grit Scale

We used the short Grit scale, which has eight items, four for each of the two grit's components: Consistency of Interest (CI) and Perseverance of Effort (PE).

The four items for CI are:

Q1. New Ideas Distract Me from Previous Ones

Q3. I Have Been Obsessed with A Project for a Short Time but Lost Interest

Q5. I Often Set a Goal but Later Choose to Pursue a Different One

Q6. I have difficulty Maintaining Interest in a Projects Longer than a Few Months

The four items for PE are:

Q2. Setbacks Don't Discourage Me

Q4. I am Hard Worker

Q7. I Finish Whatever I Begin

Q8. I am Diligent

We performed a confirmatory factor analysis on the grit scale in the statistical program R with lavaan package (Rosseel, 2012). First we constructed a one-factor model where all the items load onto a single (grit) construct (Figure D1 A). This model had a bad fit (see the box Model fit in Figure D1 A). The two-factor model, where one half of the items were loading on the CI and the other half of the items on the PE, had a much better fit (Figure D1 B). The formal test of the model fit indicated that the two-factor model had a significantly better fit ($\chi 2 = 838$, df = 1, $p < .001$). The two-factor model was, however, not describing the data particularly well (see Model fit box in Figure D1 B). The main problem appeared to be Q2, which had a poor loading on PE (only .25). Once Q2 was left out and only

other three items were forming the PE component, the revised model improved (Figure D1 C). The revised two-factor model (Figure D1 C) had a significantly better fit than the original two-factor model with Q2 (Figure D1 B) – $\chi 2 = 38$, df = 6, $p < .001$. We have consequently used the revised two-factor model in our main analyses.

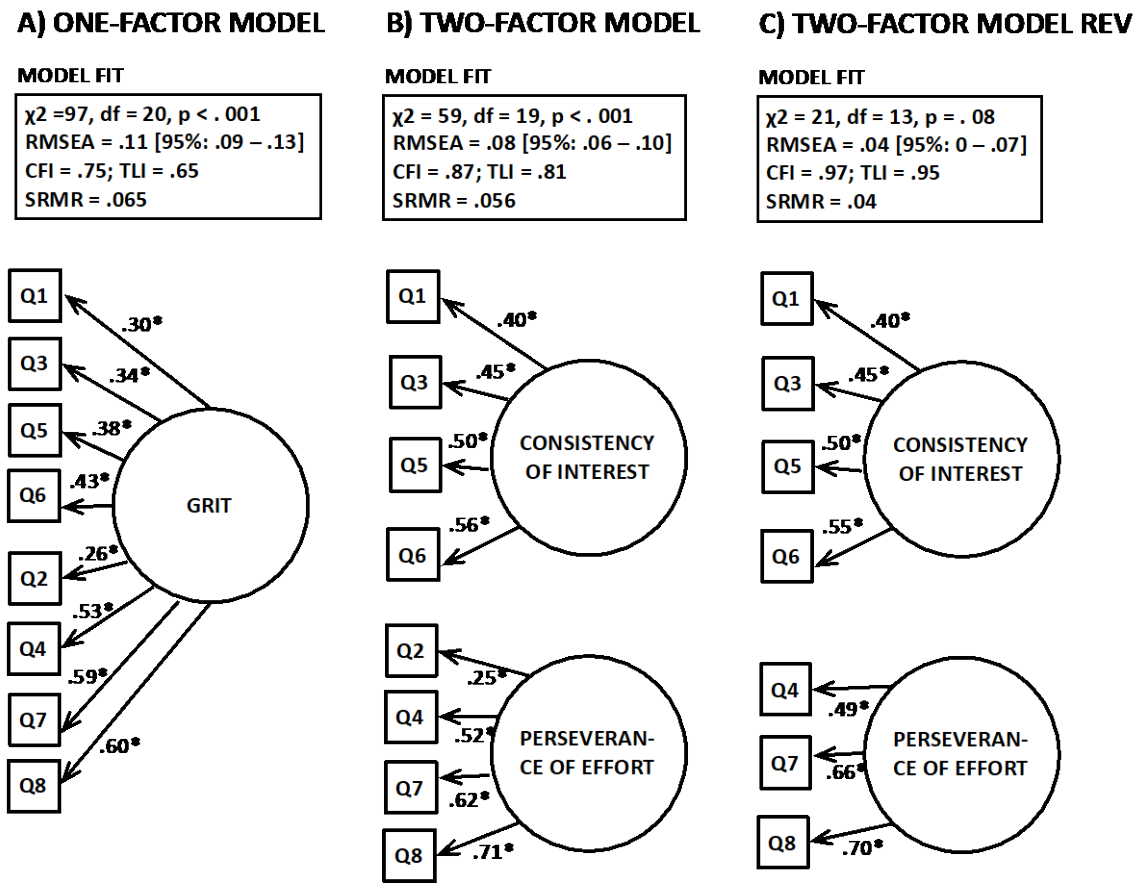

Figure D1. CFA on Grit Scale. A) One-factor model where all items load on the single construct. B) Two-factor model where CI and PE constructs are identified separately. C) Revised two-factor model without Q2 in PE.

Section 2: The shape of the curve: model fit comparison

The linear model was considerably worse when it comes to the fit compared to the quadratic model ($\chi2 = 1106$, df = 1, $p < .001$). This confirms that the accumulation of practice is not constant over the years as it significantly accelerates in the later phase. As with the total practice the linear model was considerably worse than the quadratic model for competition ($\chi2 = 733$, df = 1, $p < .001$), for coach-led practice ($\chi2 = 1325$, df = 1, $p < .001$), for self-led practice ($\chi2 = 112$, df = 1, $p < .001$), for indirect activities ($\chi2 = 898$, df = 1, $p < .001$) and for play with peers ($\chi2 = 4$, df = 1, $p = .49$)

Table D1. *Linear vs. Quadratic model Formal Test*

	Total Practice		**Competition**		**Coach-led Practice**		**Self-led Practice**		**Play with peers**		**Indirect Activities**	
	Linear	**Quad.**	**Linear**	**Quad.**	**Linear**	**Quad.**	**Linear**	**Quad.**	**Linear**	**Quad.**	**Linear**	**Quad.**
Predictors	*β (SE)*	*β (SE)*	*β (SE)*	*β (SE)*	*β (SE)*	*β (SE)*	*β (SE)*	*β (SE)*	*β (SE)*	*β (SE)*	*β (SE)*	*β (SE)*
Intercept	198* (32)	543* (34)	8* (2)	28* (2)	20* (5)	74* (6)	59* (10)	85* (10)	114* (11)	110* (11)	33 (20)	243* (20)
Age	889* (25)	486* (26)	50* (1)	27* (1)	160* (4)	51* (5)	130* (7)	98* (7)	135* (5)	141* (6)	412* (17)	167* (18)
Age2		67* (2)		4* (.1)		18* (.3)		5* (.5)		0.9* (.4)		40* (1)
Model fit												
ICC	0.95	0.98	0.91	0.95	0.88	0.95	0.97	0.97	0.97	0.97	0.95	0.97
Marginal R^2 / Conditional R^2	0.52 / 0.98	0.55 / 0.99	0.57 / 0.96	0.60 / 0.98	0.57 / 0.95	0.61 / 0.98	0.24 / 0.98	0.25 / 0.98	0.29 / 0.98	0.29 / 0.98	0.36 / 0.97	0.39 / 0.98
AIC	28808	27701	18934	18206	23731	22408	23515	23404	23091	23088	27593	26694
log-Likelihood	-14398	-13843	-9461	-9096	-11859	-11197	-11751	-11695	-11539	-11537	-13790	-13340
Deviance	28812.4	27706.4	18927.6	18195.0	23728.6	22403.5	23514.5	23402.5	23090.2	23085.9	27595.7	26697.5
Deviance Diff. χ2 (df = 1)		1106*		733*		1325*		112*		4*		898*

Section 3: The shape of the curve: breaking point analysis

Two lines method

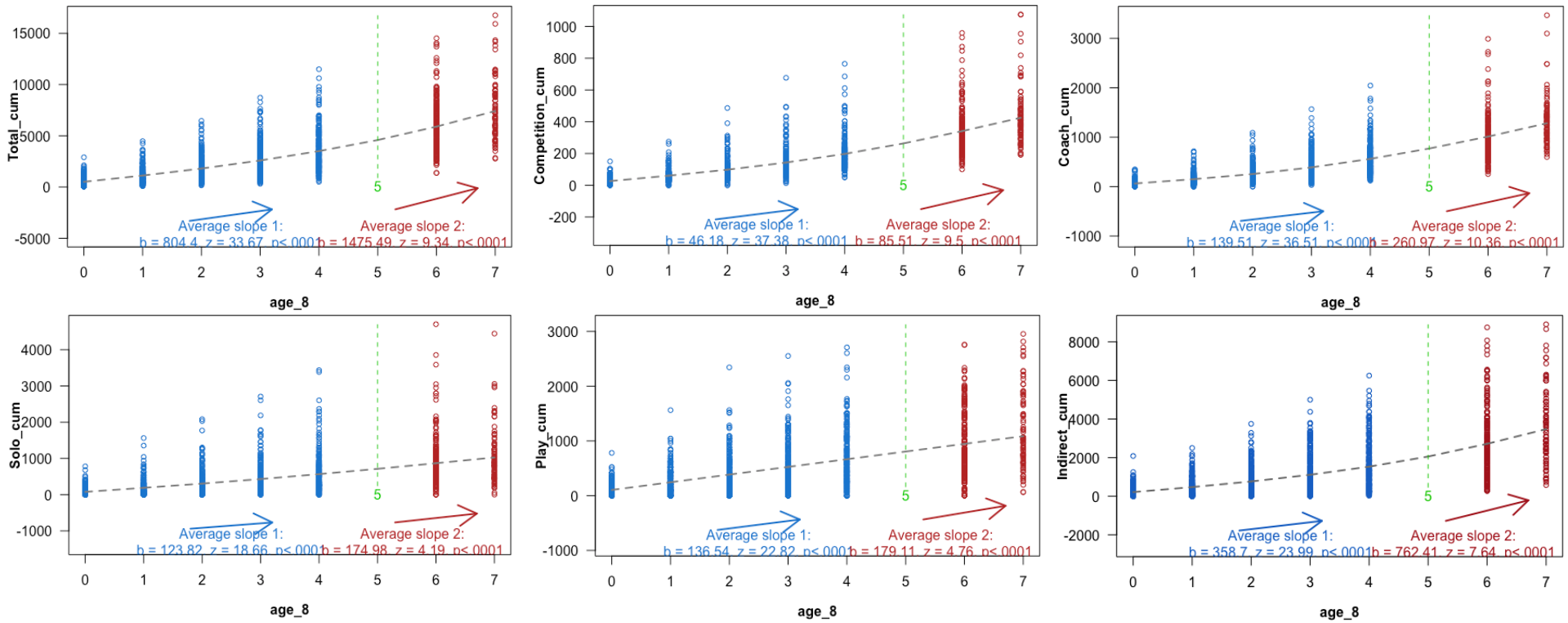

Figure D2. Linear vs Quadric model – two-lines method.

Section 4: Multilevel model specification

The final model for grit as a single composite measure has the following form:

Level 1: $PRACTICE_{ij} = \pi 0_i + \pi 1_i AGE_{ij} + \pi 2_i AGE^2_{ij} + \varepsilon_{ij}$

Level 2: $\pi 0_i = \gamma 00 + \gamma 01 GRIT + \zeta 0_i$

$\pi 1_i = \gamma 10 + \gamma 11 GRIT + \zeta 1_i$

$\pi 2_i = \gamma 20 + \gamma 21 GRIT + \zeta 2_i$

and the single equation version has the following form:

$PRACTICE_{ij} = \gamma 00 + \gamma 01 GRIT + \gamma 10 AGE_{ij} + \gamma 11 (GRIT \times AGE_{ij}) + \gamma 20 AGE^2_{ij} + \gamma 21 (GRIT \times AGE^2_{ij}) + \zeta 0_i + \zeta 1_i Age + \zeta 2_i Age^2 + \varepsilon_{ij}$

where PRACTICE is the outcome variable (e.g., individual practice types), AGE is a time variable representing measurement occasions (e.g., exact age at the time of testing, in this case starting from age 8), AGE^2 is the quadratic term of age, which captures the accelerated effect, while $\pi 0_i$ and $\pi 1_i$ represents the initial status (intercept) and the rate of change (slope) of PRACTICE depending on the values of AGE. The subscript *i* refers to individual players, while *j* stands for different measurement occasions/ years. The last part ε_{ij} is the error term. This part of the model captures the change within the units of analysis (e.g., how the scores of a particular player change over occasions), that is provides a variability estimate.

Level 2 parameters define the level 1 coefficients: initial rate ($\pi 0_i$) is composed of the average initial status for all individuals ($\gamma 00$) and the effect of explanatory variable, here grit, ($\gamma 01$) while the rate of change ($\pi 1_i$) is also made of the average rate of change for all individuals ($\gamma 10$) and the effect that grit has on the rate of change ($\gamma 11$). In addition to the mentioned parameters, also called fixed effects, there are also error terms ($\zeta 0_i$ and $\zeta 1_i$) in both equations in level 2 that describe the variations of each individual in the initial status and rate of change from the overall initial status and rate of change.

The model where the composite grit is replaced by CI and PE components has the following form:

Level 1: $PRACTICE_{ij} = \pi 0_i + \pi 1_i AGE_{ij} + \pi 2_i AGE^2_{ij} + \varepsilon_{ij}$

Level 2: $\pi 0_i = \gamma 00 + \gamma 01CI + \gamma 02PE + \zeta 0_i$

$\pi 1_i = \gamma 10 + \gamma 11CI + \gamma 12PE + \zeta 1_i$

$\pi 2_i = \gamma 20 + \gamma 21CI + \gamma 22PE + \zeta 2_i$

and the single equation version has the following form:

$PRACTICE_{ij} = \gamma 00 + \gamma 01CI + \gamma 02PE + \gamma 10AGE_{ij} + \gamma 11 (CI \times AGE_{ij}) + \gamma 12 (PE \times AGE_{ij}) + \gamma 20AGE^2_{ij} + \gamma 21 (CI \times AGE^2_{ij}) + \gamma 22 (PE \times AGE^2_{ij}) + \zeta 0_i + \zeta 1_i Age + \zeta 2_i Age^2 + \varepsilon_{ij}$

Section 5: Descriptive Analysis

Table D2. Model 1 – Practice represented as Total amount of practice.

	Total practice (Hrs)							
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Valid	323	314	310	309	303	296	199	90
Missing	122	131	135	136	142	149	246	355
Mean	555.13	1176.70	1905.59	2740.40	3717.68	4819.53	6213.68	7971.83
Std. Error of Mean	27.25	52.88	77.04	100.03	125.01	149.28	215.55	333.10

Table D3. Model 1 – Practice represented as Competition.

	Competition (Hrs)							
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Valid	351	346	342	341	338	333	224	100
Missing	94	99	103	104	107	112	221	345
Mean	31.41	63.76	103.85	150.96	207.37	274.64	354.25	441.36
Std. Error of Mean	2.38	3.67	5.48	7.28	9.05	10.49	15.63	18.74

Table D4. Model 1 – Practice represented as Coach-led practice.

	Coach-led practice (Hrs)							
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Valid	349	342	337	336	334	327	221	96
Missing	96	103	108	109	111	118	224	349
Mean	66.48	147.15	254.40	394.14	572.70	798.41	1014.00	1376.84
Std. Error of Mean	3.61	7.17	11.15	15.65	20.00	24.33	35.07	65.04

Table D5. Model 1 – Practice represented as Self-led practice.

	Self-led practice (Hrs)							
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Valid	331	322	318	317	314	308	209	91
Missing	114	123	127	128	131	137	236	354
Mean	89.63	187.45	306.51	437.64	572.65	732.60	888.92	1118.17
Std. Error of Mean	6.86	12.96	19.62	25.47	31.42	37.86	50.80	80.24

Table D6. Model 1 – Practice represented as Play with peers.

	Play with peers (Hrs)							
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Valid	348	342	336	335	331	326	220	99
Missing	97	103	109	110	114	119	225	346
Mean	115.72	246.65	389.38	528.94	671.60	804.34	965.97	1133.89
Std. Error of Mean	7.36	14.95	21.90	28.23	33.62	38.09	52.99	73.14

Table D7. Model 1 – Practice represented as Indirect involvement.

	Indirect involvement							
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Valid	340	336	331	330	326	321	217	101
Missing	105	109	114	115	119	124	228	344
Mean	228.44	477.95	775.76	1124.99	1567.10	2071.37	2785.82	3705.20
Std. Error of Mean	17.16	31.41	45.80	59.67	75.35	90.01	135.56	201.61

Table D8. Correlations between Grit (and its components, Interest and Perseverance) and practice activities over years

	Age	GRIT	Interest	Perseverance
Coach-led practice	Year 15	-0.04	-0.02	-0.05
	Year 14	-0.04	-0.06	-0.02
	Year 13	**0.04**	-0.02	**0.09**
	Year 12	**0.07**	**0.04**	**0.08**
	Year 11	**0.05**	0.00	**0.07**
	Year 10	**0.13**	**0.11**	**0.12**
	Year 9	**0.19**	**0.19**	**0.11**
	Year 8	**0.16**	**0.12**	**0.13**
Competition	Year 15	**0.13**	**0.18**	0.03
	Year 14	**0.08**	**0.14**	**0.10**
	Year 13	**0.10**	**0.13**	**0.06**
	Year 12	**0.10**	**0.13**	0.01
	Year 11	**0.04**	**0.07**	-0.02
	Year 10	**0.10**	**0.08**	**0.08**
	Year 9	**0.07**	**0.06**	0.03
	Year 8	0.01	-0.01	0.00
Self-led practice	Year 15	**0.10**	**0.09**	**0.07**
	Year 14	**0.15**	**0.16**	**0.12**
	Year 13	**0.12**	**0.12**	**0.11**
	Year 12	**0.13**	**0.16**	**0.06**
	Year 11	**0.09**	**0.11**	0.03
	Year 10	**0.12**	**0.12**	**0.08**
	Year 9	**0.07**	**0.09**	0.02
	Year 8	**0.10**	**0.14**	0.00
Play with peers	Year 15	**-0.04**	-0.02	-0.04
	Year 14	0.00	0.02	0.00
	Year 13	0.00	-0.02	**0.05**
	Year 12	**0.07**	**0.06**	**0.05**
	Year 11	**0.07**	**0.10**	0.03
	Year 10	**0.09**	**0.13**	0.05
	Year 9	**0.09**	**0.13**	**0.06**
	Year 8	**0.12**	**0.14**	**0.09**
Indirect involvement	Year 15	**0.20**	**0.22**	**0.11**
	Year 14	**0.09**	**0.08**	**0.07**
	Year 13	**0.09**	**0.10**	**0.17**
	Year 12	**0.14**	**0.12**	**0.14**
	Year 11	**0.16**	**0.19**	**0.12**
	Year 10	**0.12**	**0.16**	**0.08**
	Year 9	**0.11**	**0.15**	**0.05**
	Year 8	**0.08**	**0.11**	0.03

Note. Coefficients in bold are significant at $p < .05$.

Chapter 5: Aging curves of sport expertise - Appendix E

Other Basketball Performance Measures (PER and VORP)

Table E1. *Deviance information criterion for exponential functions used to model the age-related changes in VORP and PER, treating the pre-peak increase and post-peak decrease separately.*

	PER		VORP	
	Pre-peak	Post-peak	Pre-peak	Post-peak
Power law	45,614	27,569	24,870	19,026
Exponential	45,307	28,176	25,118	20,000
Logistic	45,286	NA	NA	NA
Linear	45,032	27,580	25,252	19,264

Note: The NA (not available estimates) indicate that models with specified functions for the pre-peak increase or post-peak decrease could not be estimated.

Table E2. *Estimates of the intercept and the slope for each of the measures used, given separately for the pre-peak increase and post-peak decrease.*

			Parameters	
		Function	Intercept	Slope
			Mean (95% CI)	Mean (95% CI)
PER	Pre-peak	Linear	12.34 (12.01 – 12.51)	0.0045 (-.0018 – .011)
	Post-peak	Power law	12.02 (11.81 – 12.28)	-0.0029 (-.0072 – .0012)
VOR	Pre-peak	Power law	0.062 (.048 – 0.77)	0.035 (.004 – .065)
	Post-peak	Power law	0.340 (0.304 – 0.374)	-0.030 (-0.048 – -0.0115)

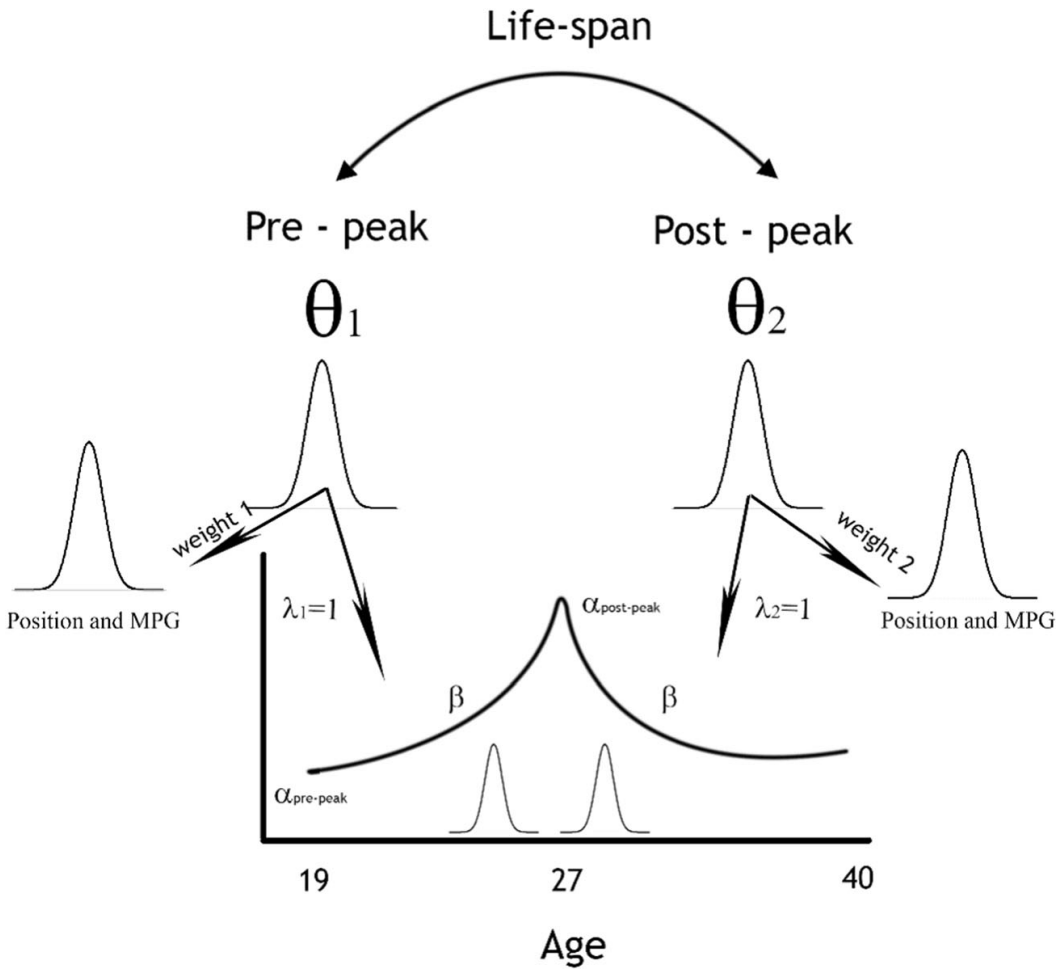

Figure E1. Illustrative representation of the B-Ianus model of age-related changes in sports (Model 1). Performance is modeled as a pre-peak increase (before 27 years old) and post-peak decrease (after 27 years). The slopes of the increase and decrease (β) are adjusted for every participant, indicated by normal distributions as the basis of the functions. The slopes are loaded onto latent factors by the λ parameter; setting this parameter to 1 defines the measurement scale of the latent factor. The player's position during their career and the total minutes per game were also loaded onto the latent structures through the weight parameters. Finally, the pre-peak increase and post-peak decrease estimates, adjusted for other variables in the factorial structure, are correlated with each other. This is illustrated by the Life-span parameter.

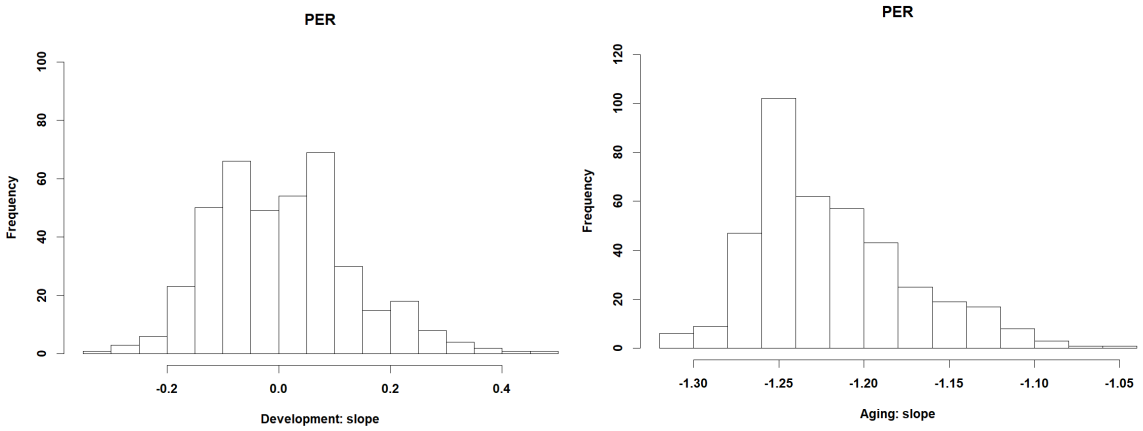

Figure E2. Estimated parameters for pre-peak (development) and post-peak changes (aging). The figures show the possible values of parameters for the slope of pre-peak (left) and post-peak functions (right) when we model the PER changes with a linear function until the peak and an approximate power-law relationship with the linear one after the peak. The slopes in this case are represented in linear (development) and log-log space (aging).

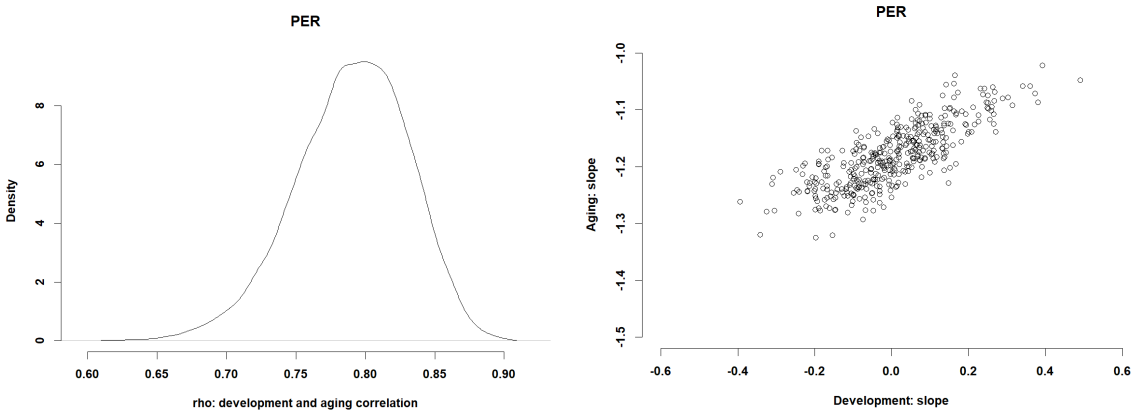

Figure E3. The interaction between the slope of the pre-peak increase and the slope of the post-peak decrease for the 400 random players in the database (left). Sizes of the correlation between the pre-peak and post-peak slopes (right).The x-axis shows slope size for the pre-peak change, while the y-axis illustrate slope size for the post-peak change. The positive values indicate stronger increase and shallower decline, while negative values show shallower increase to the peak and stronger decline after it.

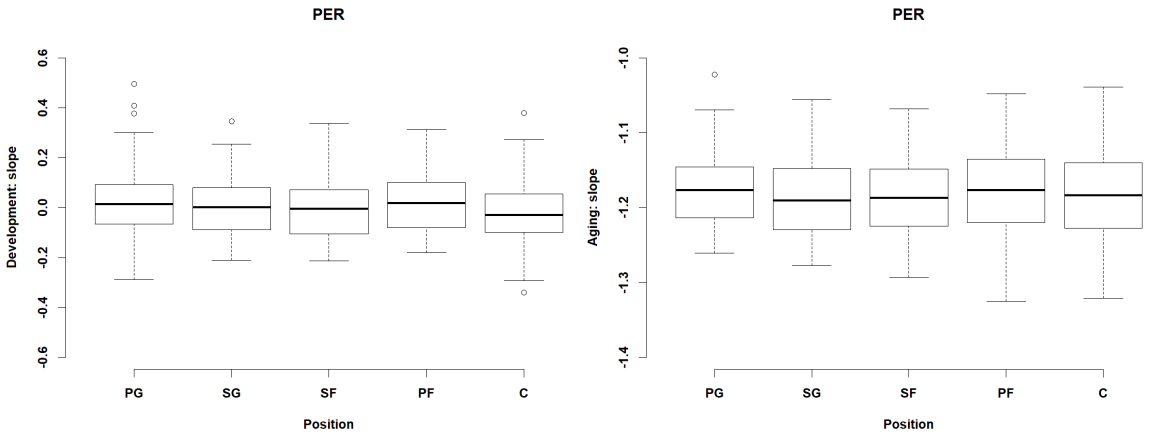

Figure E4. Difference in the size of the slope for the win shares based on the different positions in basketball: PG - point guard, SG - shooting guard, SF - small forward, PF - power forward and C - center. The y-axis illustrates size of the slope for the pre-peak and post-peak change, while the x-axis shows different positions in basketball.

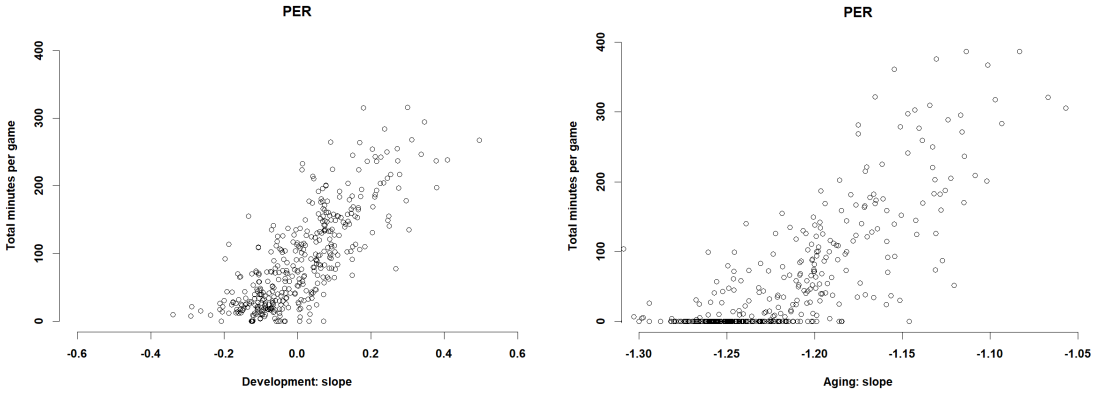

Figure E5. Interaction of the pre-peak and post-peak slope for PER performance with the total minutes per game contributed by players during their careers. The y-axis illustrates the total number of minutes per games players contributed during the pre-peak and post-peak period, while the slope for the functions estimated on the pre-peak and post-peak changes is illustrated on the x-axis.

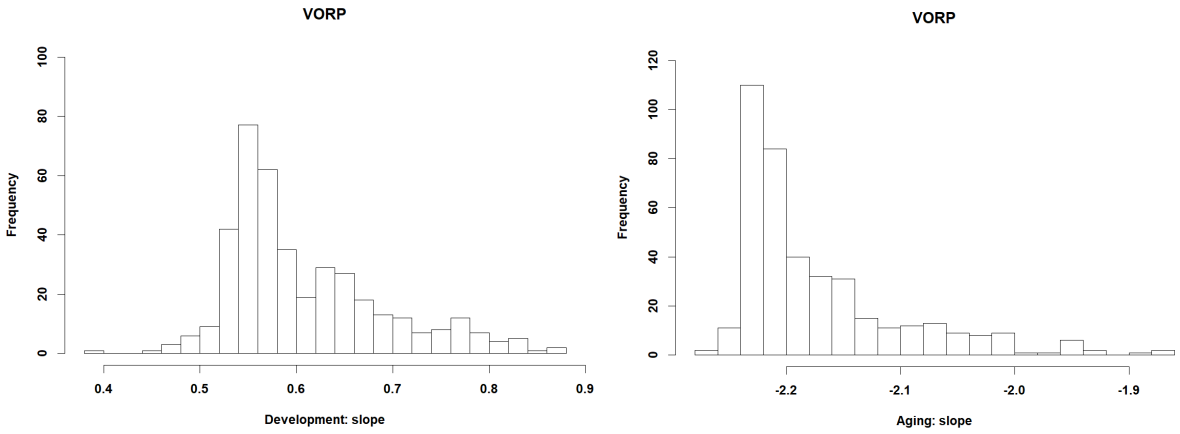

Figure E6. Estimated parameters for pre-peak (development) and post-peak changes (aging). The figures show the possible values of parameters for the intercept and slope of pre-peak and post-peak functions when we approximate power-law changes in the VORP measure with linear function before and after the peak. The slopes in this case are represented in log-log space (development and aging).

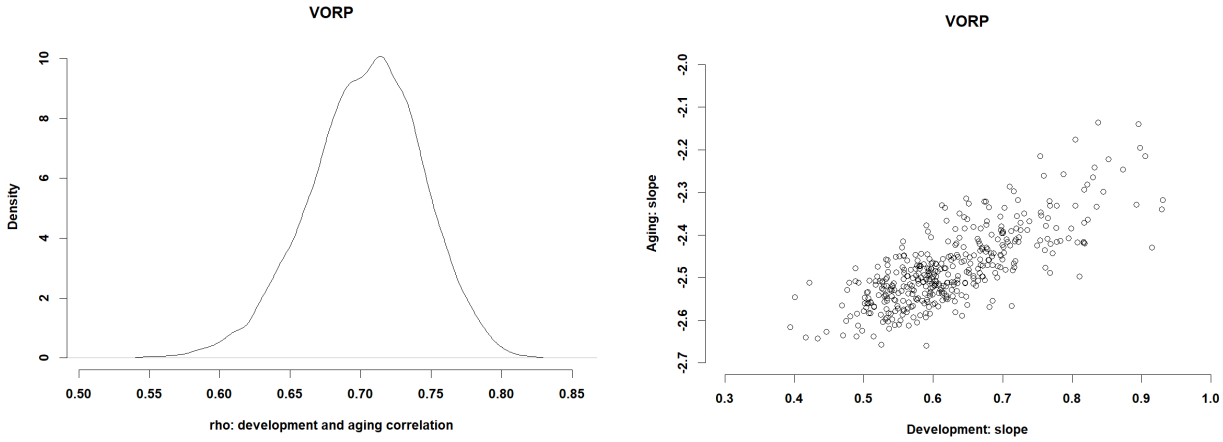

Figure E7: Interaction of the pre-peak and post-peak slope for VORP performance with the total minutes per game contributed by players during their careers. The y-axis illustrates the total number of minutes per games players contribute during the pre-peak and post-peak period, while the slope for the functions estimated on the pre-peak and post-peak changes is illustrated on the x-axis. The positive values indicate stronger increase and shallower decline while negative values show shallower increase to the peak and stronger decline after it.

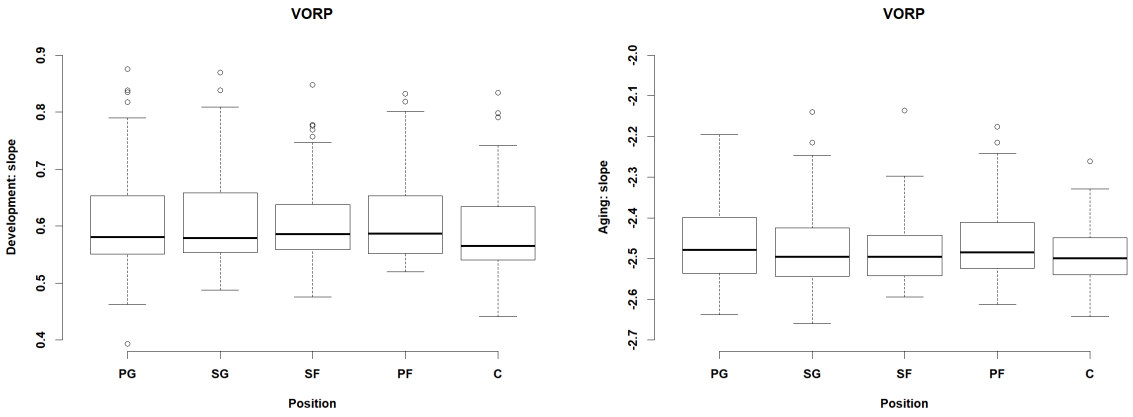

Figure E8. Difference in the size of the slope for the VORP measure based on the different positions in basketball: PG - point guard, SG - shooting guard, SF - small forward, PF - power forward and C - center. The y-axis illustrates the size of the slope for the pre-peak and post-peak change, while the x-axis shows different positions in basketball.

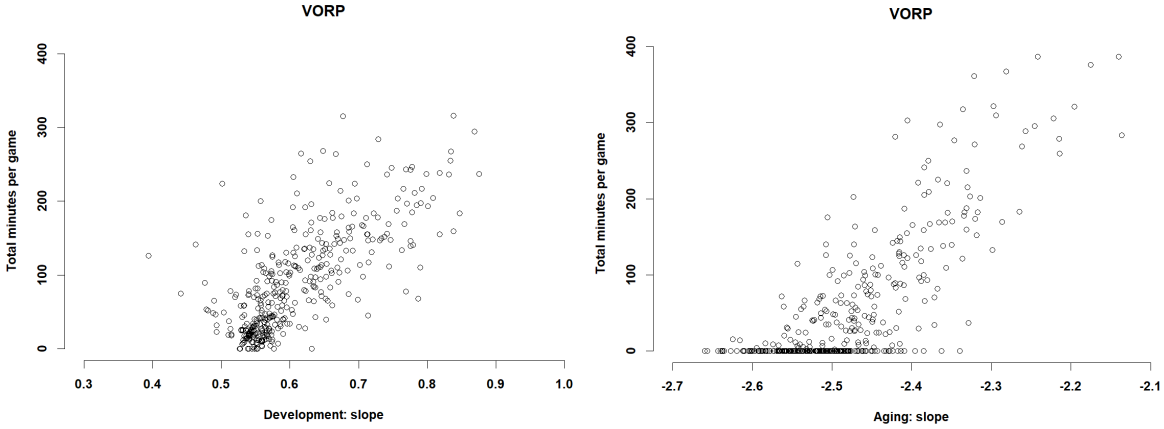

Figure E9. Interaction of the pre-peak and post-peak slope for VORP performance with the total minutes per game contributed by players during their careers. The y-axis illustrates the total number of minutes per games players contribute during the pre-peak and post-peak period, while the slope for the functions estimated on the pre-peak and post-peak changes is illustrated on the x-axis.

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