Cognitive Processes and Development of Chess Genius: An Integrative Approach

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Abstract

The 21st century has witnessed the emergence of several chess prodigies. This poses a challenge to the main attempt to account for individual differences in high-level performance: the deliberate practice framework. The main alternative to this approach is the view that intelligence plays an important role in chess expertise. However, studies have shown that intelligence may be important only in the first stages of the chess players' careers. In this chapter we present the practice-plasticity-processes model, which incorporates neural plasticity and cognitive processes (domain-specific pattern recognition and heuristics) as explanatory variables. A mathematical simulation shows that the model was able to capture the existence of prodigies and three out of four other effects encountered in the chess expertise literature. Further research should improve the model to account for all the effects. If this model receives empirical support in further research, it would provide a very parsimonious account of chess genius.

Keywords: genius, expertise, chess prodigies, deliberate practice, intelligence, neural plasticity, cognitive processes, development, critical period, mathematical model

Introduction

There has not been a better time to write about chess genius. In January 1st 2013, the 22-year old Norwegian player, Magnus Carlsen, reached the highest international rating – 2861 Elo points– in the history of chess, above the likes of Garry Kasparov, Anatoly Karpov and the late Bobby Fischer. This is one out of many achievements by Carlsen. In 2004 Magnus became a grandmaster at the age of 13 years and 148 days; he became the youngest player in history to break the 2600 Elo points barrier at the age of 15 years and 32 days, the 2700 Elo points barrier at the age of 16 years and 213 days, and the 2800 Elo points barrier at 18 years and 336 days. On January 1st 2010, at the age of 19 years and 32 days, he became the youngest chess player in history to achieve the Number 1 in the world ranking.

Carlsen is not the sole example of impressive achievements at very young ages. The 21st century has witnessed extraordinary chess performances by teenagers. Sergey Karjakin, Ukraine-born Russian holds the record for being the youngest player in obtaining both the international master title at the age of 11 years and 11 months (in 2001) and the grandmaster title (12 years and 7 months, 2002). Just after turning 12 he was hired by Ukrainian Ruslan Ponomariov – another player with remarkable achievements at young ages – as a second for his World Championship match. Teimour Radjabov, born in Azerbaijan in 1987, was the youngest player ever to get into the top 100 international rating list at the age of 14, in 2002. Hou Yifan, from China, obtained the women grandmaster title at the age of 13 in 2007, and she became the youngest female achieving the overall grandmaster title at the age of 14 years, 6 months and 2 days. This remarkable achievement improves on Judith Polgar's, the strongest female chess player in the history of chess, who obtained the overall grandmaster title at the age of 15 years and 4 months.

This is only a summary of an increasing number of recent remarkable achievements by young chess players, some of them well documented by Howard (1999). How can this phenomenon be explained? The purpose of this chapter is to present a model – the practice-plasticity-processes (PPP) model – that aims at solving problems of previous attempts to account for this phenomenon. This model integrates insights from the approach investigating the development of expertise and the approach interested in cognitive processes underlying expert performance. We also examine the feasibility of the model with a mathematical simulation. This analysis entails not only to what extent the model explains the phenomenon of chess prodigies, but also four other effects documented in the literature of chess expertise: the strong correlation between accumulated number of hours of practice and current chess skill; the existence of a critical period in chess; relationship between intelligence and chess skill in children much stronger than that in adults; and decline in chess skill in older adults.

The chapter continues as follows. We first briefly present the major attempt to explain high-level expert performance – the deliberate practice framework (Ericsson, Krampe, & Tesch-Römer, 1993; Ericsson, 2007). Notice that this framework is presented in much greater detail in another chapter of this book (Ericsson, 2013). We then expose criticisms to this framework and describe alternative proposals. After discussing the problems of those previous attempts, we depict the characteristics that a new model should have. One of these characteristics is the incorporation of accounts of the cognitive processes underlying expert performance. Thus, we present two such accounts: the template theory (Gobet & Simon, 1996) and the SEARCH model (Gobet, 1997). Afterwards we introduce the practice-plasticity-processes model, and, with the purpose of exploring its feasibility, we introduce two simpler models. We then conduct a mathematical simulation and evaluate to what extent the three models qualitatively capture five phenomena encountered in the literature of chess expertise. We conclude with a discussion of the implications of the model and future work.

Previous attempts to explain the existence of remarkable achievements in young chess players

The most influential attempt to explain high level expert performance is the deliberate practice framework (Ericsson et al., 1993). After briefly describing this framework, we discuss criticisms against it and present alternative proposals.

Deliberate practice

The central tenet of the deliberate practice framework is the monotonic benefit assumption: "…the amount of time an individual is engaged in deliberate practice activities is monotonically related to that individual's acquired performance." (Ericsson et al., 1993, p. 368) Note that this assumption does not establish a causal relationship between deliberate practice and acquired performance. However, later in the article Ericsson et al. make clear that the assumption implies causality: "…individual differences in ultimate performance can largely be accounted for by differential amounts of past and current levels of practice." (Ericsson et al., p. 392). They then seem to reject the possibility of individual differences in innate ability:

"Our theoretical framework can also provide a sufficient account of the major facts about the nature and scarcity of exceptional performance. Our account does not depend on scarcity of innate ability (talent)…" (Ericsson et al., p. 392)

Deliberate practice comprises activities deliberately developed to correct mistakes. For example, trying to anticipate which the best move in chess positions of grandmasters' games is, and receiving feedback by comparing one's choice with the optimal move. Deliberate practice requires ample attention, it is not typically enjoyable, and it consumes a lot of energy. These activities should be carried out for just a few hours a day because excessive practice increases the risk of injuries and burnout (especially in sports). The proponents of the deliberate practice framework acknowledge the involvement of inherited factors, but these are limited to motivation, general activity levels (which may influence the amount of deliberate practice), and (in some sports) height. Moreover, Ericsson et al. (2012) stated that the number of hours of playing (in competition) does not influence chess performance.

Several studies found significant correlations between measures of deliberate practice and chess skill (Bilalić, McLeod, & Gobet, 2007; Charness, Tuffiash, Krampe, Reingold, & Vasyukova, 2005; deBruin, Smits, Rikers, & Schmidt, 2008; Gobet & Campitelli, 2007), lending support to the deliberate practice framework. However, as shown by Hambrick, Oswald, Altmann, Meinz, Gobet, and Campitelli (in press), deliberate practice, on average, accounts only for 34% of the variance in chess rating, even when measurement error of practice and chess rating is taken into account. In the next section we briefly review the criticisms to the deliberate practice framework.

Criticisms to the deliberate practice framework

Campitelli and Gobet (2011) claimed that deliberate practice is a necessary condition to achieve high levels of chess skill. Based on Gobet and Campitelli's (2007) and Campitelli and Gobet's (2008) studies, they showed that the player with fewer hours of practice to achieve the master level still dedicated more than 3,000 hours of practice. However, they stated that deliberate practice is not a sufficient condition to achieve high levels of chess skill. There are players that dedicated more than 20,000 hours to chess who did not achieve the master level. Hambrick et al. (in press) showed that, although the mean number of hours of individual practice of a group of masters and a group of experts differ, there is a substantial overlap in their distributions.

Probably the most important challenge for the deliberate practice framework is the existence of child prodigies. Ericsson et al. (1993) discussed this issue taking as example Bobby Fischer and Judit Polgar, who both attained the grandmaster title at the age of 15. They indicated that their remarkable achievements could be accounted for by amount of deliberate practice. Both Fischer and Polgar started formal chess training very early on, and they spent about 10 years of intense dedication to chess before becoming grandmaster. Thus, they had accumulated a sufficient number of hours of deliberate practice.

This explanation has the problem of not explaining why players with the same dedication to chess do not achieve the same levels of skill. Howard (2011) scrutinized the case of the Polgar sisters. This is an interesting case because Laszlo Polgar trained his daughters (Susan, Sofia and Judit, in order of age) from the age of 4 or 5, and all three attained high levels of skill. Thus, this case is typically used as evidence that, with sufficient practice, anyone can become a top expert. However, Howard showed that, although the sisters received a similar number of hours of training, they differed substantially in their achievements: Judit's peak world ranking was 8th, Susan's was 106th, and Sofia's was 346th. This suggests that differences other than the number of hours of deliberate practice influenced their skill level. Moreover, Howard presented the ranking progression of Magnus Carlsen, who allegedly achieved the 1st spot in the world ranking with much less dedication to chess than that of the Polgar sisters.

It is possible that, despite engaging in deliberate practice in the same environment, its quality may have been different (e.g., Judit may have benefited from the improvement in training techniques) or in their interest in chess, or that Howard's assumption that they approximately had the same number of hours of deliberate practice is not correct. Moreover, it is also possible that Carlsen's self-report of training discipline is not accurate. Because there is no objective way of elucidating these issues, the mathematical simulation presented in this chapter is important. For example, it will give us information on how well the deliberate practice framework can capture the existence of child prodigies.

In other studies, Howard (2012a, 2012b) found that the number of games played was a stronger predictor of chess rating than the number of hours of studying chess. Thus, he suggested that playing games is a type of practice. This is counter to the deliberate practice framework, which explicitly excludes competition from deliberate practice, and it is in line with Gobet and Campitelli's (2007) finding that group practice (which includes playing games and tournaments) correlated with chess rating slightly higher than individual practice.

Alternatives to deliberate practice

Given that deliberate practice seems to be a necessary but not sufficient condition to achieve high performance, researchers investigated the role of some non-practice variables. Gobet and Campitelli (2007) investigated the role of handedness and critical period in chess rating. They found a higher percentage of non-right handers in the chess sample than in the general population. However, no differences were found within the chess sample. This study showed a significant correlation between the age at which players started playing seriously and their current chess rating (even after controlling for the number of hours of practice), and that almost all the players who obtained a chess title started playing chess seriously at the age of 12 or earlier. Gobet and Chassy (2008) found that grandmasters (and to a lesser extent all expert chess players) in the Northern hemisphere are more likely to be borne in the first half of the year, and that this distribution differs from the distribution of the general population.

Those three effects are linked to characteristics of the brain. Handedness and season of birth are thought to be related to the existence of viruses during pregnancy, which would have an effect in brain development within the uterus, and the critical period is linked to the existence of higher neural plasticity at young ages. Although these studies showed that factors not related to practice are linked to chess expertise, they did not incorporate these findings into a comprehensive framework.

Given that chess is seen as an intellectual activity (Howard, 1999, 2005; Newell, Shaw, & Simon, 1958), the quest for the intelligence and cognitive factors that enable chess skill is understandable. However, it turned out remarkably difficult to find any association between chess skill on the one side, and intelligence, on the other, at least among established adult chess players. A number of studies failed to demonstrate that chess players are more intelligent than non-chess players (Djakow, Petrowski, & Rudik, 1927, Nejati & Nejati, 2012; Unterrainer, Kaller, Halsband, & Rahm, 2006) while other studies failed to find a link between chess skill and intelligence within chess players (Doll & Mayr, 1987; Grabner, Neubauer, & Stern, 2006; Lane (unpublished in Cranberg & Albert, 1988, p. 161); Waters, Gobet, & Leyden, 2002). The only study that found a statistically significant link between intelligence and chess skill was Grabner, Stern and Neubauer (2007).

In contrast, the few studies on children consistently found a link between chess skill and intelligence. Frydman and Lynn (1992) found that an elite sample of children chess players had a higher IQ score than their average peers. The difference was particularly pronounced in the "performance IQ" subscales, as opposed to the "verbal IQ" subscales. The performance IQ also distinguished stronger from weaker children chess players. Horgan and Morgan (1990) found that intelligence (as measured by Raven matrices) of an elite children sample was higher than their average peers and that intelligence also partly explains their chess improvement over the next year. Finally, Bilalić et al. (2007) found that intelligence was highly correlated with chess skill in a sample of chess playing children.

There is a recurring pattern in the studies of intelligence and chess skill. It is difficult to establish the link between the two in adult samples, whereas the link is regularly found among children. One line of explanation of this curious pattern is that children, even when they are among the best of their age, are at the very beginning of their chess activities. Differences in amount of practice are possible, but they ought to be rather small given the limited time that could be spent on chess. Consequently, the differences in chess skill are more likely to reflect other factors, such as intelligence. Bilalić et al.'s (2007) study confirmed this assumption. There was a clear positive correlation between intelligence and chess skill in the whole sample, but the elite subsample, composed of children who played chess more intensively and slightly longer, showed the opposite pattern. More intelligent children played chess worse in the elite subsample. This negative link between chess skill and intelligence is explained by differing amounts of practice. More intelligent children also happened to practice less in the elite subsample.

Using another approach, Howard (1999, 2005) showed that there was a decline in the median age of the top 10, top 50, and top 100 players from 36 to 38 years of age in 1970 to 30 years of age in 2004. Moreover, he found a decrease in the age at which players who eventually got into the top 100 and top 500 ranking entered the international rating list, from 22 to 24 years in 1971 to less than 15 years in 2001. Howard hypothesizes that these effects are due to an increase in intelligence in the population. Given that young children are more intelligent now than in 1970, they fare better when they play against adults; therefore, the age of top players is decreasing. Gobet, Campitelli, and Waters (2002) provided an alternative explanation: professionalization of chess, the emergence of computers as a study tool, and the reduction of time control may have benefited the young children. Another plausible explanation is mathematical. If the rate of participation of children in chess has increased, then it is mathematically more likely that some of those children will obtain more extreme values in a distribution of chess rating (see Bilalić & McLeod, 2006; Bilalić, Smallbone, McLeod, & Gobet, 2009; Charness & Gerchack, 1996; Chabris & Glickman, 2006, for participation rates explanations of gender differences and dominance of the ex-Soviet Union in chess).

As suggested by this brief review, deliberate practice is a necessary, but not a sufficient, condition to achieve high levels of expert performance in chess. However, previous studies have not incorporated non-practice factors in a comprehensive account of the development of chess skill. In the next section, we discuss the characteristics that a model aiming at explaining the development of chess skill should have.

In search for a new model of the development of chess expertise

A comprehensive model of the development of chess expertise should account for the existence of young chess players with remarkable achievements, as described in the introduction, and other effects encountered in the literature of chess expertise. Another requirement is that it integrates research into the development of chess expertise with research into the cognitive processes underlying chess expert performance. Finally, the model should be as simple as possible; thus, one has to show that adding complexity (i.e., more explanatory variables) provides a better account of the effects than simpler models.

In this section, we present the five effects that we will use to evaluate the feasibility of our model, and in the following section we will depict theories and models of cognitive processes underlying expert performance in chess. Table 1 shows the five criteria and here we describe them in more detail.

Existence of young players who attained high levels of chess skill

As explained in the introduction, the 21st century has witnessed the emergence of a number of very young players achieving remarkably high levels of chess skill. A model of development of chess skill should be able to capture this phenomenon.

Relationship between practice and chess skill

As explained earlier, several studies have found significant correlations between practice and chess skill (Bilalić et al. 2007; Charness et al., 2005; deBruin et al., 2008; Gobet & Campitelli, 2007). Moreover, Howard (2012a, 2012b) and Gobet and Campitelli (2007) showed a significant correlation between chess rating and chess playing. A model that explains expert performance should be able to capture these effects.

Critical period for the acquisition of chess skill

Ericsson et al. (1993) analyzed Krogius' (1976) data and found a correlation between the age at starting to play chess and the age of first achieving international performance. Gobet and Campitelli (2007) also found a significant correlation between starting to play chess seriously and current chess rating, even after controlling for number of hours of practice. A model of development of expert performance should be able to capture this correlation.

Differential relationship between intelligence and chess skill in children and adults

As shown above, several studies found a relationship between intelligence and chess skill in children (Bilalić et al., 2007; Frydman & Lynn, 1992; Horgan & Morgan, 1990). On the other hand, this link has been elusive in adults, with only one study finding a link (Grabner et al., 2007). Therefore, the proposed model should show a higher correlation between chess skill and intelligence in children than in adults.

Decline in chess skill in older adults

Using both cross-sectional and longitudinal data, Charness, Krampe and Mayr (1996) showed that, on average, chess players reach their peak performance at 35 years of age, and after that there is a slow decline, with the chess skill at 65 years of age being similar to that at 20 years of age. This is a very important criterion for the evaluation of the model. The same model that explains remarkable achievements at young ages should be able to account for poor performance in older adults. This poses the challenge of identifying mechanisms for rapid increase in performance, as well as mechanisms for performance decrease. As we will show later, simple models have difficulties in capturing this effect.

Cognitive processes underlying chess expertise

The purpose of the practice-plasticity-processes model (PPP) is not only to provide an explanation of the effects described on the previous section, but also to integrate theories of chess experts' cognitive processes with approaches investigating the development of chess expertise. In this section we briefly describe one theory (the template theory, Gobet & Simon, 1996) and a model (the SEARCH model, Gobet, 1997).

Template Theory

Template theory (Gobet & Simon, 1996, 2000) is a modification and extension of chunking theory (Simon & Chase, 1973). It assumes that expertise is underpinned by the acquisition of a large number of chunks, which are perceptual units giving access to semantic and procedural knowledge. Chunks consist of group of primitives (e.g., in chess, a group of pieces located in specific squares), and they are stored in long-term memory (LTM).

When some patterns recur often in a player's environment, the chunks elicited by these patterns evolve into more complex data structures, known as templates. Templates are schemas and as such consist both of a core, which holds constant values, and slots, which hold variable values. For instance, the core of a chess template stores information similar to the chunks proposed by Simon and Chase (1973), and the variable information in the slots could consist of the location of a piece, the type of a piece, and of other chunks. Both chunks and templates provide access to semantic and procedural knowledge – for example, the key features of the situation and strengths and weaknesses, possible moves and plans. Another important aspect of templates is that they can be connected to other templates. Thus, it is possible to carry out search using templates as problem states; as the detail of the moves can be abstracted from, this kind of search is more abstract than the search carried out at the move level.

In addition to long-term memory, template theory postulates the presence of a visual short-term memory (STM), the capacity of which is limited to 4 chunks. STM is highly dynamic, both because chunks stored in it constantly change and because the information in templates is continuously updated by new information coming from the environment. Template theory is implemented in the CHREST (Chunk hierarchy and REtrieval STructures) computer program (Gobet, Lane, Croker, Cheng, Jones, Oliver, et al., 2001; Gobet & Simon, 2000). The model has a number of time parameters (e.g., 8 seconds to create a new chunk) and capacity parameters (e.g., 4 items in visual short-term memory) (De Groot & Gobet, 1996; Gobet & Simon, 2000). The program learns by receiving a large database of domain-representative items (in chess, positions from master games), simulating eye movements, and incrementally acquiring chunks and templates. Various skill levels can be simulated by creating networks of various sizes, which, together with the presence of time and capacity parameters, makes it possible to make clear-cut and quantitative predictions.

In chess, the model has simulated a number of phenomena such as the pattern of eye movements during the 5-second presentation of a chess position and performance, number of chunks recalled and the type of errors made when recalling different types of positions. Beyond chess, CHREST has been used in several domains including awele, Go, physics, computer programming, concept formation, and language acquisition (see Gobet & Lane, 2010, for an overview.)

SEARCH

With respect to problem solving, the key assumption of template theory is that recognized chunks or templates give access to possible actions, and that this information facilitates search by making it more selective. This idea is implemented in the SEARCH computer model (Gobet, 1997), that computes behavioral variables (e.g., depth of search or number of moves generated per minute) as a function of the number of domain-specific chunks, templates, and heuristics stored in LTM. Heuristics include simple search techniques (e.g., “take a piece back” or “check the King”) as well as more abstract rules (e.g., “occupy the center”). Their main characteristic, in comparison with chunks and templates, is that they are general and require some conscious computation in order to produce a move.

SEARCH assumes that information present in the mind’s eye is subject to rapid decay, and therefore that it is lost unless it is updated by information from the external world or from memory structures. Search is assumed to be carried out in a forward fashion, by recursively trying to find patterns (chunks or templates) in the mind’s eye. Templates facilitate search in three ways: they allow rapid encoding of information in LTM, they allow search to be carried out in the template space, and they counteract the loss of information occurring in the mind’s eye because of interference and decay. Computer simulations show that SEARCH accounts for empirical phenomena such as the small skill difference in average depth of search that has been documented in the literature.

The practice-plasticity-processes (PPP) model and two simpler models

The practice-plasticity-processes model (PPP) is depicted in Figure 3. It contains twelve variables distributed into six levels of explanation, with age (not shown in the figure) being a factor acting at different levels. As mentioned earlier, one of the criteria to assess the feasibility of the proposed model is to show that its complexity is required to account for more effects encountered in the literature. Thus, before describing PPP, we present two simpler models that aim to implement previous proposals mathematically. The simplest model is practice-motivation (PM), which is our implementation of the deliberate practice framework. The second model is practice-intelligence (PI), which is our implementation of the proposals that intelligence plays a role on the development of chess expertise.

In the simplicity-complexity continuum, the PPP model is located at the complexity extreme. However, in the practice-innate talent continuum the PPP model occupies the center, and complexity is the price we need to pay to position our model in this place. Before explaining why PPP is located between PM and PI in the practice-talent debate, we present PM and PI. The presentation of the models in this section is descriptive. Some aspects of the mathematical formalization of the models are presented in the following section (for a full mathematical formalization of the models and coding in R, contact the first author).

Practice-motivation (PM) model

The simplest model to account for individual differences in chess performance is PM (see Figure 1). This model comprises one general inherited trait – motivation[1] –, two domain-specific processes (i.e., chunk and template based pattern recognition and heuristics), two domain-specific behaviors (practice and playing), one domain-specific (acquired) trait –chess skill –, and one domain-specific performance measure (i.e., chess rating). Notice that these two variables (chess skill and chess rating) seem to be identical, and, indeed the difference between them will not play an important role in the simulations. However, they reflect different aspects of chess expertise. For example, a player may spend two "sabbatical" years training to improve their skill but not playing tournaments. The improvements in chess skill during these two years would not be reflected in chess rating because this player is not participating in rated competitions.

The rationale of this model is fairly simple. Chess players differ in their degree of motivation to engage in resource consuming practice[2]. The more practice is accumulated the higher the number of chess patterns and heuristics acquired, and in turn the higher the skill, and thus rating will improve. Because of their success in tournaments, players with higher rating engage in more practice and also play more. Practicing more leads to further improvements in number of learned patterns and heuristics, but playing more does not. This model (and the other two models as well) makes the additional assumption that the number of hours of practice and the number of hours of play, on average, are a function of age, with 6-

[1] Although motivation is more often considered a state, we treat it here as a trait to best represent the deliberate practice framework, which acknowledges the existence of inherited traits, such as motivation, that may account for the individual differences in engagement in deliberate practice. For an account of motivation as trait refer to Brophy (1987).

[2] In order to avoid a discussion about differences between our implementation of the deliberate practice framework and Ericsson et al.'s we use the term "practice" and not Ericsson et al.'s (1993) term "deliberate practice". Although we are referring to the same phenomena, in the practice model we incorporate assumptions that Ericsson and colleagues may not agree with (e.g., some of our simulations imply that some chess players engage in more than 4 hours per day of practice per day).

year old players and older adults practicing and playing less than young adults (this is not shown in the Figure).

The practice-intelligence (PI) model

PI is represented in Figure 2. It builds upon PM and incorporates a new inherited trait – intelligence – and four causal links: the effect of intelligence on pattern recognition, heuristics and skill, and the effect of playing on skill. This model reflects Howard's (2012a, 2012b), and Gobet and Campitelli's (2007) view on the importance of playing games in improving skill. It also reflects Howard's view on the importance of individual differences in intelligence as a causal factor of individual differences in chess skill.

The practice-plasticity-processes (PPP) model

PPP is illustrated in Figure 3. Before explaining it in detail we discuss why PPP is in the middle of the practice vs. innate talent continuum. PM is in the practice extreme, for it assumes that chess skill is completely explained by the number of hours of deliberate practice. PI is located in the innate talent extreme, because it assumes that chess skill is a function of the number of hours of practice and intelligence, the latter being an inherited trait[3]. In PI intelligence plays a role both on the learning of domain-specific patterns and heuristics (i.e., more intelligent people learn more chess patterns and heuristics per unit of deliberate practice), and during playing a game (i.e., more intelligent people apply their higher reasoning abilities or superior working memory capacity to choose better moves). In PPP the role of inherited individual differences in brain characteristics (not intelligence) is

[3] To our knowledge no researcher has proposed the extreme of eliminating domain-specific practice as one of the predictors of chess skill.

circumscribed to learning domain-specific knowledge. Thus, general reasoning abilities do not play a role in PPP.

The critical components of this model are plasticity, chess chunks/templates-based pattern recognition, and chess heuristics. The incorporation of pattern recognition and heuristics is inspired by Gobet’s (1997) SEARCH model.

PPP assumes that chess skill is a trait composed by domain-specific pattern recognition, and heuristic processes. The capability of recognizing patterns increases as a function of the chunks and templates acquired through practice. The model makes the assumption that the number of chess patterns and chess heuristics acquired is a function of the number of hours of practice and playing chess. The acquisition of chunks, templates and heuristics is mediated by neural plasticity. The more plastic the brain is the higher the number of chunks, templates, and heuristics acquired. In the model we make the assumption that plasticity reduces dramatically at around the age of 12, and that this may explain the critical period in chess.

However, this explanation on its own is flawed because it implies that two-year old children are able to learn chess chunks, templates, and heuristics at a faster rate than adults, because their brains are more plastic. Given that this is not the case there should be a mechanism that neutralizes the effects of plasticity on learning. Given that infants are much more capable of learning relationships between objects than abstract concepts (e.g., Piaget & Inhelder, 1973), our model incorporates a mechanism that neutralizes the learning of chess heuristics (which are abstract strategies), and another mechanism that neutralizes the learning of chunks and templates (which are objects) to a lesser extent.

This model also incorporates a conception of intelligence based on neural plasticity (see Garlick, 2002). This approach considers that intelligence is the consequence of the interaction between neural plasticity and stimulation. That is, individual differences in neural plasticity and individual differences in environmental stimulation are the cause of individual differences in intelligence.

Moreover, unlike the practice-intelligence model, there is no a causal link between intelligence and chess skill. But, given that plasticity is related both to intelligence and to chess skill, then it is expected that chess skill and intelligence have a weak correlation.

Mathematical simulation

This analysis simulates how the values of relevant variables are distributed in a sample of 10,000 chess players with an age range from 6 years of age to 45 years of age. Then, it simulates that these players participate in competitions for a period of 30 years, and a group of 250 6-year old children enter into the sample each year. At the end of year 30 the sample contains 17,250 players.

The simulation includes probabilistic and deterministic variables. The simulation of the probabilistic variables works by making assumptions about their distribution. Then, a random number generator that samples from the assumed distributions is used to produce a sample of values. The values of the deterministic variables are assigned by computation of the respective formulas.

The simulation has a cross-sectional component and a longitudinal component. The cross-sectional component is used to assign values to the 10,000 chess players at year 1, and to the 250 new players at each subsequent year. The longitudinal component works by assigning values to players at a particular year based on the values of variables at the previous year. The purpose of using the longitudinal approach is to capture effects that eventuate years later. For example, a child with high plasticity at age 6 would not possess higher chess skill than a player with low plasticity at age 20. The effects of high plasticity interact with practice over time, thus a longitudinal approach is necessary to capture this effect.

We now present the mathematical formalization of the most important variables and then the results of the simulation in terms of how well the models capture the five effects described above.

Variables

For all the models, chess rating is a normalized value of chess skill with a mean of 1500 and a standard deviation of 200. This procedure aims at obtaining similar values to the Elo rating system (Elo, 1978), which has a theoretical mean of 1500 and a standard deviation of 200. However, because the rating of the world chess federation (FIDE) used to have entry thresholds (recently eliminated), the actual distribution does not exactly resemble the theoretical distribution. Therefore, we will observe in the simulations very extreme values that are not observed in the rating list of the World Chess Federation. Chess rating is expressed as:

$$chessrating_{ij} = 1500 + 200 \times [(chessskill_{ij} - meanchesskill_{j}) / sdchesskill_{j}],$$

where $chessskill_{ij}$ represents the chess skill of player $_{i}$ in year of simulation $_{j}$; $meanchesskill_{j}$ is the mean chess skill of the sample at year of simulation $_{j}$, and $sdchesskill_{j}$ is the chess skill standard deviation of the sample. Chess skill is obtained in the same way for PM and PPP:

$$chessskill(PM)_{ij} = accumulatedpatterns_{ij} + 2 \times accumulatedheuristics_{ij} + random\ error_{ij}$$

$$chessskill(PPP)_{ij} = accumulatedpatterns_{ij} + 2 \times accumulatedheuristics_{ij} + random\ error_{ij}$$

This formula implements the assumption that chess player’s skills are determined by the number of domain-specific patterns (templates and chunks) and domain-specific heuristics. The fact that the number of accumulated heuristics has twice as much weight as the number of accumulated patterns should not lead to the idea that attempting to learning chess heuristics is more important than trying to learning chess patterns. As we will see later, for each hour of practice players are able to learn 10 times more patterns than heuristics. These assumptions may be contested, but relaxing these assumptions would not modify differences between models.

In PI chess skill is determined by patterns and heuristics, as well as individual differences in intelligence:

$$\text{chessskill(PPP)}_{ij} = \text{accumulatedpatterns}_{ij} + 2 \times \text{accumulatedheuristics}_{ij} + \text{inddiffintelligence}_{ij} \times .1 \times (\text{accumulatedpatterns}_{ij} + 2 \times \text{accumulatedheuristics}_{ij}) + \text{random error}_{ij},$$

where inddiffintelligence is individual differences in intelligence expressed as standard deviations in player $_i$ at simulation year $_j$, and it is calculated by (intelligence score – 100) / 15. The formula indicates that players with a higher intelligence score are more skillful in chess than those with lower intelligence. For example, by using their higher general reasoning ability or their superior working memory capacity to choose better moves during chess games.

The models differ in their assumptions about how players learn chess patterns and chess heuristics:

$$\text{accumulatedpatterns(PM)}_{ij} = \text{accumulatedpatterns}_{ij-1} + \text{practice}_{ij-1} + \text{random error}_{ij}$$

$$\text{accumulatedheuristics(PM)}_{ij} = \text{accumulatedheuristics}_{ij-1} + .1 \times \text{practice}_{ij-1} + \text{random error}_{ij}$$

The formulae indicate that in PM one pattern is learned per hour of practice, and one heuristic is learned per ten hours of practice. These are cumulative functions that add the new learned patterns or heuristics to the pool of previously learned patterns or heuristics. Note that for practical reasons the number of hours of practice in the previous simulation year have an effect on the number of learned patterns at the beginning of the current year. No other factors, except for random error, play a role on acquiring chess knowledge. This is different in the other models:

$$\begin{aligned}\text{accumulatedpatterns(PI)}_{ij} = {} & \text{accumulatedpatterns}_{ij-1} + \text{practice}_{ij-1} + \text{play}_{ij-1} + \\ & \text{inddiffintelligence}_{ij-1} \times .25 \times (\text{practice}_{ij-1} + \text{play}_{ij-1}) + \\ & \text{random error}_{ij}\end{aligned}$$

$$\begin{aligned}\text{accumulatedheuristics(PI)}_{ij} = {} & \text{accumulatedheuristics}_{ij-1} + .1 \times \text{practice}_{ij-1} + .1 \times \text{play}_{ij-1} + \\ & \text{inddiffintelligence}_{ij-1} \times .25 \times (.1 \times \text{practice}_{ij-1} + .1 \times \text{play}_{ij-1}) + \\ & \text{random error}_{ij}\end{aligned}$$

In PI playing chess games also influences the learning of patterns and heuristics. Moreover, the rate of learning varies as a function of intelligence. Now it is clearer why PI represents the extreme of the practice vs. talent spectrum: in PI intelligence plays a role on chess skill directly (i.e., intelligence affects the way people play chess games) and indirectly (i.e., intelligence plays a role on the way people learn chess patterns and heuristics). On the other hand, in PPP individual differences not related to domain-specific practice only play a role on learning:

$$\begin{aligned}\text{accumulatedpatterns(PPP)}_{ij} = {} & \text{accumulatedpatterns}_{ij-1} + \text{practice}_{ij-1} \times \text{plasticity}_{ij-1} + \\ & \text{play}_{ij-1} \times \text{plasticity}_{ij-1} - \\ & \text{ploss}_{ij-1} \times (\text{practice}_{ij-1} \times \text{plasticity}_{ij-1} + \text{play}_{ij-1} \times \text{plasticity}_{ij-1}) \\ & - \text{ploss}_{ij-1} \times .2 \times \text{accumulatedpatterns}_{ij-1} + \text{random error}_{ij}\end{aligned}$$

$$\begin{aligned}\text{accumulatedheuristics(PPP)}_{ij} = {} & \text{accumulatedheuristics}_{ij-1} + \text{practice}_{ij-1} \times \text{plasticity}_{ij-1} + \\ & \text{play}_{ij-1} \times \text{plasticity}_{ij-1} - \\ & \text{hloss}_{ij-1} \times (\text{practice}_{ij-1} \times \text{plasticity}_{ij-1} + \text{play}_{ij-1} \times \text{plasticity}_{ij-1}) \\ & - \text{hloss}_{ij-1} \times .2 \times \text{accumulatedheuristics}_{ij-1} + \text{random error}_{ij-1}\end{aligned}$$

These formulae indicate that, like in PI, PPP assumes that playing chess is important to acquire domain-specific patterns and heuristics. The learning rate is a function of plasticity, with players with higher plasticity learning more patterns and heuristics per hour of practice or playing. The model also includes two loss functions (ploss and hloss), indicating that a fraction of the learned patterns or heuristics, and also a fraction of the patterns or heuristics accumulated in previous years, are lost. The loss functions differ in that heuristics are lost at a higher rate than patterns. Both functions have a U shape, with infants and older adults losing a high fraction of what they learn, and young adults retaining most of their learned patterns and heuristics.

Results

Before presenting the results of the simulation, we should make the following warning. The figures obtained in the simulation should not be taken at face value. The important aspect of the simulation is capturing data patterns. The figures may not coincide with figures in published data, but the pattern of results may be consistent with the data.

Criterion 1: Existence of young players with remarkable achievements

The first criterion used to evaluate the models is to what extent the models are able to capture the existence of young players with remarkable achievements. Figure 4 shows the lowest ranking (i.e., the best ranking) achieved by players below the age of 21 from year 10 to year 30. It provides several pieces of important information. First, in PPP the best young player is always better ranked than the best young player in the other models. This does not necessarily mean that PPP is a better model than the others, because, at this stage we are not able to make a quantitative comparison of the models with data. For example, we cannot compare the number of young players that make the top 100 each year in the models with the actual number of young players that achieve that rank in the chess world ranking. However, Figure 4 does show that capturing the existence of remarkable young players is easier for PPP.

Second, the ranking of young players becomes worse in later years of the simulation, in all the models, but less so in PPP. One explanation of this effect is that young strong players remain strong when they become adults (i.e., when they become 21 years old or older in our analysis). Thus, although new strong young players emerge, they are not better than the previously strong young players (who are now adults), thus the number of new young players in the top decreases. This may also explain the data presented by Howard (2005), in which the general trend of age in the top 10 in the world is decreasing since 1970, but there are a number of continuous years in which there is an increase of age in the top 10.

Criterion 2: Correlation of chess rating with chess practice and playing

The second criterion is the correlation of practice and play with chess skill. All the models captured this effect without difficulty. This is because practice is in the function that determines the accumulated number of patterns and heuristics in the three models. Moreover, although playing influences the learning of patterns and heuristics only in PM and PPP, the chess rating achieved affects the number of hours of playing (and practice as well) in all the models. The highest correlations of chess rating with practice and playing from year 10 to year 30 was in PM (practice: $M = .91$, $SD = .002$; play: $M = .91$, $SD = .002$), the second highest was in PI (practice: $M = .89$, $SD = .006$; play: $M = .89$, $SD = .006$), and the lowest was in PPP (practice: $M = .74$, $SD = .012$; play: $M = .74$, $SD = .012$).

Again, a comparison between these figures and those in the chess expertise literature is not appropriate. It may seem that PPP is the best model because correlations between chess rating and practice or play was never shown to be as high as those in PM and PI. However, this may have to do with the chosen standard deviation in the random errors of the functions determining the learning of patterns and heuristics. Increasing the standard deviation of the error would easily decrease the value of the correlations. On the other hand, increasing the random error deviation too much is not advisable because it reduces the explanatory value of the model.

Our conservative evaluation is that all the models face well in this criterion.

Criterion 3: Critical period

The third criterion is the existence of a critical period (i.e., players who start playing younger achieve higher levels of chess skill). In order not to confound the age at starting playing chess and the starting year in the simulation, in this analysis we only used the 10,000 players that started playing chess at the same time (i.e., year 1 of the simulation) but at different ages (from 6 to 45). Because the number of hours of practice and playing is affected by age, we expected to find a negative correlation between starting age and chess rating in all models.

The highest average negative correlation between chess rating and age at starting to play chess from year 10 to year 30 was in PPP (M = -.35, SD = .02), the second highest was in PM (M = -.15, SD = .07), and the lowest in PI (M = -.06, SD = .05). Given that in PPP individual differences in plasticity, which is a function of age, influences the rate of learning, it is not surprising that PPP captured this effect very well.

Ericsson et al. (1993) stated that the explanation of the critical period is that players that begin playing chess earlier engage in more deliberate practice. If their explanation is correct, the PM model should capture the effect without need of additional variables. The fact that PM showed a weak correlation of chess rating with starting age indicates that part of the effect may be explained by the number of hours of practice, but not all of it.

The almost lack of correlation in PI was not predicted. A possible explanation is that the effect of individual differences in intelligence (which remain stable at all ages) in chess skill in the model is too strong, and it eliminates age effects.

Criterion 4: Greater correlation between intelligence and chess rating in children than in adults

Figure 5 shows the correlation of intelligence with chess rating in children (6 to 16 years old), young adults (17 to 50 years old) and older adults (more than 50 years old). PM shows no correlation between intelligence and chess rating; this is because in PM these two variables are completely independent.

PPP does not do well in this criterion. The correlation between chess rating and intelligence is close to zero in children and it increases with age. The same increasing trend in age is observed in PI. When we tried to improve the results in this criterion by changing some parameters we had problems in the other criteria. We also conducted the same analysis using three children groups (6 to 8 years old; 9 to 12 years old; 13 to 16 years old). In this analysis the correlations in the children groups were higher in PI, but still not higher than those of the adult groups. Therefore, a challenge for future research is for all the models to capture this effect.

It is worth noting that when we used absolute values (instead of normalized values) of intelligence we were able to capture the effect in the three models. However, this is not appropriate because the effect encountered in the chess expertise literature is with standardized scores.

Criterion 5: Decline in chess skill in older adults

Figure 6 shows that both PM and PI struggle to capture this effect, while PPP can capture it well. The reason of this result is that plasticity and loss in PPP vary with age, with children having high plasticity and high loss, adults with low plasticity and low loss, and older adults having low plasticity and high loss. The loss of patterns and heuristics in older adults explains why the chess skill of older adults is lower than that of young adults.

PM and PI (and also PPP) have also age effects within their models in the function that links age with hours of practice and playing. However, the decrease in hours of practice is not very strong in that function, thus the decrease in performance in older adults in PM and PI is very low.

Summary of results

The purpose of the mathematical simulation was to study the feasibility of the practice-plasticity-processes (PPP) model. We set ourselves two challenges: capturing five effects encountered in the literature, and showing that simpler models are not as successful as PPP. PPP captured four of the five effects encountered in the chess expertise literature. This was better than the simpler models, which captured at most three criteria. The criterion that was elusive for PPP was the finding that the correlation between chess rating and intelligence is higher in children than in adults.

Conclusions and future research

We started the chapter presenting a number of young players who achieved high levels of performance in chess at very young ages. We then posed the challenge of trying to find an explanation for those achievements. The expertise literature offers two main theoretical approaches to explain high performance in chess. The first approach is experimental, and is concerned with cognitive processes underlying chess expertise. The main framework in this approach comprises the template theory (Gobet & Simon, 1996) and the SEARCH model (Gobet, 1997); the more relevant domain-specific patterns (i.e., chunks and templates) one has, the better chess player one is. The second approach is correlational, and is concerned with the development of expertise. The main framework here is deliberate practice (Ericsson et al., 1993, see also Ericsson, 2013, in this book). The more hours of deliberate practice one engages in, the higher the skill level achieved.

Two of us (Gobet & Campitelli, 2007; Campitelli & Gobet, 2011) proposed that a large number of hours of deliberate practice is a necessary but not a sufficient condition to achieve high levels of expertise. However, no theoretical model or framework has been proposed to go beyond the deliberate practice framework. There have only been claims that other factors are important for the achievement of high levels of performance in chess.

In this chapter, we explored two alternatives to the deliberate practice framework. Because chess is an intellectual game, it has been proposed that general intelligence is the factor that, together with practice, accounts for differences in chess skill (e.g., Howard, 1999, 2005). This view implies that general intelligence influences chess expertise at least at two levels: first, learning of domain-specific patterns and heuristics, and second, playing better moves during games due to superior general reasoning abilities, superior working memory capacity, or any other ability associated with intelligence. Bilalić et al. (2007) showed that intelligence plays a large role in children who have little practice, but as soon as practice starts to accumulate, intelligence has less influence on chess skill.

Therefore, in this chapter we proposed a model that lies in the middle in the practice vs. talent continuum. Unfortunately, the price of doing this is to add complexity to the other proposals. We proposed the practice-plasticity-processes model, which states that individual differences in neural plasticity interact with practice and playing to determine the number of relevant domain-specific patterns and heuristics learned. This means that the effect of the general factor (i.e., neural plasticity) is only restricted to the learning of patterns and heuristics. Individual differences in non-domain-specific practice or playing do not play a role during playing game. In this model, like in the deliberate practice framework and in the template theory and SEARCH model, chess skill is very domain-specific.

We studied the feasibility of the practice-plasticity-processes model by simulating data and making a qualitative comparison of the simulated data with five effects found in the literature of chess expertise. PPP captured very well the existence of young players with remarkable achievements, the correlation between chess rating and hours of practice and hours of playing, the correlation between starting age and chess rating, and the decrease in performance in older adults. This is better than the simpler models, which could not capture all four phenomena. Neither model captured the higher correlation between intelligence score and chess skill in children than in adults.

The overall result is encouraging for PPP because the added complexity in the model is justified by being able to capture more findings than the other models. Future research should improve the model, so that it captures the higher correlation between chess rating and intelligence in children. The challenge lies in finding a mechanism whereby intelligence is correlated to chess skill at very early stages of chess player's career, but ceases to play a role after a critical number of domain-specific patterns and heuristics is learned.

A very important aspect of the practice-plasticity-processes model is that it is capable of capturing the existence of chess prodigies much better than the practice-intelligence model, despite the fact that the latter encompasses a much stronger non-domain-specific practice component. Another critical aspect of the model is that it explains why the endeavor of trying to show transfer from chess practice to performance in other domains has not been successful (see Gobet & Campitelli, 2006). Chess practice and competition interact with plasticity to produce domain-specific patterns and heuristics. All the patterns and almost all the heuristics are only useful for chess. Only heuristics such as "consider the options of your opponent before you play your move" could be transferable to other domains.

The presentation and exploration of feasibility of the practice-plasticity-processes model in this chapter opens a number of avenues of research. First, improvements in the chosen functions should be sought in order to capture the fourth criterion; after that, the model should face the more stringent scrutiny of reproducing real data quantitatively; finally, the generalizability of the model to other disciplines might be explored.

If the practice-plasticity-process model is supported by further research, it will offer a parsimonious explanation for the phenomenon of precocious chess genius. Chess prodigies exist due to a combination of innate high-level motivation to engage in practice, innate high plasticity, and high actual engagement in practice.

Table 1. Evaluation criteria

Evaluation Criteria
1. Existence of remarkable achievements of young players
2. Correlation practice with chess skill
3. Critical period
4. Stronger relationship between intelligence and chess skill in children
5. Decline in chess skill in older adults.

Table 2. Descriptives

PM model

	Year 10				Year 20				Year 30			
Variables	*M*	*SD*	*Min*	*Max*	*M*	*SD*	*Min*	*Max*	*M*	*SD*	*Min*	*Max*
Motivation	0	1	-3.6	4.7	0	1	-3.6	4.7	0	1	-3.6	4.7
Intelligence	115	15	60	177	115	15	60	177	115	15	60	177
Accumulated practice	3478	2031	0	13870	6866	4258	0	29870	9785	6227	0	45870
Accumulated playing	6091	3161	0	14215	12170	6965	0	30215	17494	10538	0	46215
Patterns	3522	2510	0	17487	6941	5219	0	37668	9886	7658	0	57850
Heuristics	352	238	0	1579	693	497	0	3392	986	729	0	5206
Chess skill	4225	2886	0	20100	8327	6017	0	43334	11859	8830	0	66569
Chess rating	1500	200	1207	2600	1500	200	1223	2664	1500	200	1231	2739

PI model

Variables	Year 10				Year 20				Year 30			
	M	*SD*	*Min*	*Max*	*M*	*SD*	*Min*	*Max*	*M*	*SD*	*Min*	*Max*
Motivation	0	1	-3.6	4.7	0	1	-3.6	4.7	0	1	-3.6	4.7
Intelligence	115	15	60	177	115	15	60	177	115	15	60	177
Accumulated practice	3481	2041	0	13643	6871	4279	0	29643	9791	6265	0	45643
Accumulated playing	6084	3143	0	14215	12153	6929	0	30215	17468	10492	0	46191
Patterns	12167	7837	0	57272	24247	16767	0	124874	34800	24985	0	192476
Heuristics	1216	780	0	5745	2424	1671	0	12526	3478	2492	0	19306
Chess skill	16470	11611	0	99958	32860	24761	0	217943	47200	36845	0	335927
Chess rating	1500	200	1216	2938	1500	200	1235	2995	1500	200	1244	3067

PPP model

	Year 10				Year 20				Year 30			
Variables	*M*	*SD*	*Min*	*Max*	*M*	*SD*	*Min*	*Max*	*M*	*SD*	*Min*	*Max*
Plasticity	0.35	0.23	0	1	0.35	0.23	0	1	0.35	0.23	0	1
Motivation	0	1	-3.6	4.7	0	1	-3.6	4.7	0	1	-3.6	4.7
Intelligence	115	15	76	197	115	15	76	214	115	15	76	225
Accumulated practice	3466	1962	0	13870	6841	4195	0	29870	9746	6166	0	45870
Accumulated playing	6066	3019	0	14215	12104	6715	0	30215	17380	265	0	46215
Patterns	2553	2228	0	16114	4310	4166	0	33851	5289	5475	0	50469
Heuristics	200	182	0	1500	306	315	0	2620	331	362	0	3390
Chess skill	2954	2489	0	18653	4922	4606	0	37159	5951	5933	0	54461
Chess rating	1500	200	1263	2761	1500	200	1286	2900	1500	200	1299	3135

Figure captions

Figure 1. Practice-motivation model. The shaded area represents the domain-specific components of the model, and the non-shaded area represent the general components of the model. Variables used in other models are presented for comparison. In this model intelligence, ploss, hloss, and intelligence do not play any explanatory role. The arrows indicate a causal link between variables.

Figure 2. Practice-intelligence model. In this model, intelligence is causally linked to the acquisition of patterns, heuristics and also directly to chess skill. The slashed arrows represent the links that were not present in the practice-motivation model

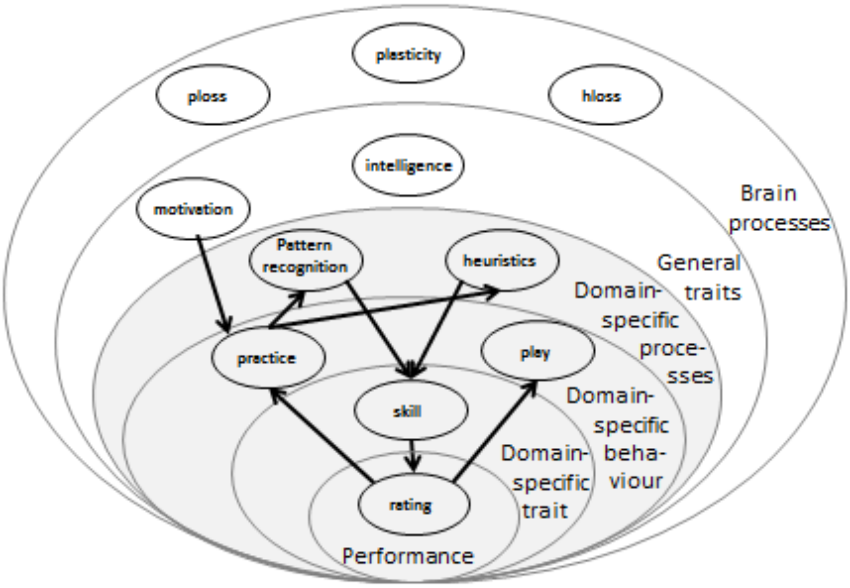
Figure 3. Practice-plasticity-processes model. All the variables participate in this model; the arrows with big slashes represent the links that were not present in the previous models. Ploss and hloss are functions that neutralize the effect of plasticity on the learning of patterns and heuristics, respectively.

Figure 4. Best ranking in young players (age < 21) from year 10 to year 30 of the simulation in each model. PM = practice-motivation model; PI = practice-intelligence model; PPP = practice-plasticity-processes model.

Figure 5. Correlation between intelligence and chess rating in children (6 to 16 years of age), young adults (17 to 50 years of age), and older adults (more than 50 years of age) in each model. PM = practice-motivation model; PI = practice-intelligence model; PPP = practice-plasticity-processes model.

Figure 6. Chess rating as a function of age group (children, younger adults, older adults) in each model. PM = practice-motivation model; PI = practice-intelligence model; PPP = practice-plasticity-processes model.

Figure 1


plasticity
ploss
hloss
intelligence
motivation
Brain processes
Pattern recognition
heuristics
General traits
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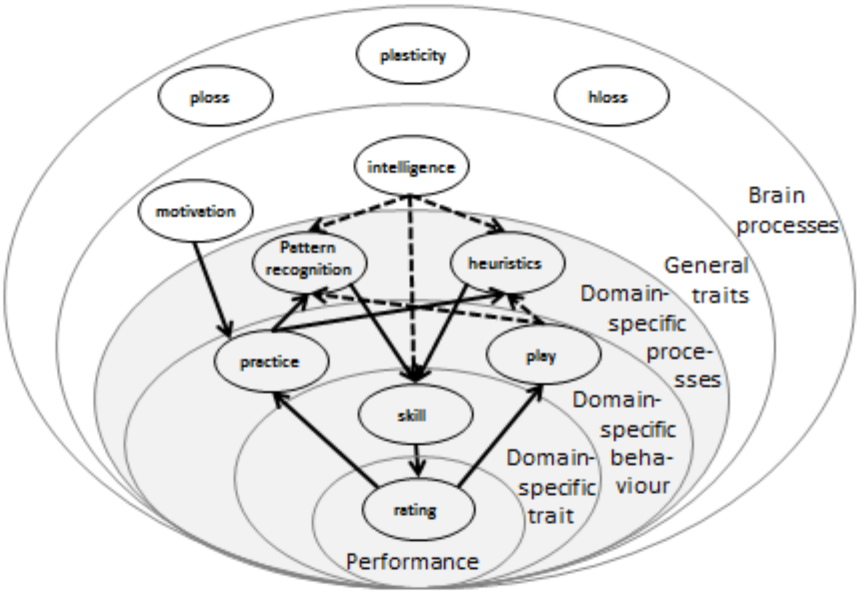
practice
play
skill
Domain-specific beha-viour
Domain-specific trait
rating
Performance

Figure 2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Brain processes
General traits
Domain-specific processes
Domain-specific behaviour
Domain-specific trait
Performance

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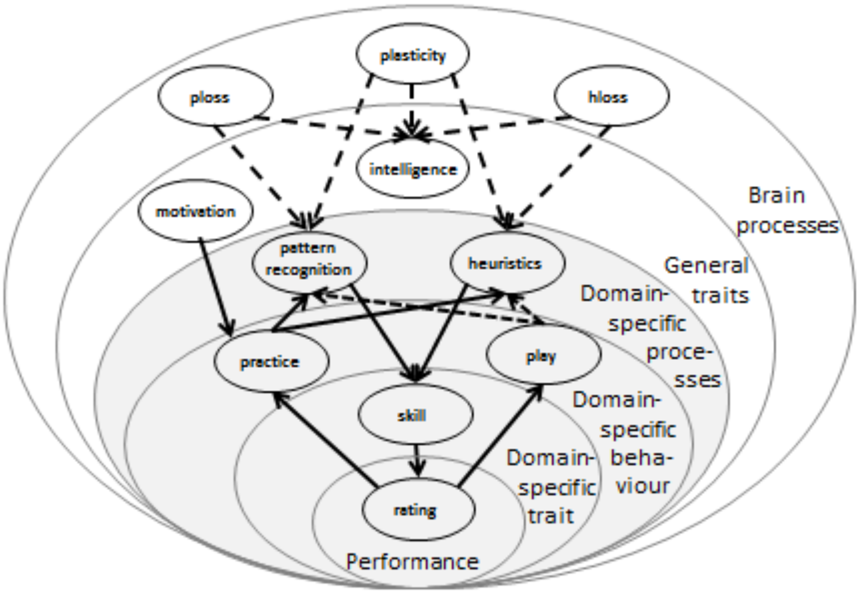
Figure 3.



plasticity
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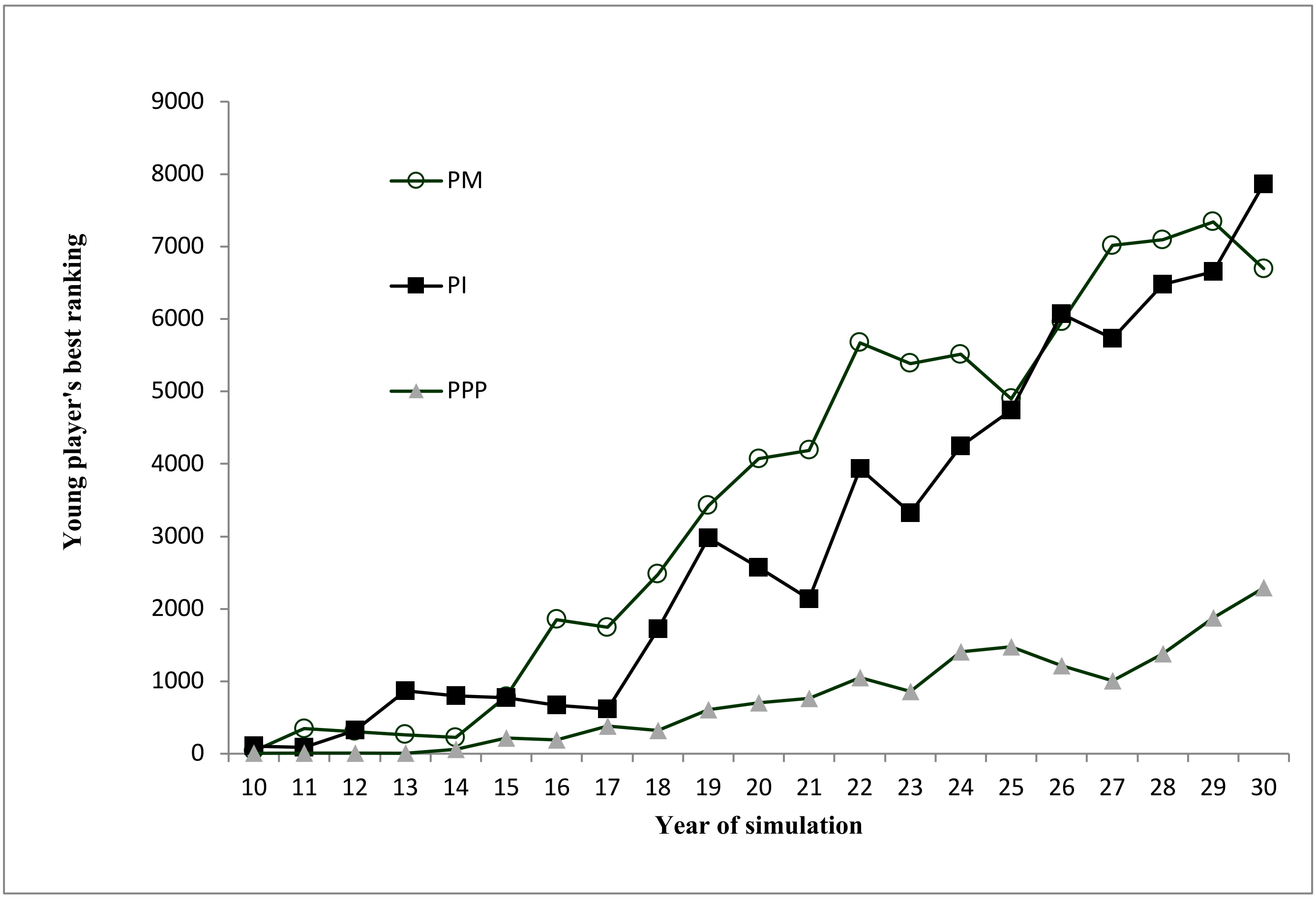
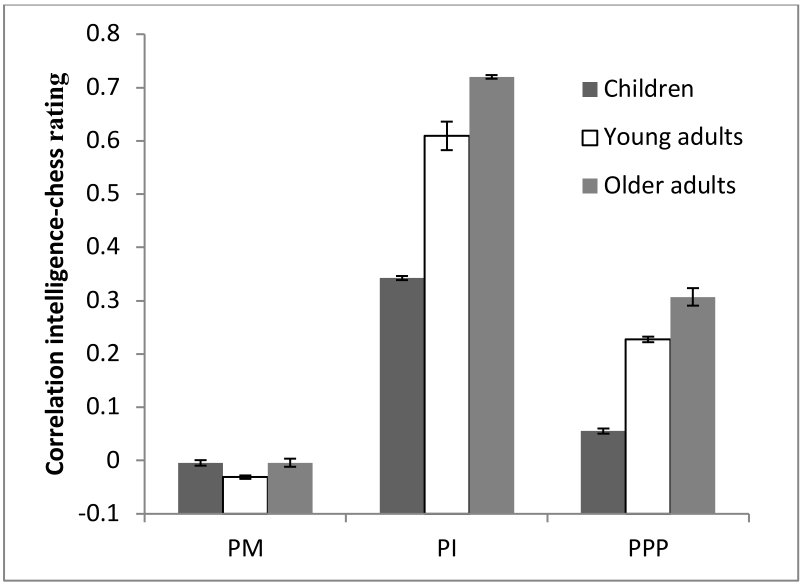
Brain processes
General traits
Domain-specific proce-sses
Domain-specific beha-viour
Domain-specific trait
Performance

Figure 4.



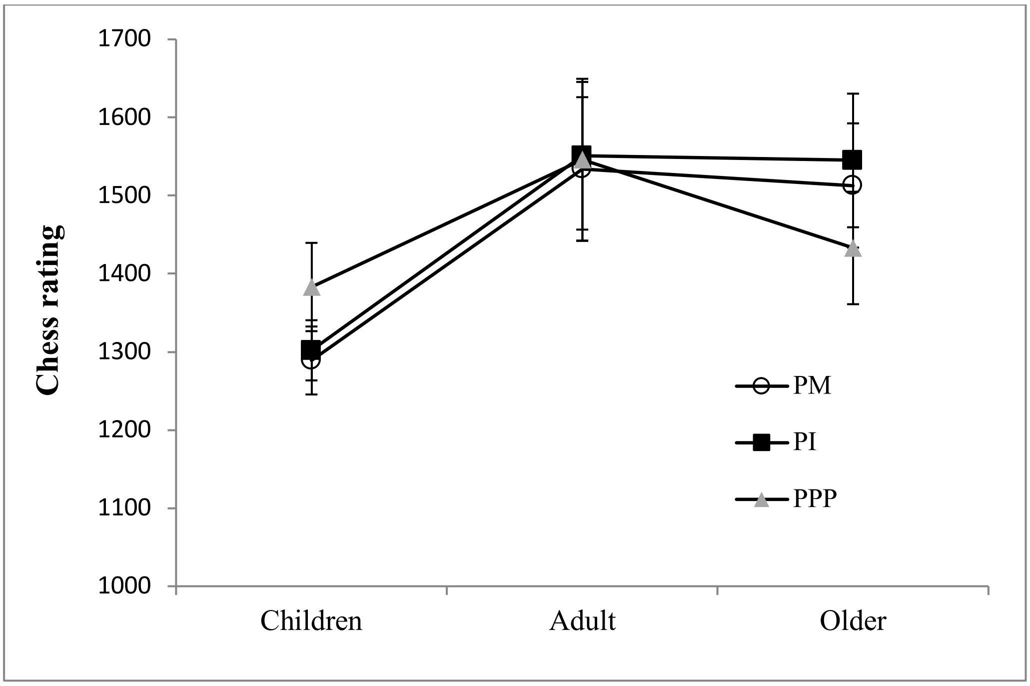
PM
PI
PPP
Young player's best ranking
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
Year of simulation

Figure 5.



0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
Correlation intelligence-chess rating
Children
Young adults
Older adults
PM
PI
PPP

Figure 6.


1700
1600
1500
1400
1300
1200
1100
1000
Chess rating
Children
Adult
Older
PM
PI
PPP

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