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Superior performance and neural efficiency: The impact of intelligence and expertise

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Abstract

Superior cognitive performance can be viewed from an intelligence perspective, emphasising general properties of the human information processing system (such as mental speed and working memory), and from an expertise perspective, highlighting the indispensable role of elaborated domain-specific knowledge and acquired skills. In exploring its neurophysiological basis, recent research has provided considerable evidence of the neural efficiency hypothesis of intelligence, indicating lower and more focussed brain activation in brighter individuals. The present EEG study investigates the impacts of intelligence and expertise on cognitive performance and the accompanying cortical activation patterns in the domain of tournament chess. Forty-seven tournament chess players of varying intelligence and expertise level worked on tasks drawing on mental speed, memory, and reasoning. Half of the tasks were representative for chess, while the other half was not. The cortical activation was quantified by means of event-related desynchronisation (ERD) in the upper alpha band. Independent effects of expertise and intelligence emerged at both, the performance and the neurophysiological level. Brighter participants performed better than less intelligent ones which was associated with more efficient brain functioning (lower ERD) across all tasks. Additionally, a high expertise level was beneficial for good task performance but exerted a topographically differentiated influence on the cortical activation patterns. The findings suggest that superior cognitive performance and the underlying cortical activation are not only a function of knowledge and domain-specific competences but also of the general efficiency of the information processing system.

Keywords: Chess; Knowledge; EEG; ERD; Learning

1. Introduction

1.1. Intelligence and neural efficiency

Individual differences in cognitive performance are usually described and explained within the framework of human intelligence. Measures of intelligence show a high predictive validity for performance indicators in various areas of life, among them years of education and vocational success (for an overview, see [59]). Intelligence can be partly traced back to general characteristics of the human information processing system, such as mental speed and working memory (WM) capacity. Brighter individuals are assumed to be capable of processing information faster than less intelligent individuals, allowing them to manipulate more information within a given time period [72]. Moreover, several studies have demonstrated substantial correlations between measures of WM capacity and intellectual performance (e.g., [13,66]), suggesting that brighter individuals have a larger mental workspace at hand to perform mental operations and are capable of allocating their attentional resources more effectively than less intelligent individuals [23,60].

In the past two decades, neurophysiological studies have considerably advanced the knowledge about potential biological bases of individual intelligence differences [41]. Increasing support could be gained for the so-called neural efficiency hypothesis of human intelligence, postulating that a higher intelligence level is associated with more efficient brain functioning [48]. Based on numerous findings of negative correlations between participants' intelligence and the amount of brain activation during cognitive performance it was postulated that intelligence is not a function of how hard, but rather how efficiently the brain works, indicated by a more focussed

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use of specific task-relevant areas [47,49]. Evidence in favour of the neural efficiency hypothesis comes from studies applying different research approaches to the human brain: positron emission tomography (PET [44]), single photon emission computed tomography (SPECT [8]), functional magnetic resonance imaging (fMRI [86,88,89]), slow potential topography [67,103], analyses of EEG alpha power [53–55,104], or event-related desynchronisation [21,39,56,74–77].

The quantification of event-related desynchronisation (ERD, originally described by [82]) has proven a particularly useful and appropriate method to measure the level and topographical distribution of cortical activation during cognitive task performance (e.g., implicit and explicit learning [107]; working memory [98,100]; reasoning [73]; visual information processing [84]). It is based on the fact that the amount of alpha background power decreases during cognitive activity as compared to a resting state (for detailed descriptions, see [83]). The functional significance of this event-related measure of oscillatory brain activity can be seen in close relation to the underlying neural networks. Alpha band ERD is assumed to reflect an increased excitability level of neurons in the involved cortical areas, which may be related, for instance, to an enhanced information transfer in thalamo-cortical circuits [78]. Recently, Klimesch et al. [65] have even demonstrated that the relationship between ERD and cognitive performance is not correlative but causal in nature.

A central finding in this context is a differential reactivity of lower and upper alpha frequency bands to specific cognitive demands (cf. [63]). Desynchronisation in the lower alpha band (e.g., 7–10 Hz) has been observed to emerge topographically widespread in response to almost any type of task and is, therefore, presumed to reflect basic arousal or alertness (see also [31]). ERD in the upper alpha band (e.g., 10–12 Hz), in contrast, usually emerges over topographically restricted (task-relevant) areas and is regarded to reflect specific (e.g., sensory–semantic) task requirements [83]. Moreover, studies within the neural efficiency framework have revealed that it is almost exclusively the faster (upper alpha) frequency range that sensitively reacts to individual differences in intelligence and other abilities (e.g., [21,39]).

Although numerous studies have found a lower and/or more focussed upper alpha ERD in brighter individuals during the performance of a variety of cognitive demands (ranging from elementary cognitive to reasoning tasks and covering verbal, numerical as well as figural material; cf. [39]), the generality of the neural efficiency effect has been qualified. A moderating variable seems to be the degree to which the tasks draw on contents stored in long-term memory [20,39,57,64]. For instance, administering a task which required extensive access to semantic memory, Klimesch et al. [64] found that good memory performers displayed a higher ERD in the upper alpha band, while the opposite pattern was observed when presenting tasks which drew less on long-term memory [39]. A second moderating variable seems to be the external criterion to which cortical activation patterns are related. Some studies from our laboratory reported higher correlations of upper alpha ERD with tests of fluid (versus crystallised) intelligence [73,39]. Moreover, it appears that a negative intelligence–activation relationship only emerges if the type of intelligence measured is directly related to the cognitive demands under investigation. In the study of Neubauer et al. [76], for instance, the neural efficiency phenomenon emerged for males only in the figural and for females only in the verbal condition. The strength of the association, however, was additionally moderated by the intelligence component: while in the females the negative relationship was observed exclusively for the verbal IQ, in the males it emerged solely for the figural IQ—in both cases, for those intelligence components that matched the cognitive tasks given in the EEG session.

1.2. Expertise and neural efficiency

The impact of intelligence on individual performance differences has sometimes been challenged by findings from expertise research (e.g., [7,70]). Studies investigating expert performers in manifold domains (for an overview, see [28]) have contributed to the notion that superior domain-specific performance is largely independent of the experts' general intelligence level. Instead, they emphasise the indispensable (and assumedly also sufficient) role of a large and elaborate knowledge base which is considered to be the result of more than a decade's experience and intense deliberate practice in the respective domain [29].

A central characteristic of experts is that they usually display superior performance only if confronted with representative tasks from their expertise domain, whereas they perform no better than non-experts (novices or laypersons)[1] in domain-unspecific or non-representative demands [27]. This was mainly demonstrated by using a memory paradigm pioneered by De Groot [17] and popularised by Chase and Simon [9], who exposed three chess players (a chess master, an intermediate player, and a beginner) to chess positions for the brief time period of 5 s. A part of the positions were meaningful game positions (i.e., middle game positions from actual tournament games), a part of them were meaningless random positions (i.e., middle game positions in which the pieces were randomly scattered across the board). The participants' task was to memorise the briefly presented position and to reconstruct it afterwards on a blank board. As expected, the master player placed the majority of pieces correctly after only one exposure to the position (on average about 16 out of 25 pieces on the board), while the intermediate player and the beginner could only reconstruct the locations of 8 and 4 pieces, respectively. However, when the players were presented the random positions, absolutely no relation was observable between memory performance and playing strength; only about three pieces were reproduced correctly by the three players (for replications, see, e.g., [37,93]). This result is usually explained in the framework of the chunking theory of expertise [36]: experts would have acquired a large database of chunks which allows them to recognise familiar patterns of pieces on a chess board and to store them parsimoniously as

[1] In contrast to laypersons who are defined as persons without any domain-specific knowledge, novices differ from experts mainly in their experience or practice. In the domain of chess, for example, novices are persons who know how to play the game and who occasionally but not regularly play chess, whereas laypersons do not even possess the core knowledge of the rules.

chunks in short-term memory (STM [38]). The superior playing strength of expert players is also explained with pattern recognition: if a player is confronted with a chess position, the respective chunks in long-term memory are automatically activated and guide the search in their knowledge base along profitable lines [15].

That experts exhibit superior memory performance only for meaningful material from their domain has not only been found in chess players but also in experts from several other domains, ranging from GO to football (for an overview, see [27]). This finding seems to rule out explanations that refer to general properties of the information processing system. If experts processed information generally faster or if they had a larger capacity of short-term or working memory, this should also be apparent for non-representative or domain-unrelated material. Direct support for the importance of domain-specific knowledge comes from studies which extended the traditional expert–novice comparison by the factor (lower versus higher) intelligence [95,94,99,106]. By analysing domain-specific memory performance, it was observed that individuals who score low on intelligence but high on domain-specific knowledge (e.g., in baseball or football) perform at least as well as participants with high intelligence and low knowledge. Moreover, domain knowledge was repeatedly found to outweigh intelligence or domain-general resources in its impact on domain-specific performance. Hambrick and Engle [50], for instance, investigated the interplay between domain knowledge and WM capacity on the memory performance for baseball radio broadcasts and observed that baseball knowledge accounted for almost 55% of the performance variance, while WM capacity revealed an independent but considerably smaller impact (accounting for less than 10% of the variance; for replication and extension, see [51]).

A recent study from our research group suggests that intelligence may not only lose its impact at the performance but also at the neurophysiological level when expertise comes into play [40]. We measured the ERD of 31 professional taxi drivers of varying non-verbal intelligence while they were performing two types of tasks. In the so-called expertise task, participants were presented potential taxi routes of their city which had to be memorised. Afterwards, several street names were displayed, and the taxi drivers had to decide whether or not the street crosses the previously memorised route. Unlike the expertise task, which directly referred to the taxi drivers' knowledge, the second experimental task was devised to be independent of their expertise but to engage their general mental ability. In this task (called intelligence task), they again had to memorise a route, but now on a fictional, abstract city map. In line with the neural efficiency hypothesis we observed that the total cortical activation of the brighter individuals was lower than that of their less intelligent counterparts, but only in the intelligence task. In the expertise task, though, no intelligence-related effect was observed. Although the results in the expertise task suggest that the professional taxi drivers may have acquired neural efficiency as a result of long-term practice and experience, this question was not addressed in this investigation as no comparison between more and less proficient taxi drivers was performed.

Neurophysiological examinations of experts and novices during cognitive performance, however, have revealed activation patterns contradicting the neural efficiency hypothesis: in most cases, experts either displayed a higher activation in task-related brain areas and/or recruited additional areas that were involved in domain-specific strategies [34,52,69,80,101]. As an example, Maguire et al. [69] compared the brain activation of 10 world-class mnemonic experts with 10 matched controls by means of fMRI. During memorising (visually presented) numbers, faces, and other figures, the experts additionally activated brain areas that are implicated in spatial memory and navigation, such as medial parietal cortex, right posterior hippocampus, and right cerebellum. In contrast, there were no regions with stronger activation in controls. In a subsequent debriefing of the subjects, 9 of 10 experts reported to apply the mnemonic "method of loci" in which items are visualised and encoded in salient places along a route acting as retrieval cue (cf. [25]). Hence, the brain regions additionally recruited by the experts most likely reflect their more effective mnemonic strategy.

1.3. Aims of the present study

To sum up, numerous studies have drawn the relatively consistent picture that superior performance in experts is determined by an elaborate knowledge base, whereas intelligence is of no or only minor relevance. However, as yet, there has been a strong focus on memory tasks in domains that may be considered not to require complex cognitive processes associated with intelligence. Therefore, the goal of the present study is to investigate the interaction between intelligence and an elaborate knowledge base more thoroughly in the cognitively demanding domain of chess expertise. This domain not only provides well-established experimental paradigms but thanks to the ELO system also an objective and precise indicator for the assessment of the individuals' level of expert knowledge [22,87]. To cover a broad range of cognitive demands, three types of tasks with chess material are employed, drawing on central components of information processing (mental speed, memory, and reasoning). Moreover, each task is administered in a representative and non-representative version for the domain of chess to examine under what conditions expertise loses its impact and intelligence comes into play.

The major focus of the present study is the registration of cortical activation while working on the experimental tasks. On doing so, we intend to clarify two aspects related to neural efficiency. The first concerns the claim according to which brighter individuals generally show more focussed and therefore lower cortical activation. In the aforementioned study with taxi drivers, Grabner et al. [40] demonstrated that the negative intelligence–cortical activation relation diminishes if experts' domain knowledge is involved. Whether this may also be the case in the cognitively more demanding domain of chess will be investigated. The second aspect refers to the impact of intelligence as compared to that of expert knowledge on cortical activation patterns. While considerable evidence exists for a negative relationship between intelligence and cortical activation, neurophysiological studies of expert performers have revealed that their activation is often higher and/or more widespread than that of novices. Hence, it is examined in which task demands and conditions the cortical activation patterns are a function of intelligence and expertise, and how the activation patterns are related to them. Additionally, given the differential impact of distinguishable intelligence components on cortical activation, the relevance of verbal, numerical, and figural intelligence is evaluated.

In accordance with our previous studies in the neural efficiency framework, the amount of cortical activation during task performance is quantified by means of the ERD in the upper alpha band. This measure was chosen because it not only displays high sensitivity to individual differences in ability and performance measures but also to different cognitive demands, including those administered in the present investigation.

2. Materials and methods

2.1. Participants

Out of an original pool of 90 Austrian tournament chess players recruited at regional chess clubs, a sample of 55 male players participated in the present study. All participants were right-handed, had normal or corrected-to-normal vision, and did not indicate any medical or psychological disorders. The data of eight participants had to be excluded from further analyses due to massive EEG artefacts (particularly muscle artefacts) during at least one experimental task. The remaining sample consisted of 47 male tournament chess players between 18 and 65 years ($M = 37.45$, S.D. = 13.16). Their playing strength was assessed by means of the national ELO ranking, which ranged between 1325 and 2338 ELO ($M = 1893$, S.D. = 227).[2] The sample also covered a broad range of intelligence (I-S-T 2000 R general IQ from 80 to 144; $M = 117.62$, S.D. = 13.97) and educational background (from basic education to university degree). The participants' intelligence structure displayed a slight advantage for numerical IQ ($M = 119.39$, S.D. = 13.87) as compared to verbal ($M = 111.69$, S.D. = 12.09) and figural IQ ($M = 110.08$, S.D. = 15.98). Participants were paid for their participation in the EEG sessions, and all gave written informed consent.

2.2. Psychometric tests

Participants were screened with regard to their cognitive abilities and various chess-related variables (such as developmental milestones, attitudes, and practice activities). The German version of the NEO-Five-Factor-Inventory (NEO-FFI [5]), the state anxiety test (STAI [68]), and an unpublished questionnaire on participants' mood (cf. [30]) were administered to be considered as control variables for the EEG data (e.g., [16]). Cognitive abilities were assessed by the well-established German intelligence structure test 2000 revised (Intelligenz-Struktur-Test 2000 R, I-S-T 2000 R [2]). This test draws on (a) verbal intelligence, (b) numerical intelligence, (c) figural intelligence, and, at a more general level as a total score consisting of the three content factors, on (d) reasoning or general intelligence.

[2] ELO rankings typically range from 1200 (for a beginner in tournament chess) to the world champion's ranking of about 2800. Every time a player participates in an official tournament and wins against a stronger opponent, his or her ELO ranking slightly increases by a certain number of points (calculated as a difference function between the players' actual game results and the expected game results based on the player's own ELO ranking and those of his or her opponents); in the case of a defeat, the player's ELO ranking decreases. Since the testing of the participants covered a time period of over 1 year and the national ELO ranking list is updated every 6 months (in January and July), the ELO rankings were aggregated over the respective time periods in the present sample (i.e. from July 2003 to July 2004).

2.3. Experimental tasks

The experimental tasks draw on speed of information processing, memory, and reasoning as cognitive processes. All tasks were realised with chess figures as stimulus material. For each cognitive process the demands of one task version were representative for the domain of chess (i.e., participants could draw on their expert knowledge of chess), while in the other task version they were not. In all tasks, the number of correctly solved items as well as the reaction times were assessed.

2.3.1. Speed task (ST)

This task is similar to the enumeration task by Saariluoma [90–92]. Participants had to count the number of minor pieces (i.e., bishops and knights) of chess positions presented on a screen as fast as possible (see Fig. 1a). When finished, participants pressed a response button, and after the stimulus had disappeared from the screen, they had to enter the correct answer (number of minor pieces on the board) into an input box. In the representative condition the test items (chess positions) were middle game positions while in the non-representative condition they were random positions. Similar to previous studies, all game positions were selected from an international database of tournament chess games [11] in which white was to move. The positions comprised between 19 and 28 pieces, the number of minor pieces was varied between 4 and 8. In the non-representative condition, positions were presented that were entirely randomised by the computer (cf. [102]). This means that not only the location of pieces on the board was random but also the selection of pieces out of the complete set (32 pieces). Random positions were selected in a way that the total number of pieces (19–28), the number of target pieces (4–8), and the black–white distribution of target pieces largely match the game positions. Since randomising might accidentally also produce meaningful middle game positions, all positions were additionally inspected by an advanced tournament player. In total, 10 practice trials and 60 test trials (30 game and 30 random positions) were presented, in which game and random positions were presented in a mixed pseudo-randomised order.

2.3.2. Memory task (MT)

A modified version of the classical board reconstruction task [9,10] was administered. Participants were presented a chess position for 10 s, and after a blank-screen period of 2 s, the same chess position was presented again but the location of one piece had changed (see Fig. 1a). By button press, they had to indicate out of four given choices which piece had been moved. In total, 6 practice trials and 50 test trials (25 game and 25 random positions) were presented in pseudo-randomised order. The selection of game positions was similar to the procedure in the ST. The pieces that had changed their location were selected in order to achieve an equal distribution of the different pieces (king, queen, bishop, knight, rook, and pawn) and a larger number of trials in which the location of the pawn had changed. It has to be noted that the location changes of the pieces in the game positions were constructed in such a way that they do not necessarily reflect a plausible next move; participants were also instructed about that. Random positions were again generated by the computer and inspected by the same tournament player as in the ST. The selection of targets for the game positions was done in a comparable way.

2.3.3. Reasoning tasks: mate-in-one task (RMT) and exchange task (RET)

The third type of task should draw on more complex reasoning processes. Undoubtedly, one cannot imagine a more representative reasoning demand than asking participants to find out the next best move for a given position. To ensure that the next best move can be determined objectively, only mate-in-one positions were administered. In total 30 test trials and additional 5 practice trials of varying difficulty level were created by a local chess grandmaster and presented to the participants. After the position appeared on the screen, the participants were required to find out as fast as possible the only move that checkmates black. By pressing a response button, the chess position disappeared on the screen. The participants then had to vocalise the correct move, which was recorded by the experimenter.

In the non-representative reasoning task also chess material should be used, but the reasoning process triggered off should be different from chess playing. Therefore, a modified version of the exchange task from Schweizer [96] was devised (reasoning exchange task, RET), where participants were presented with

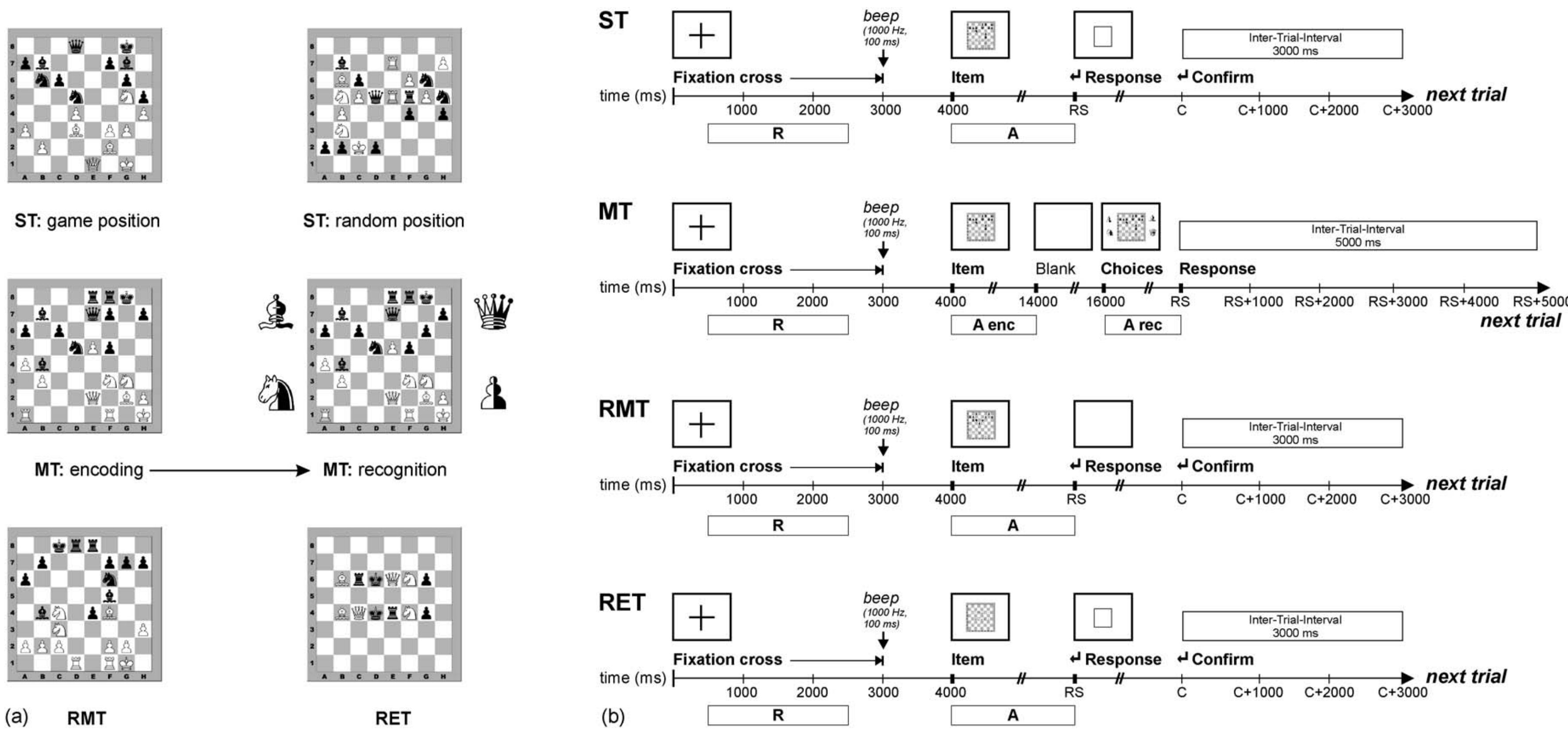

Fig. 1. (a) Example items of the experimental task. Speed task (ST), memory task (MT), and reasoning: mate-in-one task (RMT), reasoning: exchange task (RET). The correct solutions are—ST (number of minor pieces): game position (7), random position (6); MT (piece that changed location): pawn; RMT (move that checkmates black): Sc4-b6; RET (number of necessary pairwise exchanges): 3. (b) Trial sequences in the experimental tasks. R: reference interval. A: activation interval (enc, MT encoding phase; rec, MT recognition phase). RS: response (button press). C: confirmation of answer (button press).

two lists of six chess pieces on the board (see Fig. 1a). Both lists included the same pieces but differ regarding their positions. The participants were instructed to exchange the positions of neighbouring pieces of one list mentally until identical sequences of pieces are achieved, to count the number of necessary pairwise exchanges, and to indicate the correct answer after button press. This task offers the great advantage that different degrees of complexity can be constructed by varying the number of necessary exchanges [97]. In total, 35 test and 5 practice items of varying complexity level (from 1 to 4 necessary exchanges) were presented. Moreover, 11 test items comprised only white pieces, 11 only black, and 13 items 3 white and 3 black pieces; in all test items, all 6 pieces (king, queen, bishop, knight, rook, and pawn) were used.

In contrast to the other experimental tasks, in which game and random positions were presented in a pseudo-randomised order, the two reasoning tasks were presented separately.

2.4. Procedure

The EEG recording started with two 3-min EEG sequences under resting conditions, the first with eyes closed and the second with eyes open. Subsequently, the participant started to work on the first experimental task, the ST. The presentation order of the remaining experimental tasks was counter-balanced across all participants (the easiest and shortest lasting ST was presented first to prime the participants to give their answers as fast as possible in all tasks). After each task, short breaks of a few minutes were allowed. Following the last experimental task, another two 3-min EEG sequences (first with eyes open and second with eyes closed) were recorded.

2.5. Apparatus/EEG recording

For the presentation of the experimental tasks, a PC (g.STIMunit, g.tec, Austria) with external response consoles was used. In the ST and RET the response console consisted of a numerical keyboard (among others consisting of number buttons, a backspace, and an enter key) which allowed the input of the number of minor pieces and the number of exchanges, respectively. A board with six buttons (2×2 horizontally and vertically arranged plus two buttons at the bottom) was provided in the MT and RMT, by which the participants could indicate their response (pressing the response keys at the bottom), and choose from the four (also 2×2 arranged) answer options in the MT (see Fig. 1a).

The EEG was measured by means of gold electrodes (9 mm diameter) located in an electrode cap in the following 33 positions (according to the international 10–20 system): FP_1, FP_2, AF_3, AF_4, F_7, F_3, F_Z, F_4, F_8, FC_5, FC_1, FC_2, FC_6, C_3, C_Z, C_4, CP_5, CP_1, CP_2, CP_6, T_3, T_4, T_5, T_6, P_3, P_Z, P_4, PO_5, PO_3, PO_4, PO_6, O_1, and O_2. The reference electrode was placed on the nose, the ground electrode on the forehead. To register eye movements, an electrooculogram (EOG) was recorded bipolarly between two gold electrodes diagonally placed above and below the inner, respectively, the outer canthus of the right eye. Electrode impedances were kept below 5 kΩ for the EEG and below 10 kΩ for the EOG. EEG and EOG were recorded by means of a DELTAMED amplifier (ISO 1064 CE) and NEUROFILE NT recording software (IT-MED, Germany) at a bandwidth of 0.01–100 Hz and a sampling rate of 256 Hz.

2.6. EEG data analyses

Data were analysed with g.BSanalyze software (g.tec, Austria). All data were digitally filtered with a 35 Hz low pass Fast-Fourier-Transformation (FFT) filter; moreover, to correct electrode and amplifier drifts from the raw data, a moving exponential window (256 samples with an overlap of 255 samples) was calculated and subtracted.

2.6.1. Resting EEG data: quantification of IAF

The resting EEG data (eyes closed and eyes open) were analysed to determine the individual alpha frequency (IAF) as an anchor point for the definition of the upper alpha band (for a review, see [63]). The IAF can be defined either as the frequency with the highest amplitude (mean frequency) or as the centre of gravity (gravity frequency) within the alpha frequency range (approximately between 7 and 13 Hz). As a recent study by Neuper et al. [79] has demonstrated that the gravity frequency displays a considerably higher level of reliability and long-term stability than the mean frequency, in the present study the IAF was determined by means of the gravity frequency, which reflects the weighted sum of spectral estimates within the alpha frequency range. To obtain a high frequency resolution, the IAF was estimated by computing FFT on 90% overlapped 10-s Hanning windows, separately for each resting EEG condition. After averaging over all trials, the centre of gravity in the range between 7 and 13 Hz was calculated for each electrode position. For defining the upper alpha frequency range, the IAFs were first aggregated over all electrode positions and then over both resting conditions with eyes open, yielding a mean IAF of 9.59 (S.D. = 0.36; range: 8.93–10.31 Hz). The upper alpha frequency band is defined as: IAF to (IAF + 2 Hz).

2.6.2. Task EEG data: quantification of ERD

As depicted in Fig. 1b, each EEG trial started with the presentation of a fixation cross for 3000 ms, followed by an auditory warning stimulus. For all experimental tasks, the time period between 500 and 2500 ms served as reference interval for the ERD calculation. The respective activation intervals in the ST, RMT, and RET covered the entire time period from stimulus onset (after 4000 ms) to the response (pressing the response button). In the MT, two activation intervals were analysed: the time period from 4000 to 14,000 ms (encoding phase, see task description above) and from 16,000 ms to the response (recognition phase, choosing an answer option). Because of the difficulty of interpreting incorrectly solved test trials (which might be traced to a lack of competency or to a lack of motivation or both), only correctly solved trials were included in the ERD analyses. In all remaining trials, the reference intervals (during the fixation cross) and the activation intervals were checked individually for artefacts (eye movements, eye blinks, muscle artefacts, etc.) by visual inspection. Time periods containing artefacts were completely eliminated from the ERD analyses. The power of background activity in the upper alpha band was computed for both time intervals and each trial. Then, the band power in the reference and activation intervals was averaged over all (valid) trials. Only participants were included which met the criterion of at least six valid trials (i.e., correctly solved and at least 500 ms artefact free recording time) in each task version and task, respectively.[3] The percentage decrease (or increase) in power (μV^2) from the (aggregated) reference interval (R) to the (aggregated) activation interval (A) was computed according to the following formula: $\%ERD/ERS = [(R - A)/R] \times 100$. This procedure is comparable with the analyses of "task-related" band power, as described by Pfurtscheller [81]. Positive %ERD values indicate desynchronisation (decreases of alpha power, indicative of cortical activation), negative %ERD values reflect synchronisation (ERS; increases of alpha, indicative of cortical deactivation).

Based on visual inspection of the topographical distribution of ERD data for different electrode locations, for statistical analyses, the ERD data were aggregated over different electrode locations, distinguishing the hemispheres as well as anterior from posterior areas, as following: anteriofrontal left (FP_1 and AF_3), frontal left (F_7 and F_3), frontocentral left (FC_5 and FC_1), centrotemporal left (C_3 and T_3), centroparietal left (CP_5 and CP_1), parietotemporal left (P_3 and T_5), and parietooccipital left (PO_5, PO_3, and O_1), likewise for the right hemisphere using the corresponding homologous electrodes. The midline electrodes (F_Z, P_Z, and C_Z) were not included in the analyses, as also hemispheric differences were to be investigated.

2.7. Statistical analyses

In all analyses, the different task demands (speed, memory, and reasoning) and versions (representative versus non-representative) are considered simultaneously in one repeated measures design. Thereby, not only differences between cognitive demands with respect to expertise and intelligence influences can be assessed, but also the number of analyses and, thus, the probability of Type-I errors is reduced. Since general intelligence and expertise (ELO ranking) were not significantly correlated in the present sample ($r = .22$, $p = .14$), in a first step, an ANOVA for repeated measures with general IQ and ELO

[3] The average number of artefact-free trials and the average length of analysed time epochs were considerably larger than this minimum requirement—ST: 29 game (3.04 s) and 28 random trials (3.72 s); MT: 19 game (encoding: 9.72 s and recognition: 5.60 s) and 16 random trials (encoding: 9.74 s and recognition: 6.43 s); RMT: 27 trials (11.40 s); RET: 32 trials (7.93 s).

Table 1
Descriptive statistics (including estimates of reliability and validity) of the experimental tasks

	Minimum	Maximum	*M*	S.D.	Rel[a]	$Val._{ELO}$	$Val._{g}$
Solution rates (%)							
ST: game positions[b]	83.33	100.00	97.16	4.11	.50	.22	.27
ST: random positions[b]	73.33	100.00	94.54	5.92	.54	.15	.24
MT: game positions	36.00	96.00	78.64	14.26	.75	.49**	.54**
MT: random positions	24.00	92.00	63.66	16.88	.72	.25	.53**
RMT	70.00	100.00	93.55	6.75	.63	.60**	.46**
RET[b]	57.14	100.00	92.04	9.77	.80	.07	.46**
Median response latencies (s)							
ST: game positions	1.95	7.79	3.35	1.26	.99	−.49**	−.36*
ST: random positions	2.19	8.09	4.01	1.44	.98	−.43**	−.30*
MT: game positions	2.22	16.52	6.09	3.02	.90	−.47**	−.39**
MT: random positions	2.74	19.46	6.95	3.09	.89	−.33*	−.10
RMT	3.85	42.95	12.34	6.77	.92	−.70**	−.42**
RET	4.07	22.91	8.56	3.78	.96	−.27	−.52**

Note: The median response latencies were computed only for correctly solved items (similar to the following ERD analyses). Speed task (ST), memory task (MT), reasoning: mate-in-one task (RMT), and reasoning: exchange task (RET). $Val._{ELO}$: criterion validity for (correlation with) ELO ranking; $Val._{g}$: criterion validity for (correlation with) general intelligence (I-S-T 2000 R general IQ).

[a] Reliability coefficients reflect Cronbach alpha coefficients of internal consistency for the item scores (correct vs. incorrect) and the response latencies, respectively.

[b] These variables are not normally distributed; non-parametric correlations with ELO ranking (criterion validity), however, yield largely comparable coefficients.

* $p < .05$.

** $p < .01$.

as between-subjects variables (both median-split) is computed. This analysis allows the detection of potential interactions between the ability indicators (IQ and ELO). The median-split of the sample into two groups of general intelligence and expertise results in the following distributions of IQ and ELO: lower IQ group ($n = 23$; general IQ: 80–118, $M = 105.86$, S.D. = 9.41), higher IQ group ($n = 24$; general IQ: 119–144, $M = 128.88$, S.D. = 5.93); lower ELO group ($n = 24$; ELO: 1325–1942, $M = 1717$, S.D. = 164.32), higher ELO group ($n = 23$; ELO: 1947–2338, $M = 2076$, S.D. = 105). Prior to the performance and ERD analyses, the groups of higher versus lower abilities (intelligence and expertise, respectively) were investigated regarding group differences in variables that could potentially confound the effects on performance and/or cortical activation patterns, i.e., participants' personality (e.g., [32]), anxiety and mood (e.g., [16]). A MANOVA with the above-mentioned group factors as between-subjects variables and the scores of the NEO-FFI, STAI, and mood questionnaire as dependent variables did neither reveal significant main effects nor an interaction.

In a second step, it shall be examined which intellectual ability components are (besides ELO) particularly relevant for performance and for cortical activation patterns. For this purpose, an ANCOVA with the distinct intelligence components (verbal, numerical, and figural intelligence) and ELO ranking as covariates are performed. Thereby, the independent contributions of each content factor can be evaluated. This procedure is guided by the already outlined findings of a high specificity of cortical activation patterns to distinguishable indicators of intellectual ability (cf. [76]).[4]

In all analyses, degrees of freedom were corrected for violations of the sphericity assumption by means of the Greenhouse Geisser procedure; the probability of a Type-I error was maintained at .05.

3. Results

3.1. Task performance

Table 1 provides an overview of the participants' performance in the experimental tasks as well as the tasks' internal consistency and criterion validity with regard to expertise (ELO ranking) and general intelligence. Given that the solution rates in the ST and reasoning tasks are relatively high (on average above 90%), the low reliability coefficients can largely be attributed to a ceiling effect in these tasks.

The bivariate correlations of task performance with ELO ranking already point to a successful task construction. High coefficients emerged for the representative task versions, in particular for the MT (r of .49 and −.47 for the solution rate and response latency, respectively), and, even more pronounced, for the RMT (.60 and −.70, respectively), while the non-representative task demands apparently resulted in smaller coefficients—apart from the ST, in which both conditions correlate with ELO at an almost equal level. The correlations between task performance and general intelligence draw a differing picture. In contrast to playing strength, general intelligence displays high and significant associations for the task performance in the non-representative demands (except for the response latency in the MT random condition). Expectedly, also the task performance in the RET shows a stronger (and significant) relation to IQ as compared to the ELO ranking. The most obvious difference to the ELO validity, however, lies in the fact that general intelligence appears to be associated with performance in all tasks, almost independently of whether the task demand is representative or not.

In the following, the impact and interplay of intelligence and expertise is investigated more thoroughly. As the assessed response latencies appear to be more reliable performance measures than the solution rates in all tasks, these are examined first and reported more elaborately.

3.1.1. Response latencies

As described in Section 2.7, first, a four-way multiple measures ANOVA with TASK DEMAND (speed, memory,

[4] Additional analyses were conducted with age partialled out to uncover its potential moderating role on the expertise and intelligence effects. Since these analyses, however, did not change the overall pattern of results, they are not reported here.

Table 2
Effects of the ANOVA for median response latencies in the experimental tasks

	d.f.	F	η^2
Between-subjects			
ELO	1, 43	10.29**	.19
IQ-GROUP	1, 43	10.36**	.19
Within-subjects			
TASK DEMAND	1.73, 74.22	134.17**	.76
TASK DEMAND × ELO	1.73, 74.22	8.23**	.16
TASK DEMAND × IQ-GROUP	1.73, 74.22	10.08**	.19
STRUCTURE	1, 43	7.55**	.15
STRUCTURE × ELO	1, 43	12.56**	.23
TASK DEMAND × STRUCTURE	1.22, 52.36	28.26**	.40
TASK DEMAND × STRUCTURE × ELO	1.22, 52.36	6.26*	.13

Note: For the sake of clarity, only significant effects of the between- and within-subjects variables are presented.
* $p < .05$.
** $p < .01$.

and reasoning) and STRUCTURE (representative versus non-representative) as within-subjects variables, and ELO (lower versus higher playing strength) and IQ-GROUP (lower versus higher general intelligence) as between-subjects variables was computed. A summary of all significant effects is presented in Table 2.

Both between-subjects factors, ELO and IQ-GROUP, had significant and equally strong, large-sized effects on the median response latencies. As expected, stronger players responded significantly faster than weaker players (5.84 s versus 7.91 s), likewise is observable for general intelligence (5.84 s versus 7.91 s [sic!]). The response latencies also differed significantly between the different task demands (3.68 s versus 6.51 s versus 10.44 s, for ST, MT, and reasoning tasks, respectively) and between the representative and non-representative variants (7.24 s versus 6.51 s). The latter effect emerges because of the different reasoning tasks, in which the usually observable effect of smaller response latencies in game positions (representative demands) is inverted (12.34 s versus 8.56 s for RMT versus RET; as compared to ST: 3.35 s versus 4.01 s and MT: 6.08 s versus 6.94 s for game versus random positions, respectively); this effect becomes salient in the TASK DEMAND × STRUCTURE interaction. The interactions between TASK DEMAND and the between-subjects variables are presented in Fig. 2a, suggesting increasing group differences in response latencies across the ST, MT, and reasoning tasks. Here again, effects of ELO and IQ-GROUP are largely parallel and practically of equal size. The STRUCTURE × ELO interaction reveals larger differences between stronger versus weaker players in the representative than in the non-representative task demands; this effect, however, is additionally moderated by TASK DEMAND. As depicted in Fig. 2b, interactions between STRUCTURE and ELO are only observable in the MT and reasoning tasks, while in the simple enumeration task (ST), no interaction can be observed.

Finally, to evaluate whether a lower intelligence could be compensated for by a high level of expertise in task performance, the main effects of ELO and IQ-GROUP are depicted within one diagram. As revealed in Fig. 2c, across all tasks, brighter but weaker players perform at a similar level as less intelligent but stronger players.

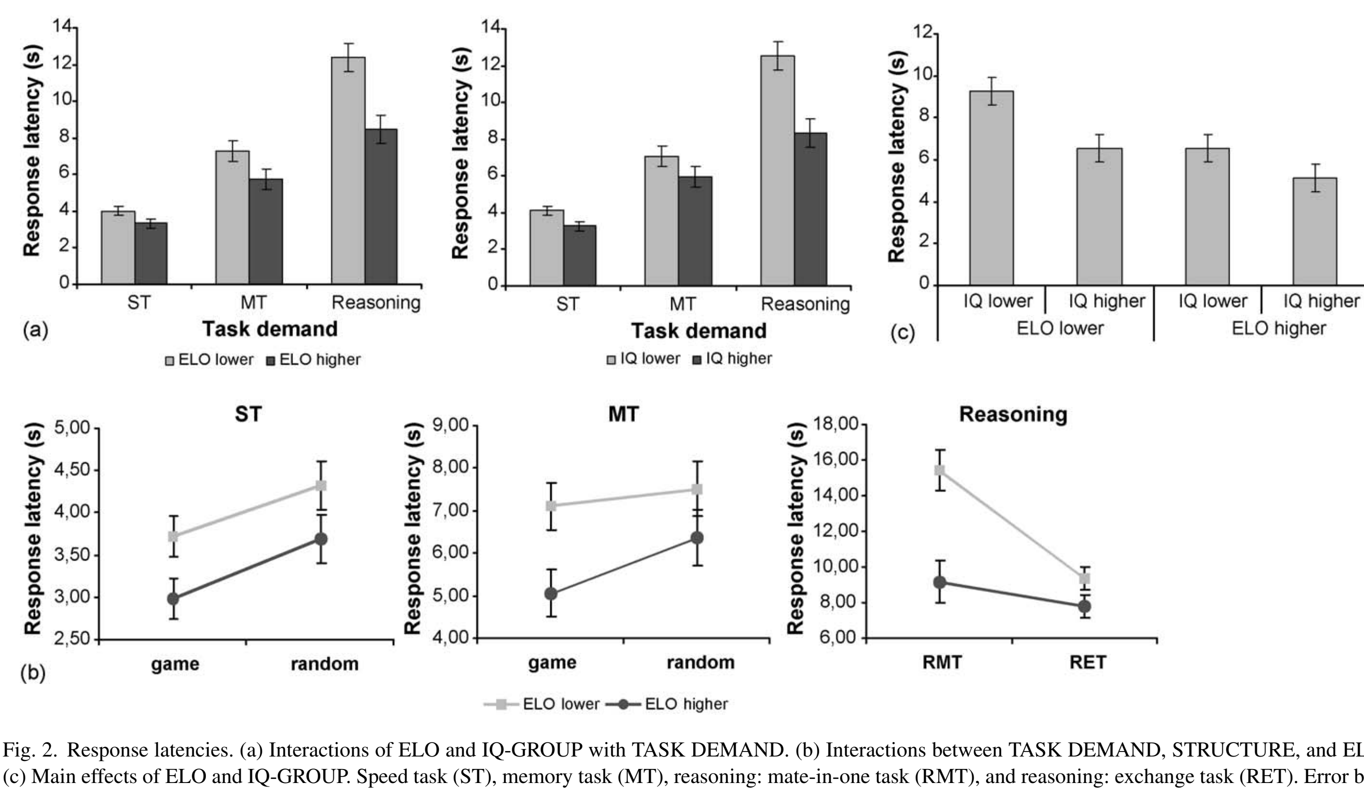

Fig. 2. Response latencies. (a) Interactions of ELO and IQ-GROUP with TASK DEMAND. (b) Interactions between TASK DEMAND, STRUCTURE, and ELO. (c) Main effects of ELO and IQ-GROUP. Speed task (ST), memory task (MT), reasoning: mate-in-one task (RMT), and reasoning: exchange task (RET). Error bars indicate ±1S.E. of the mean.

For examining the absolute and relative importance of the intelligence components independent of playing strength, a repeated measurement ANCOVA with TASK DEMAND (speed, memory, and reasoning) and STRUCTURE (representative versus non-representative) as within-subjects variables, and ELO ranking plus verbal, numerical, and figural intelligence as covariates was computed. Besides the ELO effects outlined above, a significant main effect of figural intelligence, $F(1, 42) = 6.51$, $p < .05$, $\eta^2 = .13$, and a significant interaction between TASK DEMAND and figural intelligence was observed, $F(1.71, 71.99) = 4.50$, $p < .05$, $\eta^2 = .10$. Additionally, the three-way interaction TASK DEMAND × STRUCTURE × numerical intelligence reached significance, $F(1.35, 56.59) = 6.60$, $p < .01$, $\eta^2 = .14$. In all tasks, participants with higher figural intelligence displayed lower response latencies than those with lower figural intelligence, and this effect slightly increases across the different task demands, resembling the effect of general intelligence. The three-way interaction with numerical intelligence derives from a larger group difference in the RET as compared to the other tasks and conditions.

3.1.2. Solution rates

The solution rates are analysed by means of the same statistical approach as was pursued for the response latencies. However, because of the observed ceiling effects and the lack of normality in some of the variables, these results should be interpreted with care.

The significant effects of the four-way multiple measures ANOVA with TASK DEMAND and STRUCTURE as within-subjects variables, and ELO as well as IQ-GROUP as between-subjects variables are presented in Table 3. The solution rates differed significantly between the different task demands (95.87% versus 71.08% versus 92.80%, for the ST, MT, and reasoning tasks, respectively) and between the two task variants (89.82% versus 83.34%) suggesting a higher solution rate in the representative than in the non-representative condition. As the interaction between TASK DEMAND and STRUCTURE reveals, the latter difference between the two task conditions is especially pronounced in the MT (78.67% versus 63.49%), whereas in the ST and reasoning tasks the representative and non-representative condition led to high solution rates (97.18% versus 94.55% in the ST and 93.61% versus 91.98% in the reasoning tasks). Likewise, the interaction between TASK DEMAND and the between-subjects variables indicates larger group differences in the MT (75.75% versus 66.42% for ELO higher versus lower, and 80.67% versus 61.50 % for IQ higher versus lower) as compared to the ST (97.07% versus 94.65% and 97.15% versus 94.58%, for ELO and IQ-GROUP, respectively) and the reasoning tasks (94.66% versus 90.93% and 95.23% versus 90.36%).

On average, brighter individuals outperformed less intelligent ones (91.02% versus 82.15%), and stronger players their less-skilled counterparts (89.16% versus 84.00%). Contrary to the response latencies, however, the effect of IQ-GROUP is considerably larger than the ELO effect, which seems rather due to the tasks with non-representative demands (see Fig. 3). Most interesting appears the three-way interaction between STRUCTURE and both between-subjects variables which is depicted in Fig. 3. Experts perform at a high level in the representative task demands, almost independent of intelligence, while intelligence exerts a strong impact on the performance in the group of lower playing strength. Stated differently, a high degree of expertise (or ELO) can not only compensate for a low

Table 3
Effects of the ANOVA for solution rates (%) in the experimental tasks

	d.f.	F	η^2
Between-subjects			
ELO	1, 43	20.76**	.33
IQ-GROUP	1, 43	61.29**	.59
Within subjects			
TASK DEMAND	1.62, 69.70	226.07**	.84
TASK DEMAND × ELO	1.62, 69.70	4.17*	.09
TASK DEMAND × IQ-GROUP	1.62, 69.70	25.04**	.37
STRUCTURE	1, 43	48.70**	.53
STRUCTURE × ELO × IQ-GROUP	1, 43	6.17*	.13
TASK DEMAND × STRUCTURE	1.64, 70.57	24.09**	.36

Note: For the sake of clarity, only significant effects of the between- and within-subjects variables are presented.
* $p < .05$.
** $p < .01$.

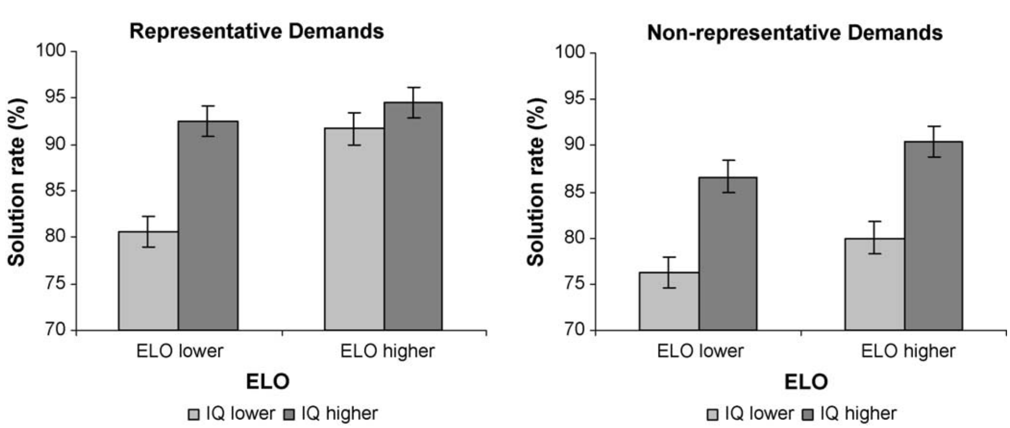

Fig. 3. Solution rates. Interaction between ELO, IQ-GROUP, and STRUCTURE. Error bars indicate ±1S.E. of the mean.

Table 4
Effects of the ANOVA for upper alpha %ERD in the experimental tasks

	d.f.	F	η^2
TASK DEMAND	2.54, 109.12	9.64**	.18
STRUCTURE	1, 43	5.99**	.12
AREA	1.79, 76.79	17.63**	.29
TASK DEMAND × AREA	3.71, 159.56	3.77**	.08
TASK DEMAND × STRUCTURE × HEMISPHERE	2.09, 89.74	4.53*	.10

Note: For the sake of clarity, only significant effects are presented.
* $p < .05$.
** $p < .01$.

intelligence—intelligence entirely loses its impact in the group of experts. In the non-representative task demands, in contrast, intelligence and expertise display independent effects, with the effects of intelligence being much more prominent than effects of ELO.

The ANCOVA with the verbal, numerical, and figural intelligence components (plus ELO ranking) revealed a significant main effect of numerical intelligence, $F(1, 42) = 9.52$, $p < .01$, $\eta^2 = .19$, and figural intelligence, $F(1, 42) = 5.48$, $p < .05$, $\eta^2 = .12$, as well as interactions of them with the experimental tasks, TASK DEMAND × numerical IQ, $F(1.41, 59.31) = 3.64$, $p < .05$, $\eta^2 = .08$; TASK DEMAND × figural IQ: $F(1.41, 59.31) = 6.52$, $p < .01$, $\eta^2 = .13$. Brighter individuals displayed higher solution rates than less intelligence ones, again particularly in the MT while the differences in the other task demands are marginal.

3.2. ERD

Similar to the task performance analyses, in a first step, the effects of general intelligence and ELO were investigated. As the MT comprised two activation intervals (encoding and recognition phases), the factor TASK DEMAND now includes four levels: speed, memory encoding, memory recognition, and reasoning.

An ANOVA for repeated measurements with TASK DEMAND (four levels as described above), STRUCTURE (representative versus non-representative), HEMISPHERE (left versus right), and AREA (anteriofrontal, AF; frontal, F; frontocentral, FC; centrotemporal, CT; centroparietal, CP; parietotemporal, PT; parietooccipital, PO) as within-subjects factors, and ELO (lower versus higher) as well as IQ-GROUP (lower versus higher) as between-subjects factors was computed for the %ERD in the upper alpha band. A summary of all significant effects is presented in Table 4.

The main effects of TASK DEMAND and STRUCTURE (see Fig. 4a) revealed that: (a) the ST was associated with a lower level of cortical activation (or %ERD, respectively) as compared to memory and reasoning demands (10.61, 21.45, 22.82, and 20.57%ERD for the four task demands) and (b) the representative task versions required lower cortical activation than the non-representative demands (16.83%ERD versus 20.89%ERD). The third main effect, AREA, shows the expected anterior to posterior increase in upper alpha %ERD, with the highest level over

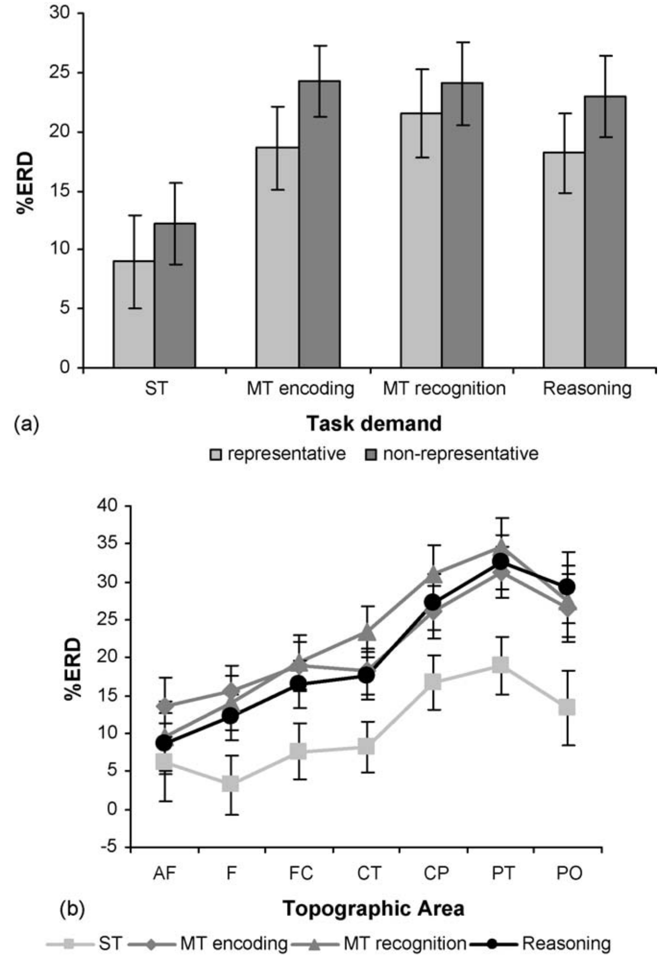

Fig. 4. %ERD. (a) Main effects of TASK DEMAND and STRUCTURE. (b) Interaction between TASK DEMAND and AREA. Error bars indicate ±1S.E. of the mean.

parietotemporal positions and the lowest amount of desynchronisation over anteriofrontal positions (see Fig. 4b). The effect of AREA, moreover, interacts with TASK DEMAND (see Fig. 4b). The interaction obviously emerges because of the smaller differences between ST and the other tasks over anteriofrontal cortices. The interaction between TASK DEMAND, STRUCTURE, and HEMISPHERE solely reflects very small activation asymmetries (in the range of a few %ERD points) in favour of the right hemisphere only in the ST random and MT encoding game and MT retrieval game conditions, whereas in the other tasks and conditions no hemispheric differences are apparent.

In a next step, similar to the performance data, the importance of distinct intelligence components for the alpha band ERD is evaluated. Therefore, an ANCOVA for repeated measures with TASK DEMAND, STRUCTURE, HEMISPHERE, and AREA as within-subjects variables, and ELO ranking as well as verbal, numerical, and figural intelligence as covariates was computed. STRUCTURE and AREA interacted with both, verbal IQ, $F(2.74, 115.02) = 3.27$, $p < .05$, $\eta^2 = .07$, and figural IQ, $F(2.74, 115.02) = 3.28$, $p < .05$, $\eta^2 = .07$; moreover, a HEMIPHERE × AREA × figural IQ interaction emerged, $F(3.12, 130.91) = 3.02$, $p < .05$, $\eta^2 = .07$. No other effects of intelligence components or ELO ranking reached statistical significance.

To begin with the effects of figural IQ (see Fig. 5a), at a gross level, the brighter individuals display a lower activation than the less intelligent counterparts. Looking at the non-representative task versions, this apparently holds true for all topographical areas, while in the representative demands, the differences are most pronounced and apparent only over anterior cortices.

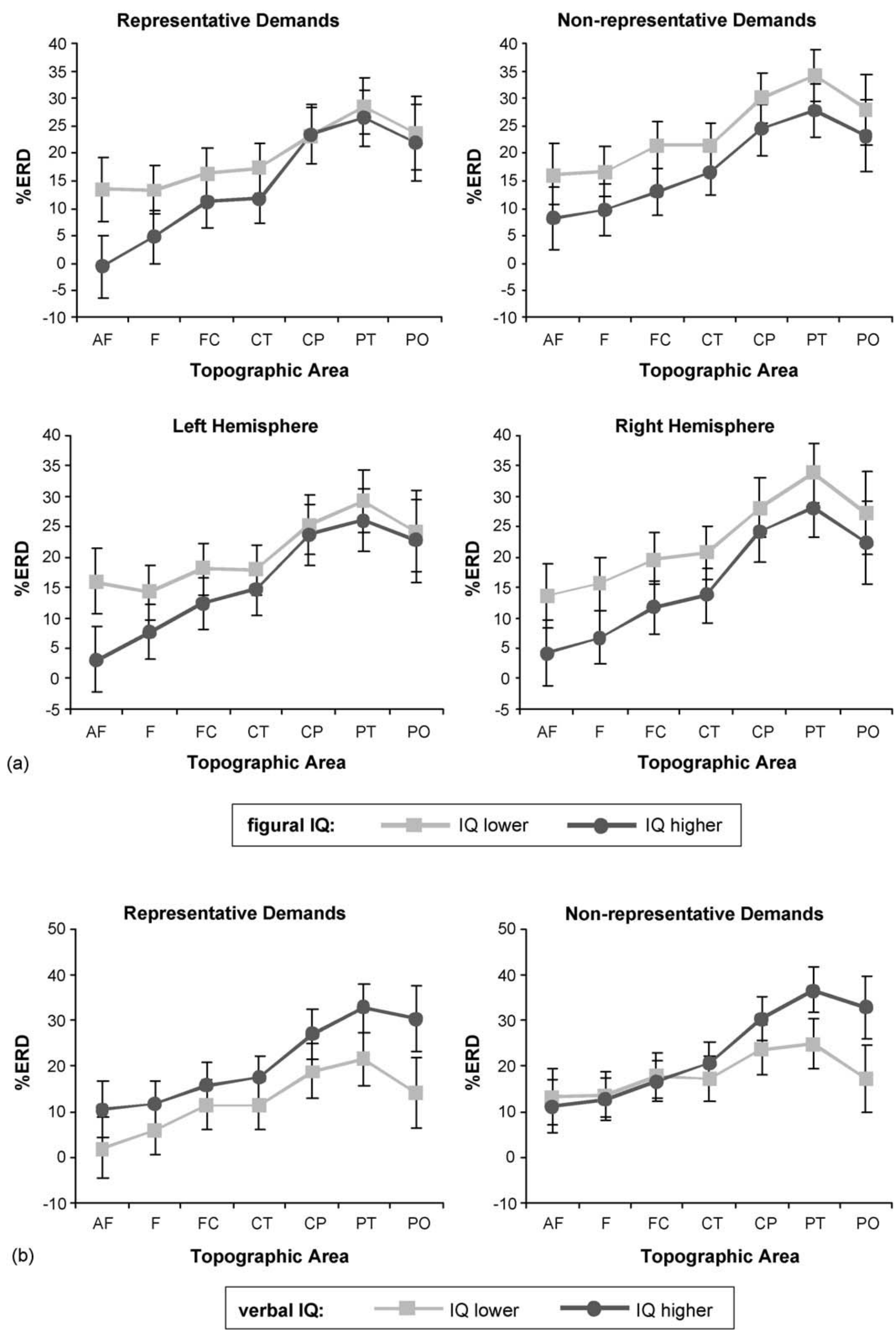

Fig. 5. %ERD. (a) Interactions of AREA and figural intelligence with STRUCTURE (first row) and HEMISPHERE (second row). (b) Interaction between STRUCTURE, AREA, and verbal intelligence. The values of the covariate effects were estimated by means of subsequent ANCOVAs with the respective intelligence component being median-split and included as between-subjects factor. Error bars indicate ±1S.E. of the mean.

The interaction with HEMISPHERE again reveals a lower activation in (figurally) brighter individuals. The topographically more consistent activation differences can be observed in the right hemisphere, whereas in the left one, a similar pattern arises as was found for the representative task versions, i.e., intelligence-related differences primarily over anterior cortical areas.

A surprisingly different result emerges for the interaction of verbal intelligence with STRUCTURE and AREA (see Fig. 5b). In general, verbally more intelligent participants display a higher level of cortical activation, which is more strongly apparent over posterior cortices and in the representative as compared to the non-representative demands.

In light of the strong expertise effects on the performance level, the observation that ELO did not impact on the amount of ERD appears surprising. At first glance, this suggests that stronger players do not differ from their weaker counterparts in the amount and topography of cortical activation during task performance. However, there might be an alternative explanation for this negative result referring to the peculiarities of the ELO system, which shall be discussed and empirically evaluated in the following. The individual's ELO ranking can be regarded as a reliable and valid statistical measure of playing strength and therefore the level of expertise. Every time a player wins (or draws) against a stronger opponent, his or her ELO ranking increases by a certain number of points; every time a player loses a game, his or her ELO ranking decreases. A central assumption in this ranking system is that chess playing strength increases only slowly over time, which is reflected in only small ranking changes following each tournament period [22]. Only those players who play chess consistently well over a rather long time period will eventually attain a high ELO ranking level. In spite of its prominence and wide application, the ELO system has been criticised with regard to some theoretical (mathematical) and practical considerations. An example for a practical problem is that some chess players try to protect their own (high) ranking (cf. [19]), for instance, by selectively participating in fewer games, by carefully choosing opponents, or by abandoning tournaments after losses in a couple of games. In this case, the official ELO ranking of a player may overestimate his or her playing strength, as not enough rated games were played. An even more important restriction from a psychometric perspective is that the ELO ranking represents an indicator of the *accumulated* playing strength rather than of the players' *current* (chess) performance level. Even though the ELO system was devised to adapt to the present performance level on the basis of the tournament results, this adaptation seems to occur too languidly. As a consequence, one might assume that a measure of how well a player is *currently* trained might be more likely associated with the *currently* displayed activation patterns than a measure of accumulated playing strength over numerous tournament games. Among all assessed expertise-related variables, the current tournament success seems to be the most promising candidate for such a measure. Consequently, participants with higher and lower tournament success are compared in their cortical activation patterns, pursuing a similar approach as in the IQ and ELO analyses.

Table 5
Correlations of task performance with ELO rankings and average result of tournament games

	$r_{\times \mathrm{TS}}$	$r_{\times \mathrm{ELO}}$
Solution rates (%)		
ST: game positions[a]	−.03	.22
ST: random positions[a]	−.02	.15
MT: game positions	.37*	.49**
MT: random positions	.36*	.25
RMT	.42**	.60**
RET[a]	.01	.07
Median response latencies (s)		
ST: game positions	−.63**	−.49**
ST: random positions	−.55**	−.43**
MT: game positions	−.37**	−.47**
MT: random positions	−.35*	−.33*
RMT	−.58**	−.70**
RET	−.31*	−.27

Note: $r_{\times \mathrm{TS}}$, correlations with average result of tournament games (tournament success); $r_{\times \mathrm{ELO}}$, correlations with ELO ranking.
[a] These variables are not normally distributed; non-parametric correlations yield largely comparable coefficients. Speed task (ST), memory task (MT), reasoning: mate-in-one task (RMT), and reasoning: exchange task (RET).
* $p < .05$.
** $p < .01$.

3.3. ERD follow-up analyses

The average result of tournament activity (%)[5] ranged from 17 to 75% ($M = 52.02$, S.D. = 12.09) and is only moderately correlated with the ELO ranking ($r = .33$, $p < .05$). Nevertheless, as given in Table 5, this expertise measure is, in general, comparably important for the performance in the experimental tasks (it should be noted, however, that the correlation with the RMT performance is slightly lower than that for ELO). For the ERD analyses, the sample was median-split into a group of lower and higher tournament successes (TS). The average result of tournament games (%) ranged from 17 to 50% in the lower TS group ($M = 42.28$, S.D. = 8.11), and from 50 to 75% in the higher TS group ($M = 61.36$, S.D. = 6.58). A MANOVA with participants' personality, state anxiety, and mood revealed no significant group difference.

Similar to the procedure applied for the ELO ranking, an ANOVA with TASK DEMAND (speed, memory encoding, memory retrieval, and reasoning), STRUCTURE (representative versus non-representative), HEMISPHERE (left versus right), and AREA (anteriofrontal to parietooccipital) as within-subjects variables, and IQ-GROUP as well as TS (tournament success: lower versus higher) as between-subjects variables was computed. Besides the already described effects of TASK DEMAND, STRUCTURE, AREA, TASK DEMAND × AREA, and TASK DEMAND × STRUCTURE × HEMISPHERE, two interactions of interest emerged: an

[5] The result of each tournament game is usually indicated as following: 1 (won game), 0.5 (draw), and 0 (defeat). For the present analyses, the percentage result of tournament games (relative to the number of games played) in the time period covered by the test sessions was computed (similar to the averaged ELO rankings).

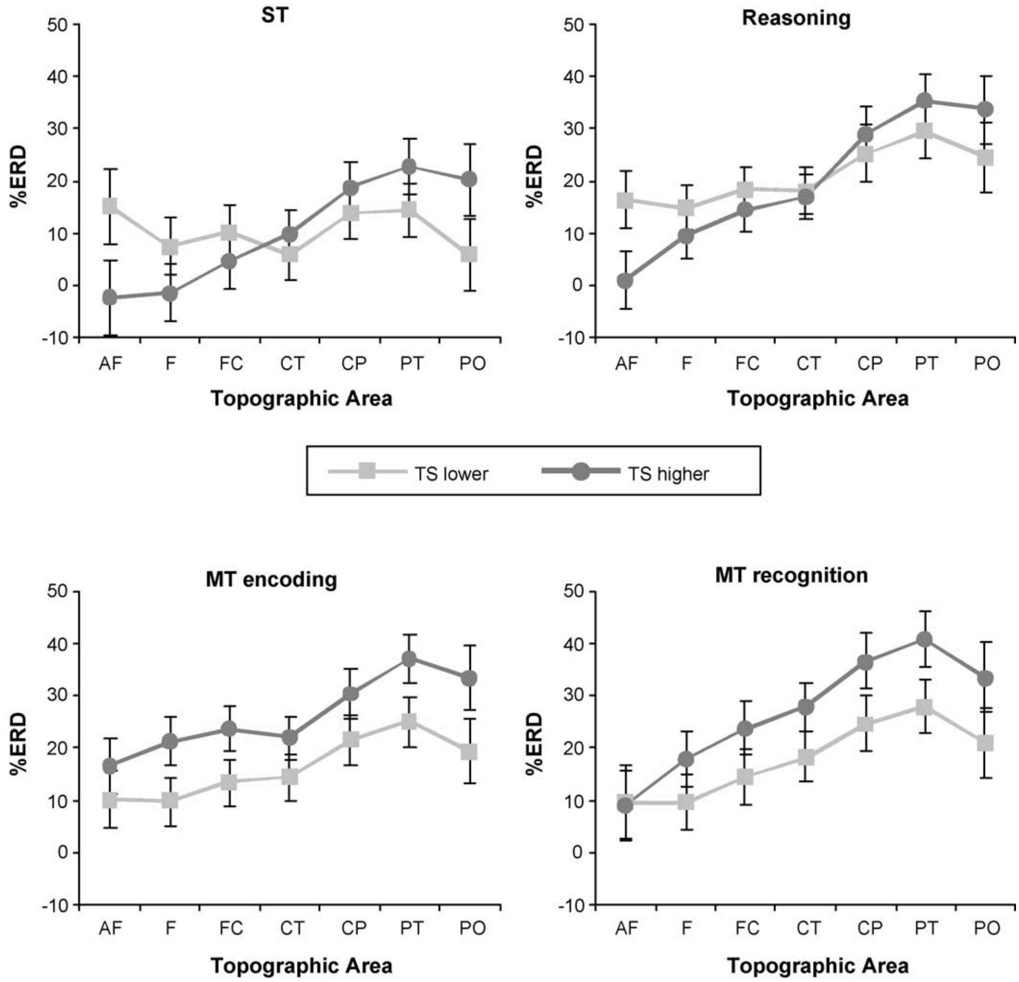

Fig. 6. %ERD. Interaction between TASK DEMAND, AREA, and tournament success (TS). Error bars indicate ±1S.E. of the mean.

interaction between AREA and TS, $F(1.85, 79.47) = 3.33$, $p < .05$, $\eta^2 = .07$, and a three-way interaction between TASK DEMAND, AREA, and TS, $F(3.74, 160.92) = 3.30$, $p < .05$, $\eta^2 = .07$. Since the first interaction is moderated by different task demands, only the latter is illustrated (see Fig. 6). The interaction between AREA and TS only reflects a smaller %ERD for the TS higher group over AF, and higher %ERDs over all other positions. The overall pattern of the three-way interaction looks very similar for the ST and the reasoning tasks. Over anterior cortices, the participants with the higher TS display less activation than those with lower TS. This difference, however, reverses over posterior cortical regions; here, the more successful players show a higher amount of activation. Looking at the topographical activation differentiation of the two groups, a clearly more focussed activation in the group of higher TS uncovers, while the activation is more or less equally distributed over the cortical areas in the lower TS group. In the MT, however, a completely different result can be observed: the higher TS group displays a higher level of activation over virtually all cortical areas. This holds comparably true for the encoding as well as the recognition phase. It should be emphasised that these effects are independent of the figural IQ effects, as an additionally computed ANCOVA revealed.

4. Discussion

4.1. Task performance: intelligence and expertise put to test

This study has revealed that intelligence and expertise impact on the performance on tasks representative for the domain of chess as well as on tasks not representative for chess independently of each other. As expected, the closer the cognitive demands match the essence of the participants' expertise, the larger is the experts' performance advantage. The small but significant effect of expertise on non-representative tasks may be traced back to the high familiarity of the players with chess material, which allows them to discriminate the crucial visual features of the target pieces very quickly [92]. The most striking finding concerning the performance data is that the expertise effects are accompanied by an effect of general intelligence. Brighter individuals outperformed less intelligent ones irrespective of whether the cognitive demand corresponded to the experts' domain or not. Moreover, both effects were additive in that a lower intelligence could obviously be compensated for by a high expertise level.

A noteworthy difference to previous studies investigating intelligence and expertise effects on domain-related performance concerns the strength of the effects. Frequently, domain-general abilities could – if at all – only marginally contribute to a high performance level (e.g., accounting for only less than 10% as compared to over 50% by domain knowledge in [50]). In the present investigation, both, general IQ and ELO, played a decisive role not only in the reasoning task but also in the classical MT. In the response latencies the main effects were of equal size; in the solution rates, intelligence even surpassed expertise in effect size. A plausible explanation for this finding might lie in the cognitive demands of the employed experimental tasks. In the ST, participants simply had to count the number of minor pieces on the board as fast as possible. The speed with which this is accomplished is a function of the players' strength and, in the stronger players, most probably points to a highly efficient perceptual system for domain-specific material acquired during long-term experience [91]. Moreover, the performance in this task might also be influenced by the participants' general speed of information processing as a central basis of human intelligence [18]. In addition, this task presumably engages central executive (attentional) processes, as it requires the participants to selectively attend to specific visual features (the minor pieces), and, concurrently to inhibit task-irrelevant information (e.g., the other pieces on the board [14]). A similar picture emerges for the MT performance which may likewise be affected by both, the elaborate knowledge base of the stronger players (e.g., allowing better performance as more chunks are recognised and stored in STM [24]) and individual differences in their general capacity to store information (in STM and/or WM [1,61]). Eventually, planning ahead (reasoning) and keeping in mind the results of intermediate steps (in WM) could not only be required in the domain-unrelated RET but also in the process of determining the correct move that leads to a checkmate.

A closer look at the three intelligence components revealed that only figural and numerical intelligence turned out as significant predictors for the performance level. Doll and Mayr [19] who found a significant correlation between numerical intelligence and chess performance assumed a higher familiarity with numerical material in expert chess players since the chess board is partly notated numerically and moves could be represented by addition and subtraction processes. In the response latencies, though, only the effect of figural IQ resembled that of general intelligence in main effect and interactions. Interestingly, the tentative explanation for the intelligence effects offered above gains additional plausibility by this finding. The importance of figural intelligence most likely does not only originate from the fact that figural stimulus material was presented (pieces on a chess board) but might also point to an involvement of the visuo-spatial component of WM [4]. Thus, the reason for the additional and strong influence of general intelligence besides ELO might be that domain-general features of the human information processing system were touched as well.

4.2. Neural efficiency: a matter of intelligence and expertise?

The major purpose of our study was to investigate the impact of expertise and intelligence at the neurophysiological level. The first question concerned whether intelligence remains (negatively) associated with cortical activation even in domain-representative expert performance. It turned out that no effect of general intelligence but only an effect of figural intelligence on the amount of cortical activation reached significance. In line with the neural efficiency hypothesis, participants with higher figural intelligence, at a gross level, displayed a lower amount of cortical activation than the figurally less intelligent participants. Hence, in contrast to the results by Grabner et al. [40], (figural) intelligence did not lose its impact on neural efficiency if expertise is involved. In both hemispheres and task versions, this effect was especially pronounced over the (anterio-) frontal cortices, thus suggesting that this cortical area might be particularly sensitive to individual intelligence differences. This finding nicely conforms to previous studies in the framework of the neural efficiency hypothesis, showing that the largest activation differences between lower and higher intelligence participants emerged over the frontal cortices [39,54,77,75].

There is wide consensus that the (pre-) frontal cortices support those cognitive processes that are crucial for numerous higher order cognitive functions [33], most notably for fluid intelligence [42]. Concretely, several executive processes, such as selective attention, inhibition, or the mental manipulation of information, which are regarded to be of utmost importance for intellectual functions, are frequently assigned to these cortical areas [12]. If (figurally) brighter individuals then display a notably lower activation in this region, it may consequently be assumed that the less intelligent individuals have relied more strongly on the functions of the prefrontal cortex, that the brighter individuals possess more efficient (and less energy-consuming) neural networks in this region, or that even both applies. Although, based on the present data, no final decision for one of these accounts can be made, the observation that the brighter individuals do not display a higher activation in any other cortical area points to a neurally more efficient brain functioning in them. This assumption gains additional support from: (a) findings of individual differences in intelligence being particularly reflected in the activation over those cortical areas which are highly relevant for task performance (e.g., [39,76,77]) and (b) recent MRI studies, revealing more frontal grey matter in brighter individuals which might result in less energy use during task performance [45].

Definitely more puzzling are the findings concerning the verbal intelligence component. In contrast to figural intelligence, here, a positive association between verbal IQ and cortical activation was observed, suggesting that (verbally) brighter individuals display less neural efficiency during task performance. This finding was observed to be specially pronounced over posterior cortices and in the representative task versions. Even though no cogent explanation for this result can presently be offered since verbal intelligence was in no way related to task performance, it corresponds to the findings of Neubauer et al. [76] who found evidence in favour of neural efficiency only if the analysed intelligence component matched the task demand: in the verbal paradigm, verbal IQ was negatively but visuo-spatial IQ positively (though non-significantly) related to ERD in females. Likewise, in the figural task version, negative

ERD–intelligence associations emerged solely for visuo-spatial IQ in males, whereas non-significant (partially negative and partially positive) correlations were found with verbal IQ. These findings were tentatively interpreted as reflections of sex differences in brain structure, facilitating spatial processing in males and verbal processing in females. In light of a recent MRI study by Haier et al. [46] who demonstrated sex differences in the relation between structural brain variation and intelligence, this explanation might also account for the present result.

The second question to be addressed was whether neural efficiency might not only be a function of intelligence but also of expertise. Significant effects of chess expertise on the ERD data, however, only emerged if the current tournament success, instead of the ELO ranking, was considered as expertise measure, which may generally point to a stronger link between neurophysiological measures and the *current* performance level. Contrary to intelligence, the expertise effect was moderated by the task demand and fundamentally differed between the memory tasks and the two other types of experimental tasks.

In the ST and reasoning tasks, the (pre-) frontal cortex again revealed cortical activation patterns in line with the neural efficiency approach in that more skilled players showed a lower activation than their less skilled counterparts. Interestingly, over the posterior (parietal) cortex this effect reversed. Looking at the topographical activation differentiation of the two groups uncovers a clearly more focussed activation in the group of higher TS, while the activation is more or less equally distributed over the cortical areas in the lower TS group. Therefore, in contrast to the figural IQ effect, it is not a generally lower activation but rather a more focussed activation that points to a higher neural efficiency in the more skilled players This finding of an anterior–posterior activation asymmetry in the higher TS players appears especially noteworthy, since it is in line with several previous investigations revealing that with increasing training or practice the activation focus shifts from anterior ("scaffolding") to more posterior (task-related) regions (e.g., [43,85]), which is usually interpreted in terms of automatisation (cf. also [62]). Practice or training leads to the development of more efficient task strategies which less strongly demand the general (executive) functions of the frontal lobe (e.g., [35]). In general, this explanation likewise seems to be applicable to the present results. Considering that the parietal cortex has not only been found to be essential in figural and visuo-spatial processing (e.g., [6]) but also to be critically involved in chess playing (e.g., [3]), the activation focus over the parietal cortices in the more skilled players might indeed reflect the availability and usage of more efficient strategies for good task performance. Contrarily, the widespread and undifferentiated activation in the less skilled players may indicate the lack of such strategies, eventually resulting in a lower performance level (see also [58]). Although using a different neurophysiological approach, the findings by Volke et al. [105] corroborate this assumption. The authors analysed evoked EEG coherence in 22 chess players (from beginners to league players) while solving different chess tasks and found that the essential brain areas involved in task processing are shifted from an anterior to a posterior position in the experts.

While the ERD results of the ST and reasoning tasks may point to a potential generalisability of the neural efficiency approach even to expertise as a domain-specific ability concept, the results in the MT seem to add to the inconsistent evidence of neural efficiency whenever memory tasks are administered. In line with previous neurophysiological expert studies, during the encoding and recognition phases more skilled players exhibited a higher cortical activation than less skilled players, practically over all cortical areas. In the last few years, some explanations have been discussed why neural efficiency is inconsistently observable in memory demands (see also [39]). Among the most plausible ones seem to be those that take the role of semantic memory in task performance into account. Doppelmayr et al. [20] proposed to replace the neural efficiency hypothesis with an inhibition hypothesis. They referred to the observation that the (upper) alpha band ERD is particularly responsive to verbal–semantic processing and argued that the inconsistent findings of neural efficiency in this frequency band are due to a differential involvement of such processing demands in task performance. If verbal–semantic processing were involved, then the brighter individuals would display a higher ERD; if verbal–semantic processing is of no relevance, the negative intelligence–activation association would emerge and reflect that brighter individuals more "efficiently" inhibit their (task-irrelevant) alpha band ERD. They substantiated their hypothesis in an EEG study of verbal analogy test performance by demonstrating that the verbal semantic task induced a larger ERD in the brighter as compared to the less intelligent individuals.

Although Doppelmayr et al.'s [20] inhibition hypothesis appears to be too strictly formulated in view of the sensitivity of upper alpha ERD to a wide variety of cognitive processes (e.g., [65,98]), a strong recruitment of prior knowledge may indeed attenuate or reverse the activation–intelligence relationship. In a recent study, Jausovec and Jausovec [57] required participants to learn associations between colours and locations in a grid. Their finding of a higher (upper alpha) ERD in the high IQ individuals was interpreted to reflect differential encoding strategies. Following the theoretical framework of the long-term WM theory by Ericsson and Kintsch [26], they argued that the brighter participants more strongly (and deliberately) involved their prior knowledge in the encoding of the colour–location associations, whereas the less intelligent individuals primarily employed (less-effective) episodic memory strategies. Consequently, the authors speculated that "it is not the focused, but rather the more widespread brain activity that would be related to good memory performance" and that "greater event-related desynchronisation in the upper alpha band displayed by high-intelligent individuals could well point to a more 'efficient' task approach" (p. 609).

To sum up, the neurophysiological results have demonstrated that brighter individuals display a more efficient brain functioning than less intelligent ones. Areas of the (pre-) frontal cortex turned out to be particularly sensitive to individual differences in intelligence, which again highlights that these brain regions are not only critical for essentially all higher order cognitive functions [60] but might also be functioning more efficiently in brighter individuals [39,45]. What is new in the present investigation, however, is that both, intelligence and expertise, impact independently of each other on neural efficiency. In contrast to the impact of intelligence on the cortical activation patterns, the expertise effect was moderated by the task type but not by the representativeness of the task demands. In the ST and reasoning tasks, the findings are in line with the prediction of the neural efficiency hypothesis in that a higher ability is associated with a topographically higher activation differentiation. Although the total ERD was comparable for both groups, the more skilled players (as compared to the less skilled ones) displayed a higher activation over the parietal cortices and a lower activation over the frontal cortices. In light of previous findings from practice or training studies, it appears that this focussed activation in stronger players results from the availability of an efficient domain specific knowledge base acquired during long-term engagement into the domain of chess. A contrary picture emerged in the MT, in which the ERD of the more skilled players was generally higher than that of the less skilled ones. Whether this activation pattern indeed reflects the usage of a larger knowledge base, of more deliberate strategies, or of both, and whether it also can be regarded as an indicator of a more efficient brain functioning, though, remains elusive.

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