The joint influence of intelligence and practice on skill development throughout the life span

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The relative importance of different factors in the development of human skills has been extensively discussed. Research on expertise indicates that focused practice may be the sole determinant of skill, while intelligence researchers underline the relative importance of abilities at even the highest level of skill. There is indeed a large body of research that acknowledges the role of both factors in skill development and retention. It is, however, unknown how intelligence and practice come together to enable the acquisition and retention of complex skills across the life span. Instead of focusing on the 2 factors, intelligence and practice, in isolation, here we look at their interplay throughout development. In a longitudinal study that tracked chess players throughout their careers, we show that both intelligence and practice positively affect the acquisition and retention of chess skill. Importantly, the nonlinear interaction between the 2 factors revealed that more intelligent individuals benefited more from practice. With the same amount of practice, they acquired chess skill more quickly than less intelligent players, reached a higher peak performance, and arrested decline in older age. Our research demonstrates the futility of scrutinizing the relative importance of highly intertwined factors in human development.

intelligence | practice | expertise | aging | chess

To claim that both intelligence and practice are necessary for the acquisition and retention of complex intellectual skills is hardly controversial. There are numerous studies demonstrating that outstanding performance (i.e., expertise) is positively related to individuals' general intellectual capacity [i.e., intelligence (1, 2)]. It is also known that thousands and thousands of hours of focused practice are necessary to become an expert in a domain (3, 4). Beyond acknowledging the importance of both factors, however, their relative contributions and interplay across development are still unclear and disputed (5). A prime example of such a controversy is the long-standing debate between researchers working on expertise and those studying intelligence. While expertise researchers have repeatedly argued that domain-specific practice is the sole determinant of expertise (6), intelligence researchers continue to emphasize the predictive value of intelligence for educational (7) and occupational attainment (8) even at exceptional performance levels (9). Against this background, there have been calls for comprehensive studies examining how these 2 factors come together in expertise development (10, 11). So far, such studies have been sorely lacking. Here, we show how intelligence and practice influence the development of expertise across the life span. Specifically, within the prototypical expertise domain of chess, we not only demonstrate that both factors positively influence the acquisition and retention of expertise, but also unravel how they interact with each other. The more intelligent the chess players were, the more they gained from the same amount of practice, even at the later stages of their career.

Expertise Mechanism and Its Relation to (Deliberate) Practice and Intelligence

Chess is the perfect domain for testing the influence of intelligence and practice on the development of intellectual skills across the life span. It is a deceptively simple game with a constrained environment and fixed rules. It is relatively easy to learn, but, as anyone who actively pursues it can attest, difficult to master. The sheer number of possible moves and configurations has even led to claims that there are more combinations in chess than there are atoms in the universe (12). The way the human mind deals with this jungle of possibilities is to pick up the inevitable regularities that arise in such demanding domains. Information about the main features of the domain and the typical relations between them, often called chunks or templates (13, 14), is the core of experts' domain-specific knowledge stored in long-term memory. Armed with thousands and thousands of such chess patterns, chess experts can quickly grasp new positions because they have accumulated combinations of chess pieces that are similar to the situation at hand, as well as ways of dealing with such situations (for theoretical accounts based on high-level cognition, see refs. 15–17).

The expertise mechanism based on domain-specific knowledge is well established in chess and other expertise domains (11). It is undisputed that the acquisition of this knowledge requires extensive immersion in the domain. An extreme environmentalist view is advocated within the expert performance framework (3),

Significance

What is often overlooked in the nature vs. nurture debate is the fact that both factors interact with each other. This omission is reflected in research where individual factors are examined in isolation. Our study reveals how intelligence and practice, factors typically associated with nature and nurture, respectively, influence the acquisition and retention of complex skills across the whole life span. It confirms one of the central tenets of intelligence theories, widely assumed but rarely empirically proven, namely that more able people benefit more from the same amount of learning activity.

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in which it is postulated that certain types of practice are not only necessary for attainment of expertise, but also sufficient. Deliberate practice, which is defined as focused activities aimed at improving deficiencies in performance, would be the sole determinant of the attained expertise level. The more time an individual engages in such practice, the higher the domain-specific performance should be. As practitioners acquire more domain-specific knowledge through deliberate practice, other factors such as intelligence are assumed to continuously lose their importance. In the final, expert stage, performance would rely exclusively on the domain-specific knowledge acquired through deliberate practice. The assumption of a diminishing role of intelligence in expertise development is also seemingly compatible with the theory of ability determinants of skilled performance (18). In consistent tasks in which stimulus–response associations remain constant, general cognitive abilities gradually lose their impact on performance as task execution becomes increasingly automated.

The link between deliberate practice and domain-specific performance has been corroborated by several correlational studies in different expertise domains (4). In chess, deliberate practice is typically defined as individual study of chess material. A meta-analysis revealed that 34% of variance in playing strength (average corrected $r = 0.57$) could be explained by the amount of deliberate practice (19). However, there is no support for the view that only deliberate practice determines experts' performance. The correlations of playing strength with the amount of group practice activities, such as playing tournament games, were found to be almost equally as strong (r range between 0.26 to 0.54) as the correlations with the amount of individual practice (r range between 0.42 and 0.54; ref. 20). More importantly, chess players varied greatly as to how much practice, deliberate or any other, they needed to reach expertise levels. One study, for instance, reported that players required between 3,000 and 23,600 h to attain the master level (21). The amount of (deliberate) practice explains a large chunk of chess expertise, but there also seem to be other factors that influence expertise development.

One such factor is intelligence. Theories of intelligence postulate that intellectually more able people will inevitably be better at mastering the problems resulting from complex intellectual domains (22, 23). Thanks to their higher speed of information processing and working memory capacity, brighter people will acquire domain-specific knowledge faster than their less able peers. In the case of chess expertise, this may mean more efficient grouping of smaller pieces of knowledge into larger units (13, 14). A recent meta-analysis (1, 24) indeed demonstrated that more intelligent individuals tend to play better chess (average $r = 0.22$, or 5% of variance explained). However, the link between intelligence and chess skill was particularly pronounced in children (average $r = 0.31$) and at lower levels of expertise (unranked samples: average $r = 0.33$). Much lower correlations were found in adults (average $r = 0.04$; not significant) and at higher expertise levels (ranked samples: average $r = 0.10$; not significant). This finding may indicate that intelligence is differentially important at various phases of expertise development. In addition, not all components of intelligence were associated with chess skill. Visuospatial intelligence showed almost a null correlation (average $r = 0.08$; not significant). Similarly, verbal intelligence was not predictive of chess performance (average $r = 0.12$; not significant). Only numerical intelligence turned out to be highly relevant in most of the included studies (average $r = 0.34$, or 12% of variance explained).

Current Study

The present body of evidence shows clear links between expert performance and both intelligence and practice. However, most of the studies examined the role of these factors separately and looked only at 1 time point in the expertise acquisition process. None of the studies explicitly investigated the relevance of both factors as well as their interaction across long-term expertise development. In the current study, we examined the individual and joint influence of intelligence and practice across the life span.

We tracked 90 chess players across their careers. Chess players were of different expertise levels and age at the time of testing. This enabled us to cover the whole range of the skill development trajectories, starting from younger age, to the point when they reach their peak, and in older age when their skill starts to deteriorate. We made use of 2 of the aspects of chess that make it a popular choice for the investigation of expertise development (25, 26). First, unlike in many other expertise domains, chess skill is measured by an objective measure, called the Elo rating (27). Elo takes into account official games in tournaments and is a reliable and valid measure of expertise (25). Second, chess as a domain offers accurate records of tournament games played, which can be taken as an approximation of practice (28). From official records, we collected 20 y of Elo ratings per player and the number of games played in each year, producing over 1,800 data points. All players were tested on 3 components of intelligence (i.e., numerical, verbal, and figural intelligence) and general intelligence, a measure derived from the 3 components (29). These intelligence components were distinguished in previous studies on the role of intelligence in (chess) expertise (1, 29).

Results

The raw data illustrate that players develop chess skill rapidly at the beginning until they reach the peak of performance at around 35 y (Fig. 1). After a few years of peak performance, players' skill starts to slowly decline.

To provide a general model of development over the life span, we modeled the data using generalized additive models (GAMs) (30). GAM is a nonlinear, data-driven method that fits a smooth function that most optimally describes the data (for a more traditional longitudinal linear multilevel model, see *SI Appendix*). Unlike linear models, nonlinear models enable us to capture systematic deviations from a straight line. This allows us to investigate hypotheses of persistent influence of intelligence throughout the life span. The additive effects of intelligence or practice on chess performance may not necessarily be linear at all times of life and stages of expertise. Should there indeed be any kind of influence of intelligence or interplays between intelligence and practice at higher levels of expertise, nonlinear models are arguably the most suitable way of capturing them (for more details, see ref. 31).

Once we fitted the basic model with age (Table 1), we turned to adding individual components of intelligence and practice

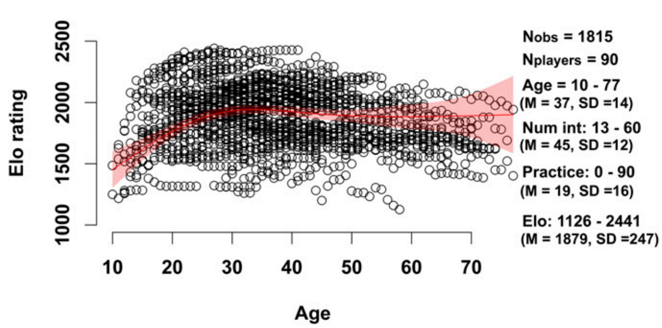

Fig. 1. Raw data of age-related changes in chess skill. The red line illustrates the average model data (Table 1, model 4) across the life span, that is, the effect of age once numerical intelligence and practice have been controlled for. The red shading around the line indicates 95% error of the estimate. M, average; Nobs, number of observations; Nplayers, number of players; Num Intelligence, numerical intelligence (raw scores, age-standardized numerical IQ M = 116, SD = 14); Practice, games played (per year).

Table 1. Models explaining the development and retention of chess skill

No.	Model	AIC	BIC	Deviance explained, %
1	Age (L and N)	24,965	25,014	10.7
2a	Age × Intelligence (N)	24,602	24,686	27.3
2b	Age × Practice (N)	24,613	24,721	27.4
3	Age × Intelligence + Age × Practice (N)	24,227	24,389	41.9
4	Age × Intelligence + Age × Practice + Intelligence × Practice (N)	24,095	24,353	47.0

The basic model starts with individual players and their age variable (model 1). That model is then used to add numerical intelligence (model 2a) and practice (model 2b) in isolation. Model 3 brings both factors together. Finally, model 4, which adds the interaction to model 3. Note: AIC, Akaike's information criteria; BIC, Bayesian information criteria; L, linear effect of the predictor; N, nonlinear effect.

(i.e., games played) separately (model 2a and model 2b). Numerical intelligence had the strongest effect of all measured intelligence types, followed by verbal intelligence and general intelligence derived from the 3 scales. Figural intelligence did not significantly explain chess expertise across age (*SI Appendix*). Numerical intelligence (Fig. 2*A*) and practice, as measured by the number of games played (Fig. 2*B*), showed beneficial effects on the level of performance. The more games players played and the more intelligent they were, the better their performance was.

Both factors explain the development and retention of chess skill. Compared with the model that features only age (model 1 in Table 1), numerical intelligence alone explains an additional 17% of results (model 2a). Similarly, practice alone explains the same amount of deviance, a measure similar to unadjusted variance (17%; model 2b). However, numerical intelligence and practice had differential effects on performance at different age levels of the players. Numerical intelligence was most beneficial in the middle of the life span, around 35 y, when the chess players were reaching the peak performance (Fig. 3*A*). Likewise, at the later postpeak stages until age 70, individuals also benefited from numerical intelligence. Take for example, 2 hypothetical groups of players (Fig. 3 *A*, *Right*), one with a score of 30 on numerical intelligence (around 100 standardized score, IQ) and another one with a score of 55 (IQ 120). They will both have around 1,700 Elo at age 15 but already starting from age 20, the more numerically able players will improve faster. They will eventually achieve a peak rating of 2,050 at age 35, compared to the peak rating of 1,900 at the same age for the numerically less able players. When they both reach age 70, the numerically more able players decline less (to 1,900) than the less numerically able players, who drop to 1,700.

Practice, on the other hand, was particularly beneficial at the beginning and toward the end of the life span (Fig. 3*B*). People who play 60 games per year will already at age 15 have a rating far superior to that of people who plays 20 games (2,000 vs. 1,600; Fig. 3 *B*, *Right*). At the peak, the age of around 30, the difference is still pronounced: rating over 2,200 for the people who play 60 games, in contrast to a rating of under 1,900 for the people who play 20 games. When they are 70 y old, playing 60 games a year would yield a rating of almost 2,100, whereas 70 y olds who play 20 games would have a rating of 1,900.

The different explanatory power of numerical intelligence and practice at different stages during players' development was also evident when we added both factors into our model. The explanation of data improved from 27% when either numerical intelligence or practice alone was included in the model, all of the way to 42% when both were included (compare model 3 with model 2a or 2b).

The beneficial effects of combining numerical intelligence and practice in order to account for performance was also evident in their close interaction across development. Adding the interaction to the model explained additional variance, bringing the explained variance to 47% (Fig. 3; model 4 in Table 1). In other words, more numerically able participants benefited significantly more from the same amount of practice than their numerically less able colleagues. This was not the case for verbal and general intelligence (*SI Appendix*).

In order to illustrate this interaction, we provide snapshots of how intelligence and practice influence performance at different age levels: 1) early, at age 20 (Fig. 4*A*), 2) at the peak at age 35 (Fig. 4*B*), and 3) late, at age 70 (Fig. 4*C*). As a general rule, when they play the same number of tournament games, the players with higher numerical intelligence develop chess skill more quickly. For example, at age 20 (Fig. 4*A*), players with numerical intelligence of 55 (IQ 120) will benefit more from the same amount of practice at lower levels of practice than players with numerical intelligence of 30 (IQ 100). More practice will inevitably mean fewer differences between the 2, hypothetically more and less numerically, able player groups. This is the case until the very high level of practice (over 60 games) when the more numerically able players will again benefit more than less numerically able players (Fig. 4 *A*, *Right*).

The same interaction is found when we look at age 35, when the players reach peak performance (Fig. 4*B*). The difference in the level of improvement achieved for a given amount of practice between players with numerical intelligence of 55 and players with numerical intelligence of 30 is particularly pronounced at the lower levels of practice. It almost disappears at higher levels of practice until it again reappears at the highest levels of practice.

The situation is even more drastic in later stages when players need to maintain their expertise (Fig. 4*C*). The differences between players with scores of 55 and 30 on numerical intelligence increase with the amount of practice.

An interactive figure that illustrates the interplay between intelligence and practice across the complete life span (for every single year) is hosted at the following link: https://nemanjavaci.shinyapps.io/3dinteraction/.

Discussion

The present findings corroborate the assumption that both intelligence and practice are, unsurprisingly, important factors in expertise acquisition and retention when considered separately. However, their explanatory power lies in the way in which they

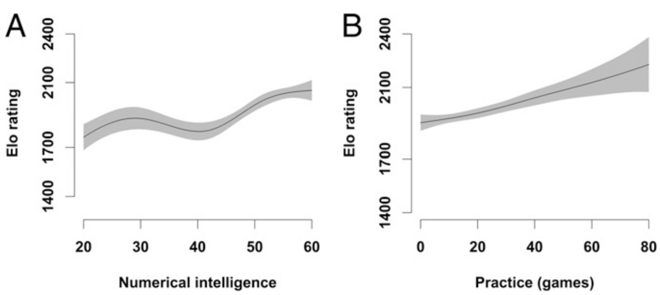

Fig. 2. The average effects of numerical intelligence (*A*) and practice (*B*) on chess skill (Elo rating).

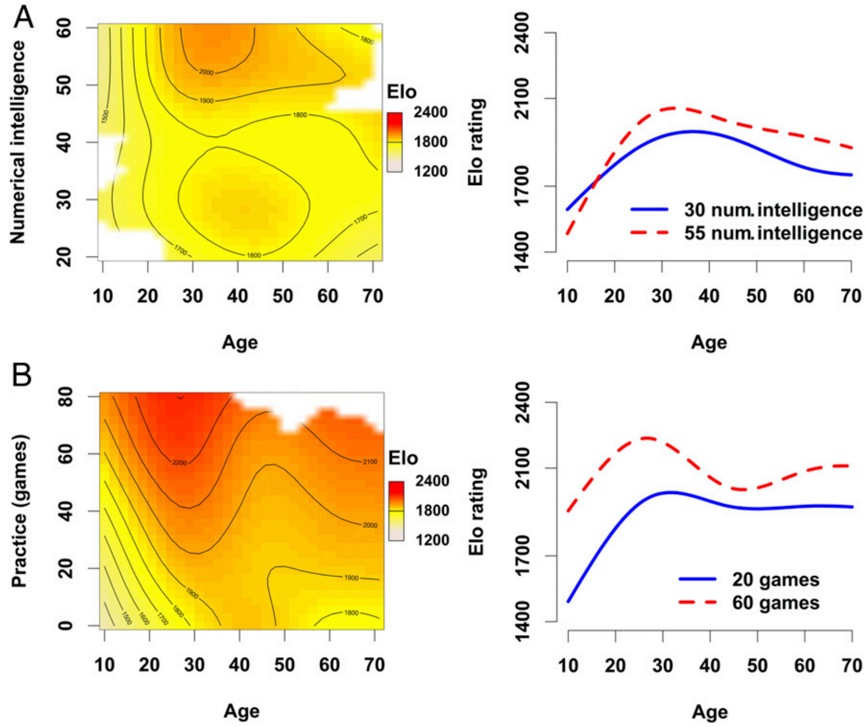

Fig. 3. The nonlinear effects of (*A*) numerical intelligence and (*B*) practice across the life span. The colors in the left-hand panel graphs indicate the Elo rating, with paler and brighter colors representing lower and higher scores, respectively. The white patches in *A* and *B* indicate that there was not enough data for the model to be estimated. Data are from model 2a and model 2b in Table 1. The right-side panel graphs present hypothetical ratings across the life span of (*A*) players who have 30 and 55 scores on numerical intelligence, and (*B*) players who play 20 and 60 games.

complement each other. Individually, they can explain only certain parts of the developmental curve. Together, they explain the changes much better across the whole life span, accounting for about 47% of variance.

Practice has its strongest effect in the beginning of expertise development (Fig. 3*B*). One possible reason is that, at this point, when there is little accumulated knowledge, almost every exploration uncovers useful information. As people acquire more information concerning the domain and their knowledge base increases, it becomes more difficult to discover new ways of dealing with challenging situations that would improve performance. This principle of diminishing returns, which is at the core of skill acquisition theories (32) and the power law of practice (33), may also go a long way toward explaining the particularly beneficial influence of practice at the start of expertise development in our study.

The same theoretical principle should be applicable to intelligence, where more capable players build their knowledge structures faster (22, 34). We found that numerical intelligence influences performance throughout the whole life span, but its strongest effect is at the age at which most players reach their peak performance. This finding disproves a long-held belief that intelligence is important at the beginning of the skill acquisition process and that its influence wanes in later stages (3, 6, 18). It also goes against theoretical considerations in which the already accumulated knowledge base, the main mechanism behind experts' outstanding performance (11, 13), leaves little for other factors to explain (3).

Many expertise domains, including chess, are so complex that it is humanly impossible to master them fully. No matter how much knowledge experts possess, there will always be situations that are not similar enough to previously encountered instances and therefore require adaptive behavior. In other words, even the best practitioners will be forced from time to time to fall back on general reasoning abilities, a hallmark of intelligence (22). The evidence for this consideration comes from skill acquisition research (18, 35), which distinguishes between consistently mapped tasks (e.g., rotary pursuit task) and inconsistently mapped tasks (e.g., air traffic control, where new situations regularly occur). Intelligence influences skill acquisition only at the beginning for consistently mapped tasks, but it remains an important predictor of skill throughout the whole period for inconsistently mapped tasks (36). Chess may in many ways be a consistent environment because of its fixed rules. Expert players may also learn how to deal with many reappearing situations. However, the sheer number of possible constellations are bound to produce less familiar situations. Although many components of chess expertise may have automated aspects akin to consistent tasks in skill acquisition literature, some aspects of chess expertise may remain beyond the reach of automatization. This theoretical explanation leaves the door open for the influence of intelligence beyond the beginning of expertise development.

Our study confirmed that figural intelligence has a limited impact on expertise development (*SI Appendix*). Although this is in line with recent meta-analytic results (1, 21), it may come as a surprise given the visuospatial nature of chess. However, the stereotype of chess masters who imagine extended continuations of moves on a mental board in their mind is inaccurate (37). The mental imagery in chess is much more abstract and is never a replica of the physical environment. This fact may also explain why verbal intelligence is related to chess expertise in our study. Being able to grasp relations and verbalize them explicitly is a big part of any expertise, including chess, which has a specific coded language (e.g., single labels for typical strategies and openings that pack a wealth of information). Most important, however, was numerical intelligence, which has also been demonstrated in the previous meta-analysis (1, 24). Chess may be a visuospatial domain on the surface, but it is full of numerical relations. The chessboard has clearly specified numerical properties; the relations in chess are numerical in nature (e.g., a rook is stronger than a

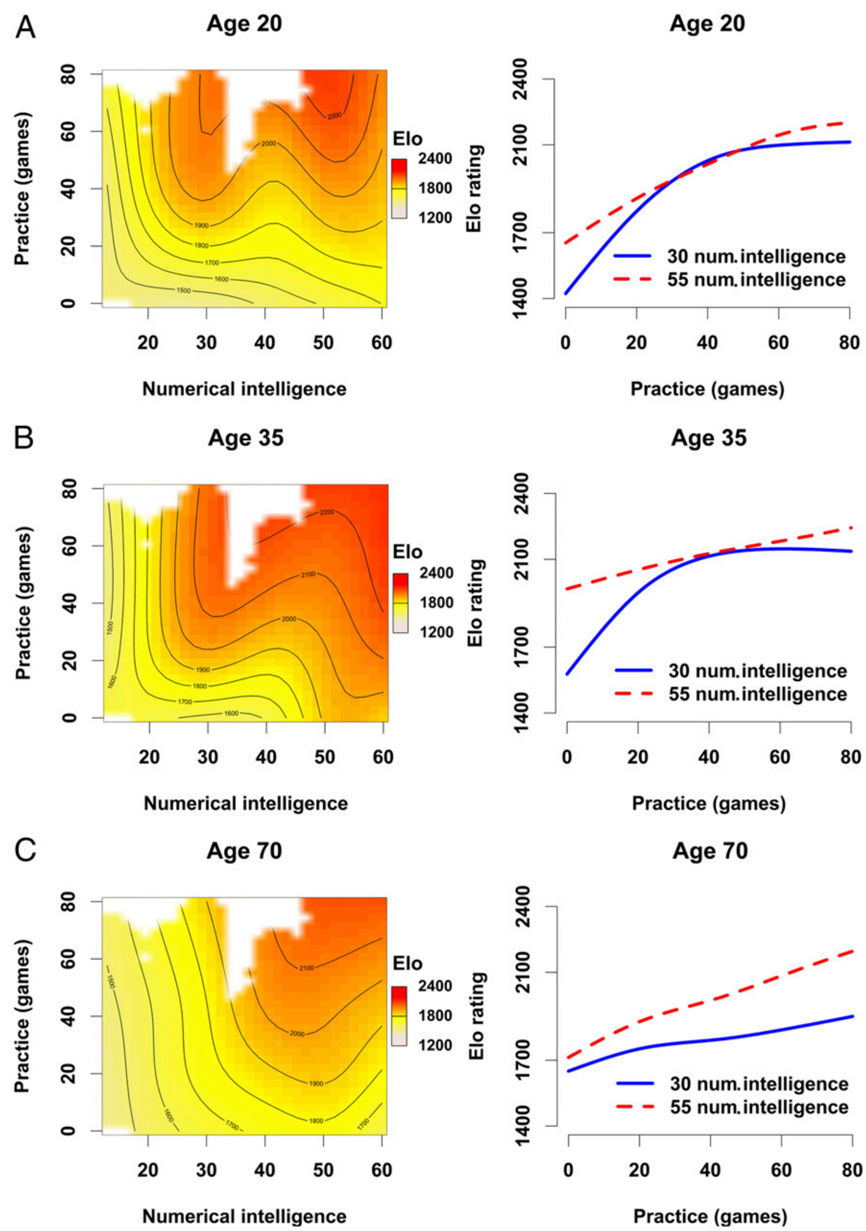

Fig. 4. Nonlinear interaction of numerical intelligence and practice at (*A*) age 20, (*B*) age 35, and (*C*) age 70. The colors in the left-hand panel graphs indicate the Elo rating, with paler and brighter colors representing lower and higher scores, respectively. The right panel shows hypothetical ratings of 2 groups of players, one with a score of 30 (around 100 in standardized scores) on numerical intelligence (blue solid line), and another with a score of 55 (around 120 in standardized scores; red interrupted line), depending on how much they practice.

knight for exactly 2 units/pawns), and those numerical relations play a considerable role when estimating whether a chosen move is worthwhile. Precisely these "calculations," where chess experts have to estimate the situation a few moves down the line, may be where numerically more able chess players reap higher benefits. The actual solution may stem from vast knowledge about similar situations, but chess experts still need to examine their initial intuition.

Together with age, our 2 factors explained a remarkable 47% of variance in chess performance. This is particularly impressive given that our proxy measure of practice was based on the number of tournament games. The officially played games are only 1 type of practice activity that can be important for expertise development (20). Deliberate practice in chess (i.e., studying alone) may not be the only explanation for the differences among experts (3), but it is certainly a relevant factor that future studies should take into account. Chess players generally tend to immerse themselves in the domain long before they actually play any official games. Accounting for this early period and different aspects of activities in general may paint an even more accurate picture of the influence of practice on expertise development. Similarly, other factors such as motivation, starting age, and personality may also prove to influence directly or indirectly (e.g., through practice) intellectual performance throughout the life span (10, 11).

Despite these limitations, our study confirms one of the central tenets of virtually all intelligence theories—more intelligent people should benefit more from the same amount of practice than less intelligent people (22, 23, 38). This claim has proved to be rather difficult to demonstrate even for simple skills (39, 40). Our study goes beyond this and demonstrates the interaction between intelligence and practice in a complex intellectual activity such as chess. Practice, for example, does not in itself guarantee the maintenance of skill in old age in numerically less intelligent players (Fig. 4C).

Above all, our study underlines how unfruitful it is to focus on a single factor in the development of human skill. Intelligence and practice are intertwined, thus making it difficult to separate the 2 and pinpoint the exact influence of each factor. Instead, it is much more advisable to identify the circumstances that may help people to acquire and retain important skills.

Methods

Participants. Ninety (90) active tournament chess players from Austria [M(age) = 36.23, SD = 13.29, range = 15 to 65 y, when tested on intelligence in 2003 and 2004] took part in the study (29). They were recruited through announcements at Austrian chess clubs and local tournaments, offering the opportunity to obtain information about their individual test results. All participants gave written informed consent that their data can be used for research purposes and be published in anonymous form. The research protocol was approved by the Research Management and Service as well as by the Institute of Psychology at the University of Graz.

Chess Data. Players' chess skill and practice data were extracted from the publicly accessible Austrian chess database (www.chess-results.com). We used the Elo ratings as an indicator of chess skill and the number of tournament games as an indicator of chess practice. The Elo ratings are regularly (every 6 mo) computed based on the players' tournament outcomes and can be considered a highly reliable and valid measure of chess expertise (for details, see refs. 27 and 29). They typically range from 800 (in beginners) to about 2,850 (the current world champion, Magnus Carlsen). The Elo ratings and number of tournament games per year were collected from 1994 to 2016 (23 time points) for each player in the sample. The entrance level for obtaining the Elo rating, i.e., the lowest rating possible, has varied over the years. Currently, it is 800 points, but at the time of testing it was 1,200 points.

Intelligence. Participants' intelligence was assessed in the years 2003 to 2004 using a well-established German intelligence structure test, IST-2000R (41). This test can be administered to individuals from age 15 with no upper limit and captures 3 content components of intelligence (i.e., verbal, numerical, and figural) as well as general intelligence (reasoning; based on the 3 content components) with high reliabilities (Cronbach's alphas for verbal, 0.88; numerical, 0.95; figural, 0.87; and general, 0.96; ref. 41). The content components have consistently been found in different theories of intelligence structure (42–44). Each component is measured by means of 3 subscales (each consisting of 20 items): verbal intelligence (sentence completion, verbal analogies, finding similarities), numerical intelligence (arithmetic problems, number series, arithmetic operators), and figural intelligence (figure selection, cube task, matrices). The results on the relationship between intelligence and Elo ratings at the time of testing were published in a previous study (29).

Descriptive Analysis. The descriptive statistics with intercorrelations can be found in *SI Appendix*, Table S1. For the analyses, the raw scores of the intelligence scales were used (also presented in *SI Appendix*, Table S1).

Data Analysis. Preliminary data screening was performed to ensure that potential data entry mistakes were eliminated. We followed the procedure from previous studies (28, 45, 46) and restricted the tails of the age distribution. In the case of this study, we excluded players under 10 y and over 80 y when presenting the modeling results (Fig. 1).

The data were analyzed using 2 different modeling approaches. For the main analysis, we used GAMs, while for the triangulation of results, we used linear mixed-effect regression with specified polynomial terms across the age, which is a standard approach in expertise research when modeling time changes.

GAMs. The GAM is a data-driven method designed to estimate the nonlinear relation between covariates and the dependent variable. A GAM replaces the usual linear function of a covariate with an unspecified smooth function: $y_i = f(x_i) + \epsilon_i$.

The model is nonparametric in the sense that we do not impose a parametric form of the function (e.g., linear, quadratic, or cubic function), but we are estimating it in an iterative process (47). To estimate the nonlinear effect or form of the function, the model needs to estimate the space of functions that can represent f in the equation. This is usually termed the basis function (47). For example, if we believe that the relationship between predictor and outcome is a fourth-order polynomial, then the space of polynomials of order 4 and below contains f. The basis of the function is then summed over all individual polynomial terms up to the fourth-order polynomial, and the relation between predictor and dependent variable can be represented by such a structure, e.g., a sigmoidal curve. In contrast to the standard linear model, in GAMs we do not have to specify the basis of the function (polynomial terms, cubic splines, etc.), as this type of modeling iteratively optimizes the smooth function (basis) and proposes an optimal structure between dependent and independent variable. In addition to the univariate nonlinear basis estimation, in the case of this study we used tensor product smooths to investigate and illustrate interactions between age, practice, and numerical intelligence: $y_i = f(x_i, z_i, t_i) + \epsilon_i$. The GAMs estimate complex nonlinear interactions in a similar manner to the univariate function, where nonlinear interactions are governed by basis of the functions for x (Practice), z (Intelligence), and t (Age). The nonlinear effect is a superposition (joint effect) between these 3 variables, by assuming that this complex nonseparable function $f(x, z, t)$ can be approximated by the product of simpler functions $f_x(x)$, $f_z(z)$, and $f_t(t)$ at sufficiently small intervals across values for each of the variables.

The results of the GAM cannot be interpreted in the standard linear regression terminology, i.e., change in the outcome dependent on the 1-unit change in independent variable. The GAMs provide information about the wiggliness of the regression line (summarization of all individual functions), and whether the line is significantly different from zero. As in the case of most data-driven and nonlinear methods, the visualization is a necessary tool when interpreting the results.

Age, practice, and numerical intelligence. In the case of the final model (model 4 in Table 1), we included age, practice (number of played games per year), and numerical intelligence in the model as the independent variable and Elo rating as the dependent variable in the mgcv package in R (30). We specified the linear and nonlinear effect for all predictors, as well as the nonlinear interactions between them.

The summary of the model is presented in *SI Appendix*, Table S2 with 2 separate outputs: parametric coefficients and smooth terms. The parametric coefficients in the case of this analysis show the linear effects of the included predictors. In the case when nonlinear effects are not included in the analysis, the parametric coefficients are identical to a standard linear or linear mixed-effect model. The nonlinear interaction and main nonlinear effect are represented in the second section of the table by *te(Age, Practice, Intelligence)* syntax. The results show significant nonlinear interaction between the practice and numerical intelligence across the lifetime. These nonlinear surfaces show the interactive influence of practice and intelligence on the development of performance (Elo rating) across the life span. Finally, the results show the adjusted R^2 and explained deviance, as well as the restricted maximum likelihood score, which is used to model selection criteria (i.e., lower values indicate better fit of the model). Before arriving at the final model, we investigated the influence of intelligence and practice separately. We first fitted the basic model that starts with player's age (model 1). We used model 1 to add various types of intelligence (model 2a for numerical intelligence) and practice (model 2b) in isolation. See *SI Appendix* for the analysis of other intelligence types as well as for corroboration of the results using a different modeling approach, namely linear mixed effects. The additional information on the interpretation of the territory maps (Figs. 3 and 4) can also be found in *SI Appendix*.

Data and Materials Availability. In order to protect the privacy of individuals involved in the study, the data cannot be shared publicly. However, requests will be considered for addressing specific research questions while maintaining the anonymity of the subjects.

The online materials can be retrieved from https://osf.io/k8w6g/.

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