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Expertise vs. Talent

Fernand Gobet*

Abstract: The study of extraordinary performance has been carried out almost independently in two research traditions, the first emphasising practice and the second emphasising talent. The practice tradition has collected empirical evidence strongly supporting chunking as a key learning mechanism and practice as a prerequisite for becoming an expert. The talent tradition has provided convincing data for the importance of (inherited) individual differences in intelligence and working memory as well as for other factors such as starting age and handedness. If future research on extraordinary performance is to be successful, these two traditions must joint efforts to understand the mechanisms involved. Given the number of variables in play, their complex interactions and the fact that they evolve as a function of time, the use of computational modelling is necessary.

Keywords:

Chess, Chunking, Complex systems, Computational modelling, Deliberate practice, Expertise, Practice, Talent

Expertise vs. Talent. This is both a good and a bad title. (I cannot take the credit or the blame for it, as this title was "imposed" on me by the organisers of the 2nd IRATDE conference.) It is a good title because it summarises in three words the state of the field devoted to the study of extraordinary performance. It is a bad title because it oversimplifies things. Other issues are of course important in the study of extreme performances. Also, it should not be "vs.", but at least "and", as in the title of a recent book of mine (Gobet, 2011). But even "and" is a bit weak, and a better title would be "Expertise × Talent", to emphasize that practice and talent interact in complex ways.

The research on extraordinary performance is highly polarized (see table 1). On the one hand, we have the tradition of research based on the study of "expertise", which emphasises practice. On the other hand, we have the tradition of research based on the study of "talent", which mostly focuses on innate talent.

Having obtained my undergraduate degree at the University of Fribourg (Switzerland) during the heydays of Jean Piaget's constructivist school of developmental psychology, I have always been suspicious of the facile opposition between talent and practice – between innate and acquired. Piaget was of course brilliant at tearing this opposition apart and showing that what was important was the dialectical adaptation between these two poles.

Thus, for many years, my study of expert performance avoided this issue – just as Piaget, I simply thought it was meaningless. I studied perception and memory in experts, mostly chess players, collecting experimental data and building computer models. To my chagrin, I had to note that few colleagues in cognitive psychology were interested in computer models. Rather than *mechanisms* – complex or simple – they were interested in answering binary questions: serial or parallel, chunks or no chunks, and of course, innate or acquired?

As is well known, innate vs. acquired has been one of the great debates in psychology. In fact, I was not able to avoid this question in two of my other domains of research. In

* *Department of Psychological Sciences, University of Liverpool, Liverpool, L69 7ZA, UK. Email: fernand.gobet@liv.ac.uk*

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Table 1. Comparison of the Two Traditions That Have Dominated the Study of Exceptional Performances: On the Left, the Talent Approach; on the Right, the Expertise Approach. After Gobet (2011)

Extraordinary Performance	
Talent	**Expertise**
Correlational studies	Experimentation and modelling
Psychology of intelligence	Cognitive psychology
Innate	Acquired
Differences between novices and experts	Similarities between novices and experts
Children/Adults	Adults
Normal and pathological	Normal

research on the acquisition of language, where together with colleagues I developed computational models of the acquisition of vocabulary and syntactic structures (Freudenthal, Pine, Aguado-Orea, & Gobet, 2007; Jones, Gobet, & Pine, 2007), this debate has been dividing the field for decades. In neuroscience, the debate about localisation of brain structures and brain plasticity still rages. In my teaching too, this question became unavoidable. I taught a class on the psychology of intelligence, and of course the dispute between the innate or acquired origin of intelligence was at the centre stage again.

Then, starting for the late 1990s, I had three PhD students – Guillermo Campitelli, Merim Bilalić, and Philippe Chassy – who forced me to think about this issue deeply. Interestingly, these three students had different views, almost spanning the entire range from pure talent to pure practice. They also collected a considerable amount of data on this issue, which turned out very useful in shaping my views.

So far, I have been talking about talent and expertise as if they form a continuum, as is often done in the field (see figure 1, top). However, a more fruitful representation is shown at the bottom of figure 1: a Cartesian plane where practice and talent form the two dimensions. Thus, one individual could score low on both dimension (white star), score high on both dimensions (black star) or have any kind of combination of them.

Chess as a Research Domain

Chess is an interesting domain for studying the question of expertise vs. talent, as large amounts of empirical data have been collected on this game, mostly from the expertise tradition. Chess has the following advantages for studying extraordinary performance (Gobet, 1998b). It is a complex game that requires many years of study to master. Its structure makes it fairly easy to design experiments. Most importantly, chess offers the advantage that skill level is precisely measured by the Elo rating (Elo, 1978), which is regularly updated. This allows for an accurate description of the learning trajectory. In fact, much of what we know about expertise comes from research into chess (Gobet, de Voogt, & Retschitzki, 2004).

In what follows, I first present findings on chess from the expertise tradition. Then, I present findings from the talent tradition. Any serious theory of expertise and talent should be able to explain these data. A discussion will follow, trying to put together what has been learnt from these two lines of research.

Research on Expertise

Research on chess has repeatedly shown the importance of knowledge. Two tasks are typical in this line of research (De Groot, 1965). In the recall task, a chess board is briefly presented (say 5 seconds), then removed from view, and participants have to replace as many pieces as they can. In the choose-a-move task, a position is presented with or

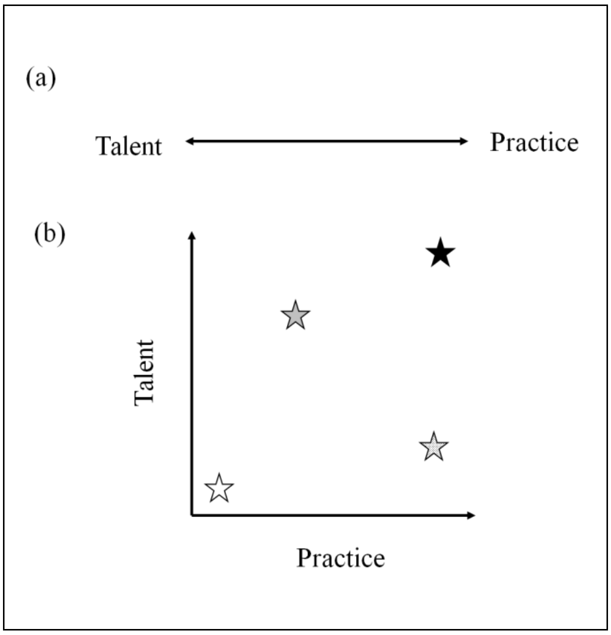

Figure 1. Two representations of the relationship between talent and practice.

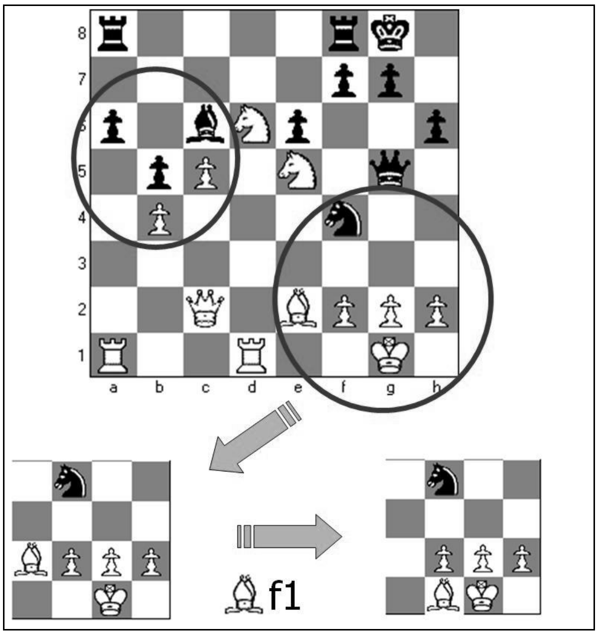

Figure 2. Illustration of the concepts of a chunk and a condition/action pair.

without time limit and participants have to select a move. In both tasks, stronger players outperform weaker players.

Critically, Chase and Simon's (1973) research has shown that the same basic knowledge structures – chunks – can account for the results of both tasks. Chunks are memory structures that are units of both perception and meaning. They are attached to relevant information, for example a move to play given a certain pattern on the board (see figure 2). Larger chunks are built recursively on smaller chunks. In a memory task, pointers to chunks can be put in short-term memory (STM). Although all players have a limited STM capacity, stronger players can store larger chunks and thus perform better in the recall task. In a choose-a-move task, the patterns on the board elicit chunks in long-term memory (LTM), which in turn give access to potentially useful information (e.g., what kind of move to play). Chase and Simon note that it takes 10 years, or 10,000 hours, of dedicated practice to reach a high level of expertise in chess and in any other domain. They justify this number by the large number of chunks (about 50,000) and the associated actions that must be acquired.

While chunking theory elegantly accounted for key empirical results, it suffered from two main weaknesses. First, it underestimated the role of high-level knowledge. Chase and Simon assumed a maximal size of 5–6 pieces, but a number of studies have shown that masters use larger chunks (see De Groot & Gobet, 1996). In some cases, the entire position can be captured by a single memory structure. Second, it overestimates the time to encode information in LTM (Charness, 1976).

Template Theory

In order to remedy these weaknesses while keeping its strengths, chunking theory was modified and expanded into template theory (Gobet & Simon, 1996b, 2000), which aimed to account both for low-level and high-level aspects of cognition. The new theory assumes an LTM, where chunks are stored, and a visual STM with a limited capacity (4 chunks). STM is dynamic, in the sense that older chunks are continuously updated by new incoming information. The largest chunk recognized so far is used to direct eye movements; the rationale is that eye movements that were useful in the past are likely to be useful in the future if a similar constellation of pieces is present on the board. The model uses time parameters, such as the time to create a new chunk (8 seconds) and the time to encode a chunk into STM (50 milliseconds).

Chunks that recur often evolve into more complex data structures – templates. Templates are schema-like structures that have both a core (with constant values) and slots (with variable values). For example, in chess, the core contains information similar to Chase and Simon's chunks, while the slots encode variable information about pieces, squares and chunks. Based on computer simulations, it takes 250 ms to encode information into slots. This is much faster than the 8 seconds needed to create a chunk (Chase & Simon, 1973). Templates are also related to other information useful in a given situation. In chess, this could be information about possible moves, evaluations, plans, and so on. Finally, templates can be linked to other templates. This makes it possible to carry out search at a higher level of abstraction than is normally possible.

As noted by Richman, Gobet, Staszewski and Simon (1996), template theory explains better than chunking theory why it takes 10,000 hours of practice to reach a high level of expertise. Time is needed to acquire chunks, learn templates, learn possible actions, link chunks or templates to actions and create links between chunks/templates that are similar. In addition, time must be factored in to combat forgetting.

CHREST

Template theory is implemented as a computer program, known as CHREST (Gobet et al., 2001). During the learning phase, the program incrementally acquires chunks and templates by scanning a large database of domain-representative items. This makes it possible to create networks of various sizes and thus simulate various expertise levels. These networks, together with assumptions about time and capacity parameters (De Groot & Gobet, 1996; Gobet & Simon, 2000), enable the model to make unambiguous and quantitative predictions. I briefly review some tasks in which such predictions were made. While the model has been used in a number of domains, such as awele, physics, computer programming, concept formation and language acquisition, I will focus on chess due to space constraints.

Perception: Eye Movements. The key insight of De Groot (1965) was that perception, and not thinking, was at the core of expertise. If this is correct, then eye movements during the first seconds of the presentation of a board should show important differences between masters and amateurs. This is what was found in a recall task with a presentation time of 5 seconds (De Groot & Gobet, 1996): masters had shorter average fixation times (250 ms vs. 300 ms), showed less variance in their fixation times, covered more squares of the board and tended to fixate important squares more often. The results are simulated by CHREST, both for masters and amateurs. Figure 3 shows the data of a master and an

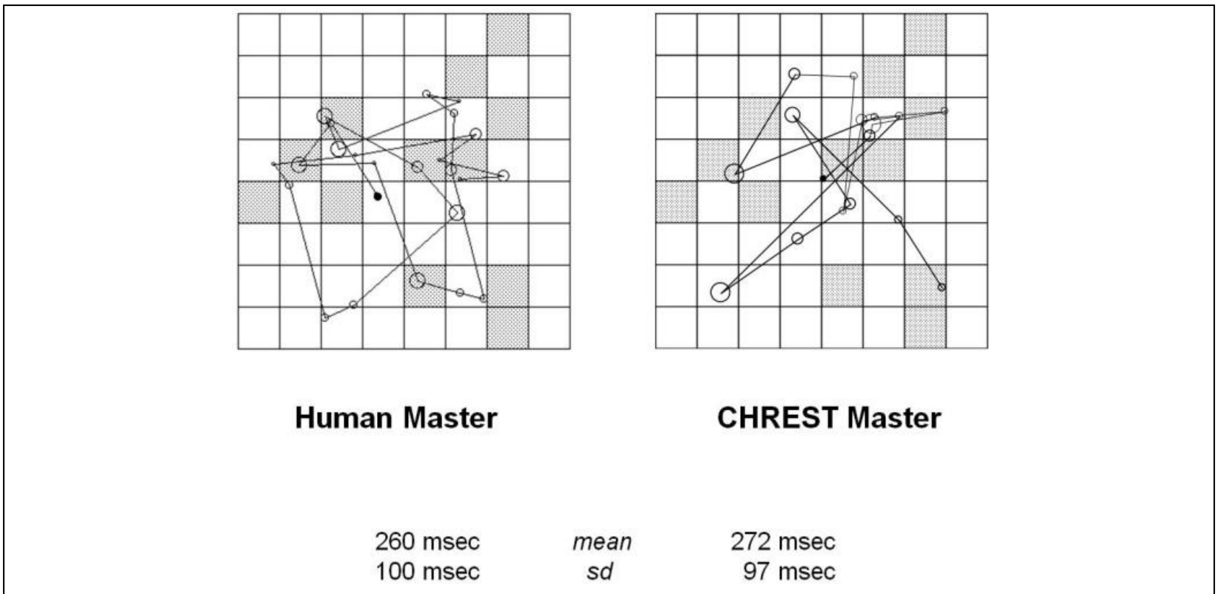

Figure 3. Eye fixations of a master and simulations with CHREST (After De Groot & Gobet, 1996).

amateur for a specific position, as well as the computer simulations. While the eye scans are not identical – there are also considerable individual differences between humans of similar skill level – the simulations capture all the key features just discussed.

Recall of Random Positions. What happens with random material? One of Chase and Simon's (1973) classical results was that masters' superiority with game positions disappears with random positions. When CHREST was developed, simulations led to a non-intuitive prediction: there should be a skill effect with random positions too, for a rather simple reason: given their larger chunk networks, masters can recognise more chunks than amateurs, just by chance. A reanalysis of the literature and the collection of new data confirmed CHREST's predictions (Gobet & Simon, 1996a; see figure 4). This result is important theoretically, for two reasons. First, it is difficult to explain for most theories of expertise (for details, see Gobet, 1998b). Second, it shows that the knowledge acquired during extended practice leads to subtle differences that are implicit and unconscious.

Look-Ahead Search. Supporting the importance of perception, De Groot (1946) did not find clear skill differences in the statistics of the choose-a-move task (e.g. number of moves considered, depth of search or rate of search). In particular, top-level grandmasters did not search more than candidate masters. More recent studies suggest that the state of affairs is more complicated and that better players do search more (Charness, 1981; Gobet, 1998a; Saariluoma, 1992). The skill differences are particularly clear with complex board positions (Campitelli & Gobet, 2004). There are also considerable differences as a function of specialisation (Bilalić, McLeod, & Gobet, 2009), which in chess depends on the kind of opening moves players adopt. Within their area of specialization, players tend to search more in depth and less in breadth. Some of these skill differences are captured by SEARCH, a probabilistic model derived from CHREST (Gobet, 1997).

The skill differences on perception, memory and problem solving that I have briefly illustrated in this section with chess are present in most, if not all domains of expertise (Ericsson, Charness, Feltovich, & Hoffman, 2006; Gobet, 2011). As shown above, they are well explained by template theory, to the point that they can be simulated by computer models. The acquisition of a large number of chunks and templates clearly suggests the importance of practice in becoming a top performer in a given domain of expertise. This is what Chase and Simon (1973) emphasised at the end of their classic article, although they were open to the possibility of talent.

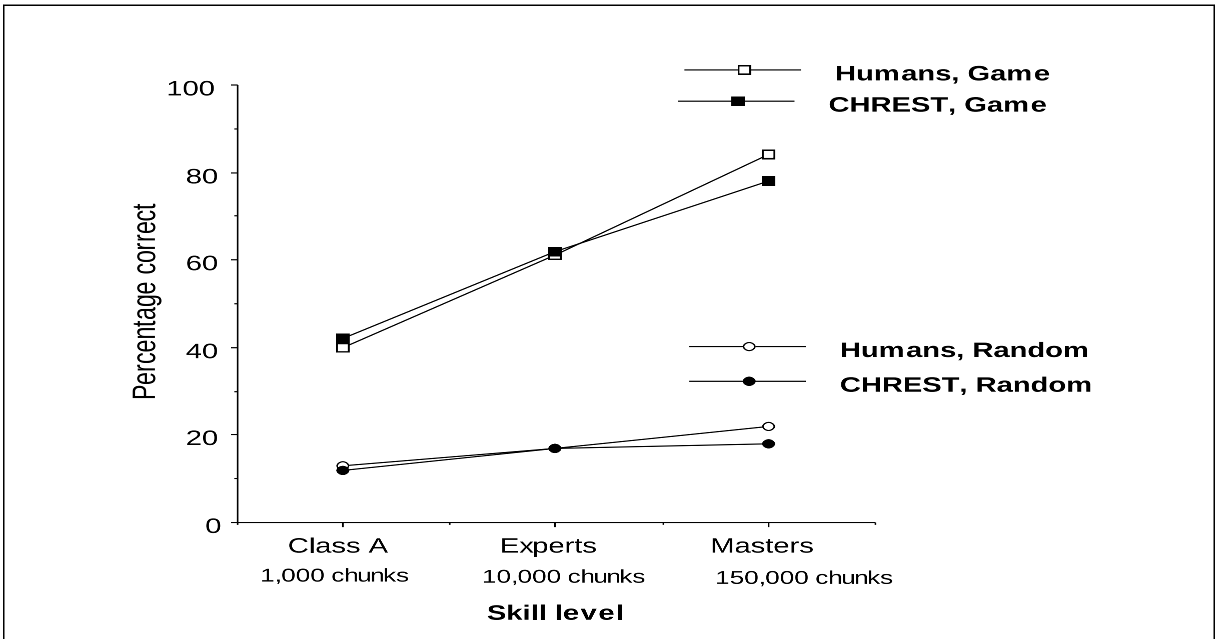

Figure 4. Percentage correct in a recall task as a function of skill level and type of position, for humans and CHREST.

Deliberate Practice

The role of practice has been made more central in the deliberate practice framework (DP; Ericsson, Krampe, & Tesch-Römer, 1993). According to DP, innate individual differences do not impose a limit on performance, except for motivation, general activity levels and height in some sports. Rather, expert performance improves monotonically with the amount of DP. Practice activities aim to improve performance by providing feedback and optimising error correction. These activities are typically effortful and not enjoyable. They can be carried out only for a few hours a day, due to the risk of injuries and burnout. Emphasis is given to individual practice, which increases the efficiency of DP activities, rather than group practice. The framework also stresses the support of the environment and in particular of the family.

Strong support for DP was provided from experiments where college students with average memory spans were trained in the digit-span task (Ericsson, Chase, & Faloon, 1980). After sufficient practice, these students could memorise longer digit sequences than individuals that were thought to enjoy innate talent. The role of DP has received support from many other domains, including chess (de Bruin, Smits, Rikers, & Schmidt, 2008; Gobet & Campitelli, 2007), music (Ericsson et al., 1993; Meinz & Hambrick, 2010) and sports (Ward, Hodges, Starkes, & Williams, 2007). In these studies, participants are typically asked to estimate retrospectively how many hours they had spent in practice activities, and the results are correlated with their skill level. The results show that higher skilled individuals engage more in DP. Chess is one of the few domains enabling quantification of expertise and thus making it possible to compute the amount of variance explained by DP. In three adult samples, the correlations between DP and skill were .42, .48 and .54 (Charness, Tuffiash, Krampe, Reingold, & Vasyukova, 2005; Gobet & Campitelli, 2007). Thus, the amount of DP explains between 17.6% and 29.2% of the variance in skill.

While the data supporting the role of DP as a necessary condition for attaining the highest levels of skill are substantial, discordant results are present as well. Contrary to DP's predictions, group practice (including competition) has been shown to be at least as efficient as individual practice, for example in chess and soccer (Campitelli & Gobet, 2008; Gobet & Campitelli, 2007; Ward et al., 2007). In addition, individual differences are considerable, as reflected in the high variability in the time needed to reach mastership in chess: while players on average took 11,000 hours of DP to become masters, some players needed as few as 3,000 hours, while others needed up to 24,000 hours (Gobet & Campitelli, 2007). This 1:8 ratio is simply inconsistent with DP. Campitelli and Gobet (2008) also present results at variance with the assumption that expert performance is a monotonic function of practice. For example, although masters had accumulated the same amount of DP as candidate masters after three years of playing chess seriously, their rating was higher (see figure 5). Figure 5 also shows that, although candidate masters had devoted much time to DP, they improved little after three years.

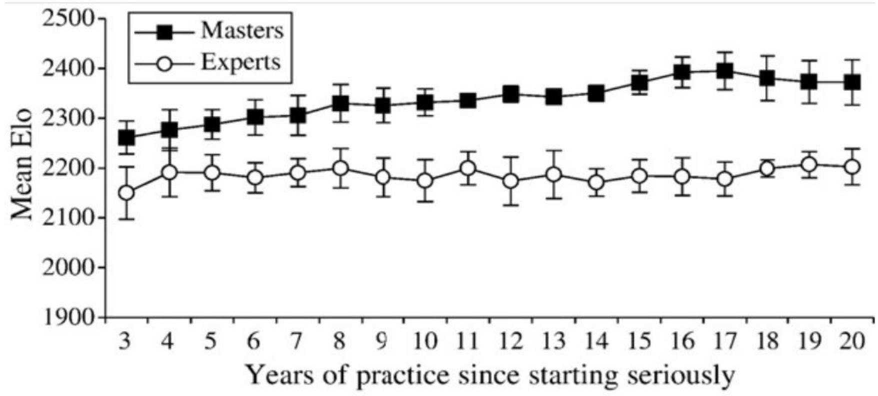

Figure 5. International rating in masters and candidate masters as a function of years of practice since starting playing seriously. Error bars indicate standard deviations. (After Campitelli & Gobet, 2008.)

Another discrepancy between theory and data consists in the training methods used. Ericsson et al. (1993) propose that, with chess players, DP consists in trying to predict the best move in published chess games and then receiving feedback. However, chess players' practice is more varied and complex, being in part supported by new computer technology (Gobet et al., 2002). Players play training games against other players (either directly or on the internet) or against computer programs. They also spend substantial time (up to 50% according to some estimates; Chassy & Gobet, 2011) studying opening theory. This consists in a number of activities, typically carried out using books and electronic databases: memorising opening variations, studying typical tactical and strategic manoeuvres, and finding new moves or ideas to surprise their future opponents (Campitelli & Gobet, 2008; Chassy & Gobet, 2011). Together, these results indicate that chess players' training includes more tasks than the type of repetitive activities emphasised by DP.

DP has also been criticised on methodological grounds (Davids, 2000; Gobet, 2011; Sternberg, 1996). The research on DP is mostly correlational and rarely uses control groups (i.e., individuals that tried but failed to become experts), and it is thus difficult to draw conclusions about the causal role of talent and (deliberate) practice. For example, it could be the case that, following self-selection, more gifted individuals remain in the domain and thus log in more DP.

Research on Talent

Intelligence

As noted above, the proponents of talent argue that practice is not sufficient for reaching the highest levels of expertise, and that other factors are in play. These can be either genetic, innate but not genetic, or occurring after birth. There is considerable evidence from the fields of personality and intelligence that there exist large individual differences, in part inherited, and it is plausible that at least some of these differences affect the acquisition of high levels of expertise (Eysenck, 1995; Mackintosh, 1998). Similarly, individual differences exist with respect to learning, attention and working memory. For example, a study on piano expertise (Meinz & Hambrick, 2010) has shown that working memory capacity accounted for expertise level beyond DP. Another example comes from research on job performance. Meta-analyses have established that *g* is the best predictor of job performance, with an average correlation of .53; this correlation is higher than correlations between job performance and education level, job experience, interviews and letters of reference (Schmidt & Hunter, 1998). With respect to expertise, it is important to note that this correlation is higher with complex occupations than with simple ones, and remains when one limits the analysis to high levels of experience (Schmidt et al., 1988).

A fair amount of research has been carried out on the relationship between chess skill and cognitive abilities, including intelligence. Three studies have shown that chess playing children have higher intelligence than children that do not play chess, and that chess skill positively correlates with IQ (Bilalić, McLeod, & Gobet 2007; Frydman & Lynn, 1992; Horgan & Morgan, 1990). The picture is more complex with adults. Some studies found no differences with respect to general intelligence and visuo-spatial memory between a chess group and a control group (Djakow, Petrowski, & Rudik, 1927; Waters, Gobet, & Leyden, 2002). Other studies (Doll & Mayr, 1987; Grabner, Stern, & Neubauer, 2007) found significant differences between chess players and control samples in intelligence measures. Grabner et al. also found a significant correlation between chess skill and intelligence, even when the amount of DP is controlled for statistically. As all masters had verbal IQ above 110 and numerical IQ above 115, their data also suggest that a certain level of intelligence is necessary to reach a high level of chess expertise.

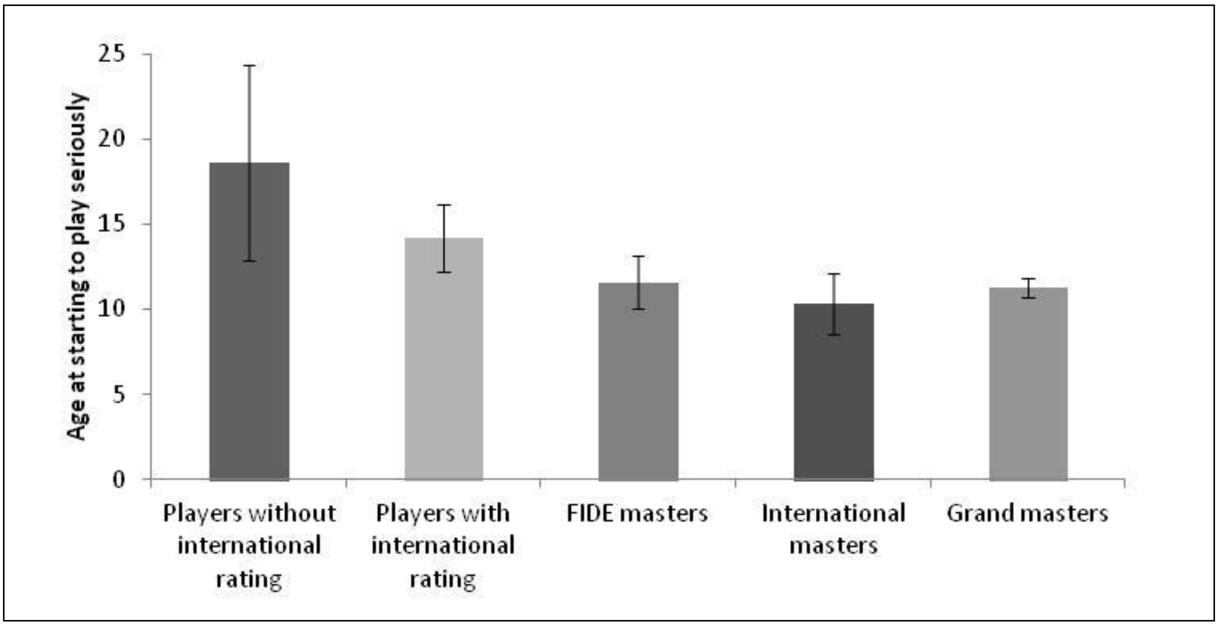

Figure 6. Average age at starting to play seriously as a function of chess skill (after Gobet & Campitelli, 2007). The error bars indicate standard deviations.

Sensitive Period

Beyond practice and innate differences, other factors are important to account for high levels of performance. In line with research on language acquisition and the development of the visual system, it seems plausible that there exists a sensitive period for starting practicing, perhaps due the fact that the human brain is more plastic at younger ages (Elo, 1978). This possibility gained support with Gobet and Campitelli's (2007) study, where the correlation between starting age and chess skill was -.37 (similar correlations were found in Charness et al., 2005, and Grabner et al., 2007). Nearly all players with an international title had started practicing chess seriously at 12 years old or earlier (see figure 6). More specifically, the probability of becoming an international-level player was .24 for players who started to play seriously at 12 or before, but only .02 for players who started after 12. This result cannot be explained by assuming that children starting earlier accumulate more DP (Ericsson et al., 1993): after controlling for DP, the partial correlation between skill and starting age was still significant (r = -.40).

Handedness

In their theory of talent, Geschwind and Galaburda (1985) proposed that, following high exposure to testosterone in the uterus, the right hemisphere of the brain develops more than normally, with a concomitant increase of the probability of being talented in visuo-spatial domains and being non-right-hander (i.e., left-handed or ambidextrous). Cranberg and Albert (1988) and Gobet and Campitelli (2007) addressed this question with chess skill using a questionnaire about hand preference and found that the proportion of non-right-handers is higher in the chess population (18%) than in the general population (around 12%). However, in both cases, handedness did not discriminate chess players of different skill levels.

Season of Birth

The season of birth offers a possible biological marker for superior performance, for example due to the effect of viruses on brain development during pregnancy. Gobet and Chassy (2008) found that expert chess players in the Northern hemisphere (N = 41,771) tended to be born more often in the first half of the year (52.3% births). This difference is statistically significant when tested against the null hypothesis that the number of births in each month is proportional to the number of days. The pattern of results also differed from the distribution of births in the overall population of European Union countries from 1973 to 2001 (N = 104,834,388; see figure 7). The effect was even stronger with grandmasters (56.9% births in the first half of the year). The standard explanation for seasonality effects in sports and school education is that children born earlier compete with younger children of the same year cohort, which gives them a considerable advantage (more physical strength and better coordination) and leads to younger children dropping out. However, this explanation does not apply to Gobet and Chassy's data: typically, there is no age selection in chess and children compete with both younger and older children and with adults. In addition, these data are international and include all sorts of cut-off dates for school entry.

Discussion

This paper has offered glimpses into the rich data that have been collected in the study of outstanding performance. While the focus has been on chess, a domain that has unique qualities for this kind of study, its conclusions generalise to most fields where some individuals vastly outperform the majority. In chess as in other domains, research has been polarised, with the tradition on talent emphasising the role of innate abilities and other factors occurring early in life, and the tradition on expertise emphasising the role of practice. From the expertise tradition, we have learnt that experts acquire a substantial amount of knowledge stored as chunks and templates. We also know that DP plays an important role in the acquisition of skill. However, individual variability in reaching the top is substantial, which counts against the monotonicity assumption, and practice encompasses more varied training activities than argued by Ericsson et al. (1993). From the talent tradition, we know that (deliberate) practice is only part of the story, and that other factors play a role in the acquisition of skill. These include starting age, seasonality of birth, handedness and individual differences in intelligence and working memory, which are in part inherited. Together, these results suggest that practice is a *necessary*, but

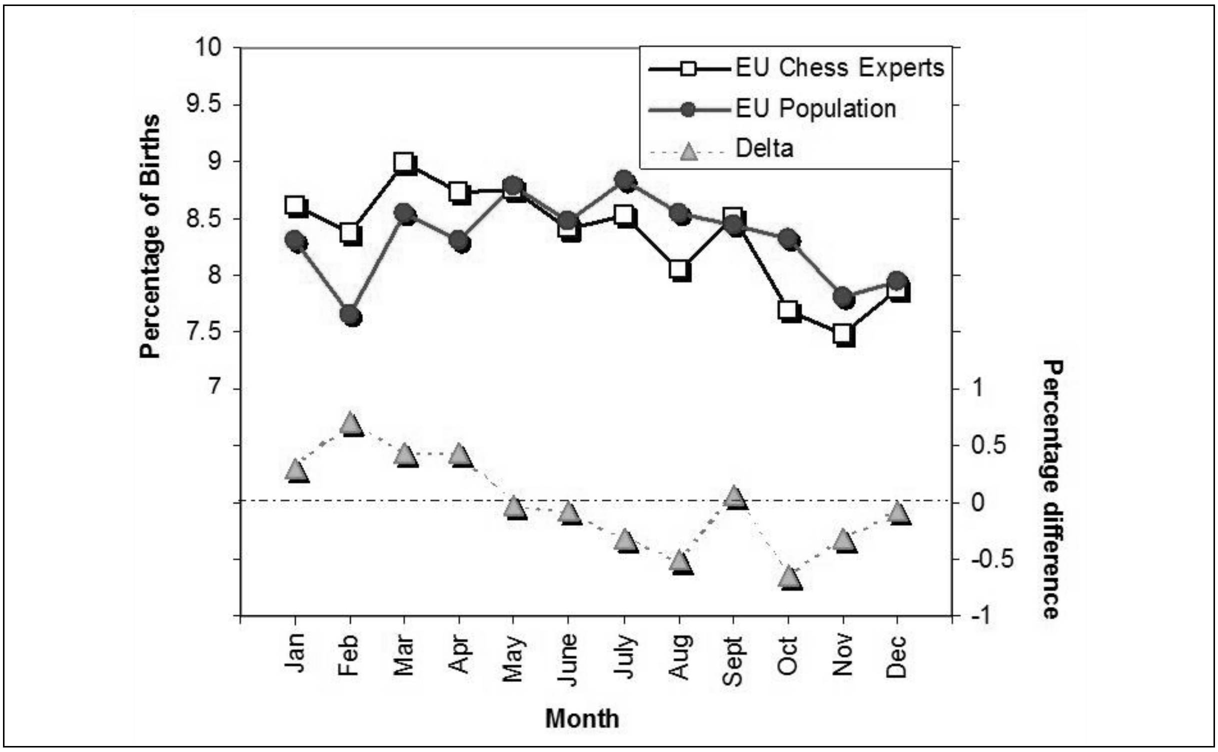

Figure 7. Percentage of monthly births for the EU population and EU chess players rated higher than 2000 points (i.e., experts). The y axis on the right shows the difference chess players percentage minus population percentage. (After Gobet & Chassy, 2008).

not sufficient condition for reaching high levels of expertise (Campitelli & Gobet, 2011; Hambrick & Meinz, 2011).

As noted by Ericsson et al. (1993), it has been extremely difficult to identify genes related to specific aspects of talent. There are at least two reasons for this. First, it is not possible to use standard behavioural-genetic methods, most importantly twin studies, because top-level performers are rare by definition. Second, it is very unlikely that the complex behaviour characterising skilled performance depends on a single gene. On the contrary, as noted by Chassy and Gobet (2010), recent research in genetics shows that cognitive processes are underpinned by the regulation of the expression of numerous genes. It is also likely that different patterns of alleles are possible for excelling in a given domain. This makes it much harder to identify the relevant genes than with traits that are coded by a single gene.

That multifarious factors are involved in the acquisition of skill has of course been noted by previous authors (Ericsson et al., 2006; Gagné, 2004; Simonton, 1999), although they have tended to favour one of the two traditions. In addition to the factors mentioned above, one can also point to the environment (family and beyond), the cultural and historical context and of course luck. One needs also be aware that seemingly small factors can have colossal future consequences (e.g., the Matthew effect in science; Merton, 1968), which suggests that the acquisition of skill might be chaotic in nature.

The complexity of the development of expertise might be illustrated by the question of how innate differences interact with practice and other factors. Let us start with the simple causal model depicted in the left handside of figure 8. The fact that performance is assumed to impact on practice by a feedback loop already makes this model non-linear. Adding one box for the environment adds considerable complexity (figure 8, right handside).

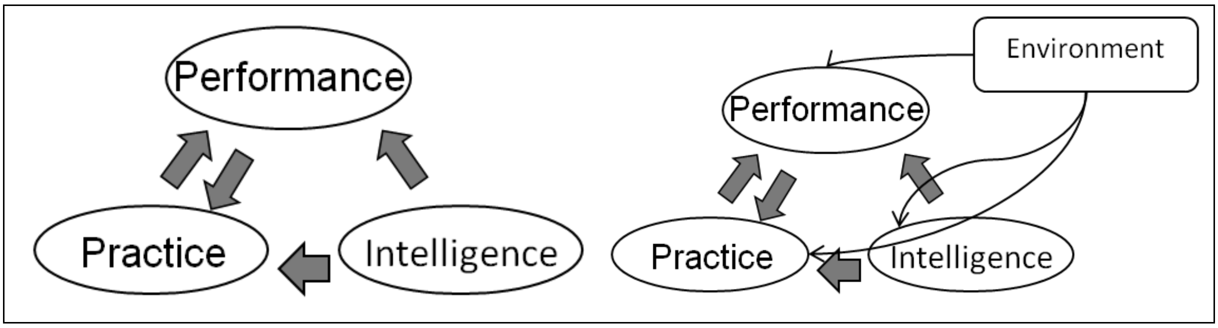

Figure 8. Two models of the link between performance, practice and intelligence.

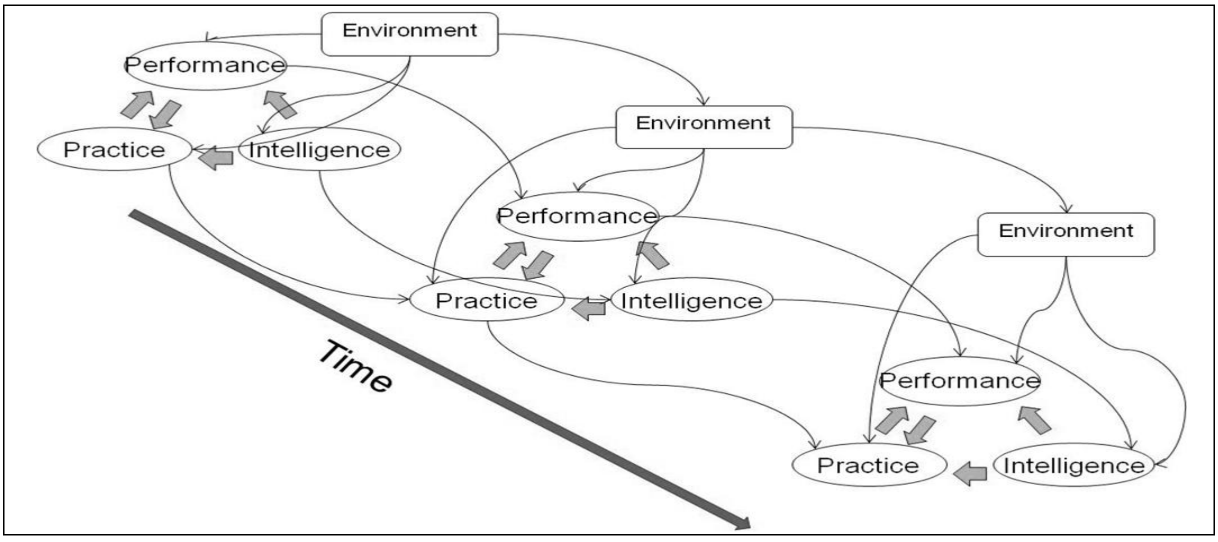

Figure 9. A more complex version of the models of figure 8, with the time dimension added.

The acquisition of skill occurs as a function of time, which means that we deal with what mathematicians and physicists call a dynamical system. As shown by figure 9, this rends the model much more complex, not only because the time dimension is added, but also because the number of causal links and possible interactions vastly increases. When we remember that the relations between variables are not necessarily linear, we realise that making predictions from such as system is prohibitively difficult.

Given the complexity and number of variables involved, their dynamic and chaotic nature, and the number of potential interactions, it is simply impossible to address the question of the acquisition of skill with verbal theories alone. Furthermore, mathematical models are likely to become rapidly intractable. This leaves us with the conclusion that the use of computational models is necessary to address such a complex question without vastly simplifying it. Progress has been made in this respect with the CHREST cognitive architecture, which captures important dynamic aspects of the acquisition of expertise, although work has admittedly focused on phenomena favoured by the practice tradition. An interesting avenue is to systematically vary CHREST parameters as proxies for individual differences. Future research should explore how CHREST and other computational models can also account for data gathered in the talent tradition.

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The Author

After having held research and teaching positions at Carnegie Mellon University, the University of Nottingham and Brunel University London, Fernand Gobet is currently Professor of Cognitive Psychology at the University of Liverpool. His main research interest is the psychology of expertise and talent, which he has studied in numerous domains including board games, physics, computer programming, music, sport, business, language acquisition, nursing and physiotherapy. His research combines experimental methods with computational modelling. He has authored six books, including four on the psychology of expertise and talent.