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The relationship between cognitive ability and chess skill: A comprehensive meta-analysis

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A B S T R A C T

Why are some people more skilled in complex domains than other people? Here, we conducted a meta-analysis to evaluate the relationship between cognitive ability and skill in chess. Chess skill correlated positively and significantly with fluid reasoning (Gf) ($\bar{r} = 0.24$), comprehension-knowledge (Gc) ($\bar{r} = 0.22$), short-term memory (Gsm) ($\bar{r} = 0.25$), and processing speed (Gs) ($\bar{r} = 0.24$); the meta-analytic average of the correlations was ($\bar{r} = 0.24$). Moreover, the correlation between Gf and chess skill was moderated by age ($\bar{r} = 0.32$ for youth samples vs. $\bar{r} = 0.11$ for adult samples), and skill level ($\bar{r} = 0.32$ for unranked samples vs. $\bar{r} = 0.14$ for ranked samples). Interestingly, chess skill correlated more strongly with numerical ability ($\bar{r} = 0.35$) than with verbal ability ($\bar{r} = 0.19$) or visuospatial ability ($\bar{r} = 0.13$). The results suggest that cognitive ability contributes meaningfully to individual differences in chess skill, particularly in young chess players and/or at lower levels of skill.

Contents

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1. Introduction

Research has convincingly established that cognitive ability (or intelligence) is a statistically and practically significant predictor of a wide range of socially relevant outcomes. For example, cognitive ability is the single best predictor of both work performance (Schmidt & Hunter, 2004) and educational achievement (Deary, Strand, Smith, & Fernandes, 2007). People who do well on tests of cognitive ability tend to perform better at work and in school, and even to live longer (Batty, Deary, & Gottfredson, 2007), than people who do less well on these tests.

Here, we consider the question of whether cognitive ability contributes to individual differences in expertise—that is, skill in a specific domain. This question has been hotly debated in psychology for well over a century. Using biographical dictionaries, Francis Galton (1869) found that eminence in fields such as music, science, and art tends to run in families, and that the likelihood of two relatives both having achieved eminent status varies with degree of biological relation. For example, considering the 300 most distinguished men in his sample, 36% of their sons achieved eminence, compared to 9.5% of their grandsons and 1.5% of their great-grandsons (see Plomin, DeFries, McClearn, & McGuffin, 2008). Galton concluded that eminence arises from "natural ability." John Watson (1930), the founder of behaviorism, countered that "practicing more intensively than others…is probably the most reasonable explanation we have today not only for success in any line, but even for genius" (p. 212).

More recently, in the spirit of Watson (1930), Ericsson and colleagues proposed that individual differences in skill largely reflect engagement in a long period of *deliberate practice* (Ericsson, Krampe, & Tesch-Römer, 1993). This view has been challenged by the finding that although deliberate practice accounts for a sizeable amount of variance in domain-specific performance, it leaves an even larger amount unexplained and potentially explainable by other factors (Macnamara, Hambrick, & Oswald, 2014; Macnamara, Moreau, & Hambrick, 2016). Ericsson and colleagues have further argued that cognitive ability, which is substantially heritable (Jensen, 1999; Plomin et al., 2008), does not correlate with expert performance. For example, in a *Harvard Business Review* article, Ericsson, Prietula, and Cokely (2007) claimed that "there is no correlation between IQ and expert performance in fields such as chess, music, sports, and medicine" (p. 116).

Nevertheless, there have been few attempts to evaluate evidence for the relationship between cognitive ability and skill through formal meta-analyses. Here, we report the first ever meta-analysis of the relationship between cognitive ability and skill in chess, the original domain for research on expertise (Simon & Chase, 1973; de Groot, 1946/1978).

1.1. Present study

Chess is an ideal domain for a meta-analysis of the relationship between cognitive ability and skill, for three reasons. First, chess is one of, if not the, single most studied domains in research on expertise—the "Drosophila" (fruit fly) of expertise research (e.g., Simon & Chase, 1973). Second, unlike in many domains, there is an objective measure of skill in chess—the Elo (1978) rating.[2] Finally, chess is a complex and purely intellectual activity.

It is somewhat surprising, then, that evidence for the relationship between chess skill and cognitive ability is inconsistent. In an early study, Djakow, Petrowski, and Rudik (1927) reported that there were no differences in visuospatial memory and general intelligence between eight grandmasters and non-chess players. More recently, in two studies, Unterrainer and colleagues found near-zero correlations between measures of cognitive ability (full-scale IQ and Raven's) and chess rating (see Unterrainer, Kaller, Halsband, & Rahm, 2006; Unterrainer, Kaller, Leonhart, & Rahm, 2011). By contrast, Frydman and Lynn (1992) found that elite Belgian youth chess players were approximately one standard deviation higher than the population mean on the performance subscale of the Wechsler Intelligence Scale for Children (WISC), which primarily reflects fluid reasoning. Furthermore, the stronger players had higher WISC performance IQ scores than the weaker players. More recently, using a relatively large sample with a wide range of chess skill, Grabner, Stern, and Neubauer (2007) found a significant positive correlation ($r = 0.35$) between full-scale IQ and chess rating. Similarly, Ferreira and Palhares (2008) studied ranked youth chess players and found a significant positive correlation ($rs = 0.32$–0.46) between fluid reasoning and Elo rating. de Bruin, Kok, Leppink, and Camp (2014) had beginning youth chess students complete a chess test, in which they were shown a chess game position and asked to predict the best next move. Performance on the chess test correlated moderately ($r = 0.47$) with scores on the WISC.

For a number of reasons, it is not clear what can be concluded from this mixed evidence (see a recent special issue of *Intelligence* for discussions of methodological issues in expertise research; Detterman, 2014). Sample sizes in studies of chess are often very small, leading to low statistical power and precision (e.g., $N = 25$ for Unterrainer et al., 2006; $N = 21$ for de Bruin et al., 2014). Moreover, samples are sometimes restricted in ranges of both cognitive ability and chess skill, limiting the degree to which the variables can correlate with each other (Ackerman, 2014). Further complicating matters, cognitive ability is sometimes assessed using tests with unknown reliability and validity, and sometimes with only a single test, leaving open the question of whether the results are test-specific (see, e.g., Li et al., 2015). Finally, samples sometimes consist of children and other times adults.

A narrative review by Campitelli and Gobet (2011) sheds more light on the inconsistent evidence for the relationship between cognitive ability and chess skill. They concluded that people high in cognitive ability are more attracted to chess than people lower in cognitive ability. More relevant to the present study, they concluded that the positive relationship between cognitive ability and chess skill is stronger in children than in adults, and at low rather than high levels of chess skill. In this study, we formally tested predictions following from the latter two of these conclusions via meta-analysis.

1.2. Research questions

The purpose of this study was to synthesize the available evidence for the relationship between cognitive ability and chess skill via meta-analysis. Our major question was whether there is a significant positive correlation between cognitive ability and chess skill. That is, do skilled chess players tend to be higher in cognitive ability than less skilled players? Using the Cattell-Horn-Carroll model of intelligence as an organizing framework (see McGrew, 2009), we considered this question in terms of both global cognitive ability (full-scale IQ) and four broad cognitive abilities: fluid reasoning (Gf), comprehension-knowledge (Gc), short-term memory (Gsm), and processing speed (Gs).

[2] This rating gives points to and ranks chess players based on their tournament games, and has been used by the International Chess Federation since 1971. Moreover, similar versions of it were adopted by national federations (for a comparison of the rating of the International Chess Federation and national ratings see Vaci, Gula, & Bilalić, 2014). Players with >2000 points are typically considered chess experts, whereas players with <800 points are considered beginners.

Gf refers to the ability to solve novel problems and adapt to new situations (Cattell, 1943), and is typically measured with tests of sequential (deductive) reasoning such as Raven's Progressive Matrices, in which the goal is to predict the next item in a pattern, or tests of quantitative reasoning such as solving mathematical problems (McGrew, 2009).[3] By contrast, Gc reflects knowledge and skills acquired through experience, and is assessed with tests of vocabulary, comprehension, and general information. Gsm is defined as the ability to remember information over a short period of time (Atkinson & Shiffrin, 1968; Baddeley & Hitch, 1974), and is measured with tests of short-term memory such as digit span, in which the goal is to remember and recall a series of digits, or tests of working memory such as *n*-back, in which the goal is to indicate whether a stimulus is the same as the one some number (n) back in a run of stimuli (Kay, as cited in Welford, 1958; Owen, McMillan, Laird, & Bullmore, 2005). Gs reflects speed of information processing, and is measured with reaction time tasks or tests that require speeded judgments (e.g., comparing letter strings; Salthouse, 1996; Sheppard & Vernon, 2008). Psychometric g reflects the variance common to these broad factors, and correlates near 1.0 with full-scale IQ (Jensen, 1999).

Each of these cognitive factors might be expected to contribute to individual differences in chess skill. Gf may underlie the ability to reason about and visualize the consequences of different chess moves (Holding, 1992; Burns, 2004), whereas Gsm could be involved in holding in working memory and comparing the consequences of multiple candidate moves. Gs has been hypothesized to underlie individual differences in both Gf and Gsm (Jensen, 1999; Salthouse, 1996), and thus may contribute indirectly to chess skill through these factors. Finally, as it encompasses vocabulary and comprehension skill, Gc may be involved in acquiring and understanding relevant concepts of chess strategy and tactics.

Following from Campitelli and Gobet's (2011) aforementioned review, we addressed two additional questions, pertaining to possible moderators of the relationship between cognitive ability and chess skill. First, does the relationship between cognitive ability and chess skill vary as a function of the skill level of the sample? Ericsson and colleagues have argued that cognitive ability predicts performance at low levels of skill, but not at high levels of skill. For example, Ericsson (2014) claimed that "acquired mechanisms gradually circumvent the role of any basic general cognitive capacities and thus reduce and even eliminate significant relations between general cognitive ability and domain-specific performance at the expert level of performance" (p. 83; see also Ericsson et al., 1993). Inconsistent with this hypothesis, a number of studies have demonstrated that the predictive validity of general mental ability for job performance does not decrease as a function of increasing job experience (Schmidt, Hunter, Outerbridge, & Goff, 1988; Schmidt & Hunter, 2004). Nevertheless, the finding that cognitive ability and chess skill correlate significantly more strongly, on average, in less skilled samples than in more skilled samples, would support Ericsson and colleagues' claim.

Second, does the relationship between cognitive ability and chess skill vary as a function of the age of the sample? Recent evidence indicates that chess skill is acquired more easily during childhood than during adulthood. In particular, there have been two reports of a negative relationship between starting age in chess and later chess rating, even after controlling for training (Gobet & Campitelli, 2007; Howard, 2012), indicating higher skill for those who start at an earlier age. Moreover, Gobet and Campitelli (2007) found that the probability of a player reaching international level status (International Master or Grandmaster) was 0.24 if they started playing chess at the age of 12 or earlier, but only 0.02 if they started playing after the age of 12. Here, we used meta-analysis to investigate whether the relationship between cognitive ability and chess skill also varies with age.

Finally, we addressed a question raised by Grabner (2014): does the relationship between cognitive ability and chess skill vary as a function of the content of the cognitive ability measure—namely, visuospatial, numerical, or verbal? A number of researchers have investigated the possibility that visuospatial abilities relate to chess skill, based on the idea that visuospatial skills are involved in perceiving, generating, and evaluating candidate moves (Waters, Gobet, & Leyden, 2002; see also Frydman & Lynn, 1992; Gobet & Campitelli, 2007; Grabner et al., 2007; Grabner, 2014). Surveying the evidence, Grabner (2014) reported a relationship between visuospatial ability and chess skill in children, but not in adults. There is also evidence that numerical ability relates to chess skill—perhaps because chess and mathematics both involve the evaluation of a problem space, followed by the sequencing of operations to reach a desired end state—and also some evidence for a correlation between verbal ability and chess skill (Grabner et al., 2007). We will assess relations of chess skill to visuospatial, numerical, and verbal abilities using additional meta-analytic models and moderator analyses.

2. Method

As in previous meta-analyses (e.g., Macnamara et al., 2014; Macnamara et al., 2016), we designed this meta-analysis and report the results in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement (Moher, Liberati, Tetzlaff, & Altman, 2009). See Fig. 1 for a flowchart depicting the major steps of the meta-analysis.

2.1. Inclusion criteria, literature search, and coding

The criteria for including a study in the meta-analysis were as follows: (1) at least one measure of cognitive ability was collected (e.g., full-scale IQ, score on Raven's Progressive Matrices); (2) at least one measure of chess skill was collected (e.g., Elo rating, score on a chess move-choice test); and (3) one or more effect sizes reflecting the relationship between cognitive ability and chess skill was reported, or information needed to compute the effect size(s) was reported or could be obtained from the author(s) of the study.

To identify studies meeting these criteria, we searched for relevant published and unpublished articles through March 1, 2016 and scanned reference lists. We also e-mailed authors of articles on chess and requested information relevant to our meta-analysis that was not accessible (e.g., unpublished data), and asked that they forward the e-mail to colleagues who might have conducted relevant studies.

Our search yielded 2287 potentially relevant articles. After examining these articles and discarding irrelevant ones (e.g., literature reviews), we identified 19 studies that met all the inclusion criteria. We coded each study and associated measures for reference information, methodological characteristics, and results (the data file is openly available at https://osf.io/4zesc/). Across studies, there were 26 independent samples, with 82 effect sizes and a total sample size of 1779 participants. For a list of studies included in the meta-analysis, see the references section; for additional characteristics of the meta-analysis, see Tables S1a–S1h in the Supplemental Material available online.

2.2. Effect sizes and moderator variables

The meta-analysis used the correlation between cognitive ability and chess skill as the measure of effect size. The majority of the effect sizes were correlations reported by the authors of the studies. For any study in which the authors only reported group-level comparisons (e.g., ranked vs. unranked chess players), we converted standardized mean differences (Cohen's *d*s) to biserial correlations (Becker, 1986; Hunter & Schmidt, 1990). Next, we classified each effect size in terms of four moderator variables: skill level of sample (ranked or unranked),

[3] Gf and spatial ability, and STM and WM, are sometimes modeled as separate factors, but often correlate near 1.0 (e.g., Morrill, McAuley, Dilley, & Hambrick, 2015). Thus, we will consider Gf and spatial ability, and STM and WM, together in this meta-analysis.

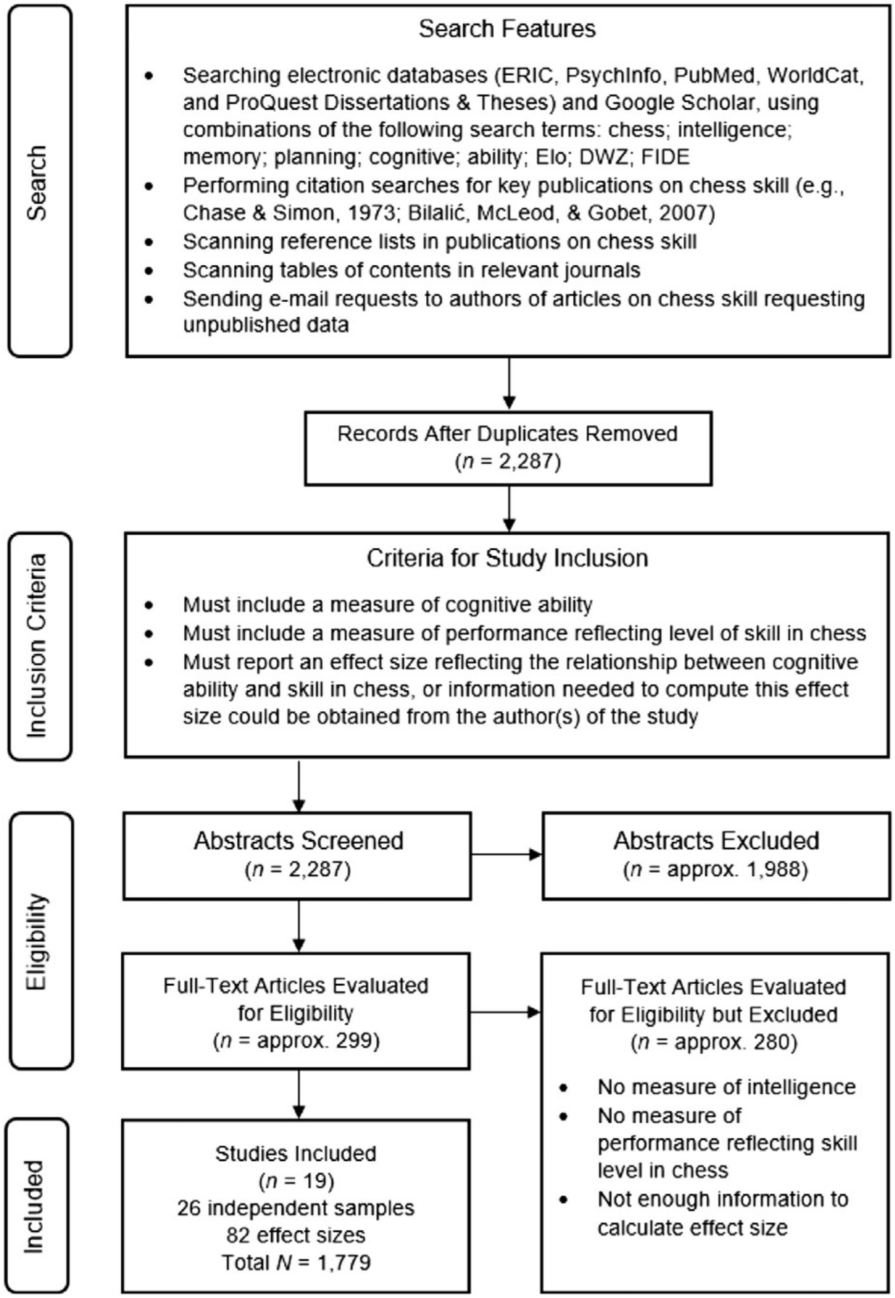


Fig. 1. Flow diagram of the literature search and study coding.

mean Elo rating of sample (higher-rated: ≥ to 2000, or lower-rated: <2000), age of sample (adult: mean age ≥ 18, or youth: mean age < 18), and measure of chess skill (chess rating or performance on a test of chess skill). Effect sizes that could not be classified by a moderator variable were not included in that particular moderator analysis.

2.3. Meta-analytic procedure

The meta-analysis involved four steps. First, we obtained correlations between cognitive ability and chess skill, along with sampling error variances. Second, we screened for outliers, which we defined as correlations whose residuals had *z*-scores of 3 or greater. None of the correlations met this criterion. Third, we estimated overall effects and heterogeneity among the correlations using random-effects meta-analysis modeling. For the Gf model—which contained the largest number of effect sizes—we tested whether some of the heterogeneity was predictable from moderator variables using mixed-effects meta-analysis modeling. Finally, we performed publication-bias analyses. We used the Comprehensive Meta-Analysis (Version 3; Biostat, Englewood, NJ) software package to conduct the meta-analyses and publication-bias analyses.

We performed these steps to produce 6 meta-analytic models. The models differed on the measure of intelligence/broad cognitive ability. Model 1 included only Gf measures; Model 2 included only Gc measures; Model 3 included only Gsm measures; Model 4 included only Gs measures; Model 5 included the meta-analytic average correlations for Models 1–4 for an estimate of psychometric g; and Model 6 included only full-scale IQ.

3. Results

The participants in the studies represented a wide range of chess skill. For example, across the 7 studies that collected Elo rating, the weighted

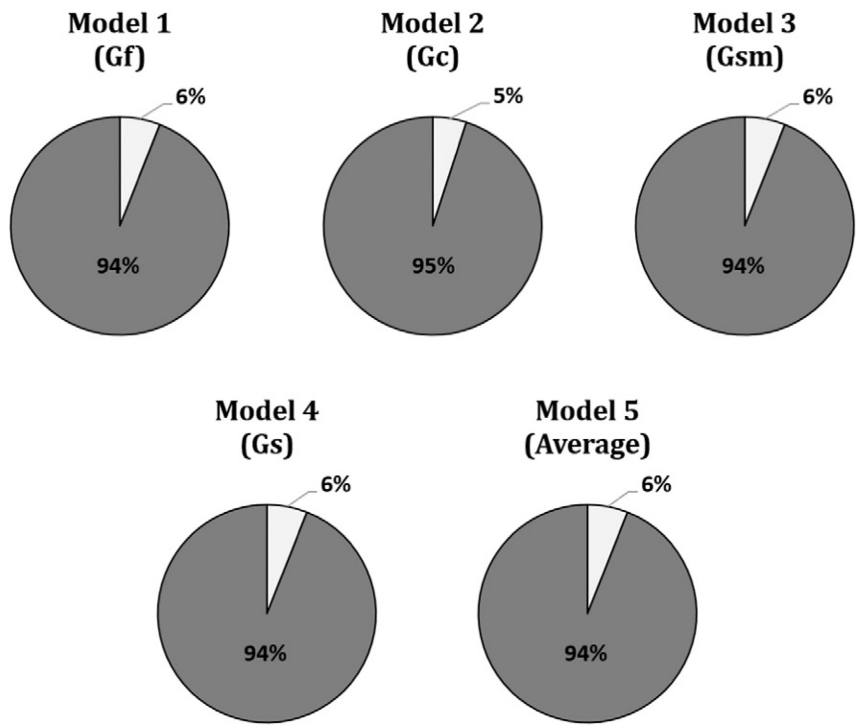


Fig. 2. Percentage of variance in chess skill explained (light gray) versus not explained (dark gray) by different measures of intelligence. Percentage of variance explained is equal to $\bar{r}^2 \times 100$.

average was 2018 ($SD = 177$) and the range was 1311 (an amateur level of skill) to 2607 (an elite level of skill). The participants in the studies also represented a wide range of intelligence/cognitive ability. For example, among the five studies that reported full-scale IQ, the weighted mean was 120.5, and the average standard deviation was 14.8, which is similar to the population standard deviation (*SD*) for many full-scale IQ assessments (i.e., $SD = 15$).

The majority of correlations (79%) between cognitive ability and chess skill were positive. High levels of cognitive ability were associated with high levels of chess skill, with effect sizes in the small-to-medium range (Cohen, 1992; see Fig. 2 and Appendix A). For Model 1, the meta-analytic average correlation was 0.24, 95% CI = [0.18, 0.30], $p < 0.001$, which indicates that Gf explained 6% of the variance in chess skill. For Model 2, the meta-analytic average correlation was 0.22, 95% CI = [0.11, 0.32], $p < 0.001$, which indicates that Gc explained 5% of the variance in chess skill. For Model 3, the meta-analytic average correlation was 0.25, 95% CI = [0.13, 0.37], $p < 0.001$, which indicates that Gsm explained 6% of the variance in chess skill. For Model 4, the meta-analytic average correlation was 0.24, 95% CI = [0.08, 0.39], $p = 0.004$, indicating that Gs explained 6% of the variance in chess skill.

Next, we performed a meta-analysis on the preceding correlations between chess skill and Gf, Gc, Gsm, and Gs. For this model (Model 5), the meta-analytic average correlation was 0.24, 95% CI = [0.19, 0.28], $p < 0.001$, indicating that, on average, the factors accounted for 6% of the variance in chess skill. Finally, we tested a model that included only full-scale IQ tests. The meta-analytic average correlation was a non-significant 0.10, 95% CI = [−0.19, 0.38], $p = 0.483$, which indicates that full-scale IQ explained <1% of the variance in chess skill.

The I^2 statistic, which indicates the percentage of between-study variability in the effect sizes that is due to heterogeneity and not random error, was substantial for Model 1 (Gf), $I^2 = 56.94$, Model 4 (Gs), $I^2 = 50.36$, and Model 6 (full-scale IQ), $I^2 = 75.13$, suggesting that there was a large degree of heterogeneity in the effect sizes. For Gf, we investigated the source of this heterogeneity by conducting moderator analyses. That is, we tested whether skill level,[4] mean rating, and age significantly moderated the relationship between Gf and chess skill. For the other ability factors, there were not enough effect sizes to perform moderator analyses (The Campbell Collaboration, 2012).

3.1. Results of the moderator analyses

3.1.1. Skill level: ranked vs. unranked

The correlation between Gf and chess skill was $\bar{r} = 0.14$, 95% CI = [0.02, 0.25], $p = 0.018$, for ranked samples and $\bar{r} = 0.32$, 95% CI = [0.27, 0.38], $p < 0.001$, for unranked samples. Thus, Gf explained 2% of the variance in chess skill for ranked samples and 10% of the variance in chess skill for unranked samples (Fig. 3a). This difference was significant, $Q(1) = 8.37$, $p = 0.004$.

3.1.2. Skill level: mean rating < 2000 vs. mean rating ≥ 2000

The correlation between Gf and chess skill was $\bar{r} = -0.10$, 95% CI = [−0.34, 0.14], $p = 0.411$, for higher-rated samples, and $\bar{r} = 0.10$, 95% CI = [−0.04, 0.23], $p = 0.147$, for lower-rated samples. Thus, although the direction of the relationship differed, Gf explained 1% of the variance in chess skill for both higher-rated and lower-rated samples. This difference was not significant, $Q(1) = 1.99$, $p = 0.159$.

3.1.3. Age

The correlation between Gf and chess skill was $\bar{r} = 0.11$, 95% CI = [−0.01, 0.22], $p = 0.071$, for adult samples and $\bar{r} = 0.32$, 95% CI =

[4] We also considered type of skill measure (i.e., rating or chess test) as a moderator. However, this moderator was completely redundant with the skill level moderator (i.e., all ranked samples used chess rating, all unranked samples used a chess test). Thus, we do not report the skill measure moderator analysis; the results are identical to those of the skill level moderator analysis.

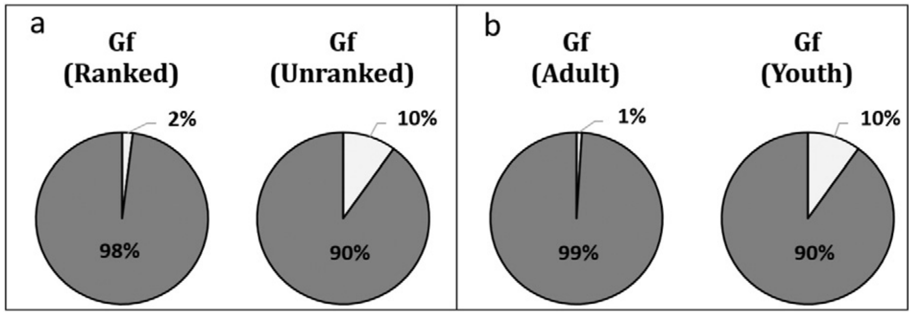


Fig. 3. Percentage of variance in chess skill explained (light gray) versus not explained (dark gray) by Gf for ranked and unranked samples (a) or by Gf for adult and youth samples (b). Percentage of variance explained is equal to $\bar{r}^2 \times 100$.

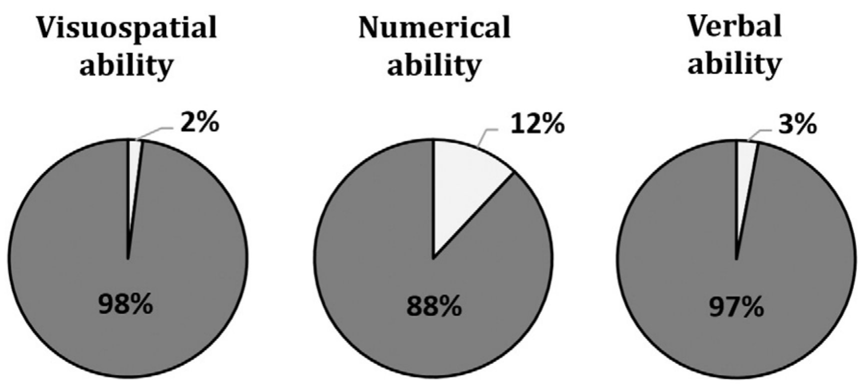


Fig. 4. Percentage of variance in chess skill explained (light gray) versus not explained (dark gray) by visuospatial ability, numerical ability, and verbal ability. Percentage of variance explained is equal to $\bar{r}^2 \times 100$.

[0.25, 0.38], $p < 0.001$, for youth samples.[5] Thus, Gf explained 1% of the variance in chess skill for adult samples and 10% of the variance in chess skill for youth samples (Fig. 3b). This difference was significant, $Q(1) = 9.83$, $p = 0.002$.

3.1.4. Rank by age

For ranked adult samples, the correlation between Gf and chess skill was $\bar{r} = 0.11$, 95% CI = [−0.01, 0.22], $p = 0.071$; for ranked youth samples, the correlation was $\bar{r} = 0.27$, 95% CI = [−0.04, 0.53], $p = 0.092$. Thus, Gf explained 1% of the variance in chess skill for ranked adult samples and 7% of the variance in chess skill for ranked youth samples. This difference was not significant, $Q(1) = 0.932$, $p = 0.334$.

3.2. Publication bias analysis

To assess whether our analyses were affected by publication bias, we created funnel plots for Models 1–6, illustrating the relation between effect size and standard error (seethe Supplemental Material available online) and conducted Duval and Tweedie's trim and fill analyses (Duval & Tweedie, 2000a, 2000b). The trim and fill analyses estimate the number of missing studies from the meta-analysis due to the suppression of the most extreme results on one side of the funnel plot. The method then imputes the effect sizes for the missing studies based on the observed data's asymmetry to create a more symmetrical funnel plot. The adjusted meta-analytic mean effect size is also reported. This adjusted mean effect size is not necessarily a more valid estimate of the overall effect, but provides information about the sensitivity of the model to publication bias due to suppression. In the present case, these analyses indicated that studies yielding a larger-than-average effect size were missing from the Gf model (10 studies). By contrast, the analyses suggested that studies yielding weaker-than-average effect sizes were missing from the Gsm, Gs, and full-scale IQ models (1 study, 3 studies, and 1 study, respectively). Given that the asymmetry fell on both sides of the means across the models, there is little evidence to suggest a systematic suppression of particular effect size magnitudes.

3.3. Additional analyses

We conducted three additional meta-analyses to assess the strength of the relationship between chess skill and visuospatial ability, numerical ability, and verbal ability. For these models, we reclassified effect sizes across all four broad cognitive ability factors (Gf, Gc, Gsm, and Gs) according to the content of the cognitive ability test, i.e., visuospatial, numerical, or verbal. We also investigated whether the strength of the relationship of chess skill to visuospatial ability and verbal ability differed depending on the skill level or age of the sample. Descriptive characteristics of each model and funnel plots illustrating the relation between each effect size and standard error are provided in the supplemental material available online.

3.3.1. Visuospatial ability

The meta-analytic average correlation between visuospatial ability and chess skill was $\bar{r} = 0.13$, 95% CI = [0.05, 0.20], $p =$

[5] One correlation in this model had a residual z-score of −3.15; this correlation was Winsorized to a residual z-score of −2.99.

0.002. Thus, visuospatial ability explained 2% of the variance in chess skill (Fig. 4). However, further analysis revealed that the correlation between visuospatial ability and chess skill was moderated by skill level of the sample. For ranked samples, the correlation between visuospatial ability and chess skill was $\bar{r} = 0.05$, 95% CI = [−0.07, 0.16], $p = 0.420$; for unranked samples, the correlation was $\bar{r} = 0.25$, 95% CI = [0.14, 0.35], $p < 0.001$. Therefore, visuospatial ability explained essentially none of the variance in chess skill for ranked samples and 6% of the variance in chess skill for unranked samples. This difference was significant, $Q(1) = 6.39$, $p = 0.011$.

The correlation between visuospatial ability and chess skill was also moderated by the age of the sample. For adult samples, the correlation between visuospatial ability and chess skill was $\bar{r} = 0.03$, 95% CI = [−0.06, 0.12], $p = 0.491$; for youth samples, the correlation was $\bar{r} = 0.24$, 95% CI = [0.14, 0.33], $p < 0.001$. Therefore, visuospatial ability explained essentially none of the variance in chess skill for adult samples and 6% of the variance in chess skill for youth samples. This difference was significant, $Q(1) = 8.85$, $p = 0.003$.

3.3.2. Numerical ability

The meta-analytic average correlation between numerical ability and chess skill was $\bar{r} = 0.35$, 95% CI = [0.30, 0.40], $p < 0.001$. Thus, numerical ability explained 12% of the variance in chess skill. There were not enough effect sizes to perform the skill level and age moderator analyses for numerical ability.

3.3.3. Verbal ability

The meta-analytic average correlation between verbal ability and chess skill was $\bar{r} = 0.19$, 95% CI = [0.08, 0.28], $p < 0.001$. Thus, verbal ability explained 3% of the variance in chess skill. The relationship between verbal ability and chess skill was not moderated by skill level of the sample. For ranked samples, the correlation between verbal ability and chess skill was $\bar{r} = 0.18$, 95% CI = [0.01, 0.33], $p = 0.039$; for unranked samples, the correlation was $\bar{r} = 0.17$, 95% CI = [0.00, 0.33], $p = 0.052$. Therefore, verbal ability explained 3% of the variance in chess skill for both ranked samples and unranked samples. This difference was not significant, $Q(1) = 0.01$, $p = 0.945$.

The relationship between verbal ability and chess skill was also not moderated by age of the sample. For adult samples, the correlation between verbal ability and chess skill was $\bar{r} = 0.25$, 95% CI = [0.12, 0.38], $p < 0.001$; for youth samples, the correlation was $\bar{r} = 0.09$, 95% CI = [−0.09, 0.27], $p = 0.340$. Therefore, verbal ability explained 6% of the variance in chess skill for adult samples and 1% of the variance in chess skill for youth samples. This difference was not significant, $Q(1) = 2.13$, $p = 0.144$.

4. General discussion

The purpose of this meta-analysis was to estimate the relationship between cognitive ability and chess skill. Results revealed that chess skill correlates significantly and positively with four broad cognitive abilities (Gf, Gc, Gsm, and Gs). Effect sizes were small-to-medium in magnitude; variance in chess skill explained by cognitive ability was similar in magnitude for Gf (6%), Gsm (6%), Gs (6%), and Gc (5%), with an average of 6%. Full-scale IQ explained <1% of the variance in chess skill.

Given that the correlations were significant for Gf, Gc, Gsm, Gs, it is somewhat surprising that the correlation was non-significant for full-scale IQ (i.e., Model 6). However, it should be noted that this model included only 6 effect sizes. Moreover, this result was largely driven by one correlation—the elite subsample from Bilalić, McLeod, and Gobet (2007; $r = -0.51$). Excluding this effect size, the meta-analytic average correlation for full-scale IQ increases from 0.10 (*ns*) to 0.24 ($p = 0.015$). This latter value is in line with the average of the correlations for Gf, Gc, Gsm, and Gs, which might be regarded as an approximation of the correlation between psychometric g and chess skill.

Moderator analyses revealed that the strength of the relation between Gf and chess skill differed significantly depending on both the skill level and age of the sample. That is, the correlation was stronger in unranked samples than in ranked samples ($\bar{r} = 0.32$ vs. 0.14), and stronger in youth samples than in adult samples ($\bar{r} = 0.32$ vs. 0.11). These findings provide some support for the hypotheses that the relationship between cognitive ability (Gf in particular) and chess skill is moderated by these factors (see Ericsson, 2014; Hambrick et al., 2012). As we have speculated elsewhere (Hambrick, Macnamara, Campitelli, Ullén, & Mosing, 2016), whether increasing skill level weakens the relationship between cognitive ability and domain-specific performance may depend on task factors. For example, it may be possible to circumvent reliance on cognitive ability in chess, but not in highly dynamic activities such as sight-reading music (Meinz & Hambrick, 2010).

At the same time, this evidence must be interpreted cautiously for at least three reasons. First, in the Gf model, there was evidence for restriction of range in Elo ratings in the ranked samples. The average reported standard deviation for samples was 148, which is substantially lower than the standard deviation of 200 for the Elo rating system (Elo, 1978). Second, skill level and age group were substantially confounded. That is, in adult samples, all chess players were ranked, whereas in youth samples, most of the players were unranked. Third, skill level was confounded with type of chess skill measure; for ranked samples, the measure was always chess rating, whereas for unranked samples, the measure was always a chess test, with the exception of one study (Gliga & Flesner, 2014) which used a chess tournament (see Table S1a in the Supplemental Material available online for the sample characteristics of Model 1). More research is necessary to definitively disentangle the effects of age, skill, and type of skill measure on the relationship between cognitive ability and chess skill.

Additional analyses revealed that the strength of the relation between cognitive ability and chess skill differed depending on the content of the measured cognitive ability. The correlation was strongest for numerical ability ($\bar{r} = 0.35$), intermediate for verbal ability ($\bar{r} = 0.19$), and weakest for visuospatial ability ($\bar{r} = 0.13$). Furthermore, the correlation between visuospatial ability and chess skill was significantly weaker for ranked samples ($\bar{r} = 0.05$) than for unranked samples ($\bar{r} = 0.25$), and significantly weaker for adult samples ($\bar{r} = 0.03$) than for youth samples ($\bar{r} = 0.24$). Again, these results should be interpreted cautiously, given restriction of range in Elo rating for ranked samples.

We did not correct individual effect sizes for the attenuation due to measurement error (i.e., unreliability), because very few studies reported reliability estimates. Because almost no measure is perfectly reliable, it must therefore be assumed that the meta-analytic correlations reported here underestimate the true relationship between intelligence and chess skill. However, both measures of chess skill and intelligence are typically found to have quite high reliability (often 0.80 or higher), and thus the degree of attenuation is likely to be small. For example, if both chess rating and full-scale IQ are assumed to have reliability of 0.90 (see Hambrick et al., 2014; Parker, Hanson, & Hunsley, 1988), then the correlation between full-scale IQ and chess skill would be 0.11 after correction for unreliability (versus 0.10 before correction), per the standard formula for correcting a correlation for unreliability (Schmidt & Hunter, 1999).

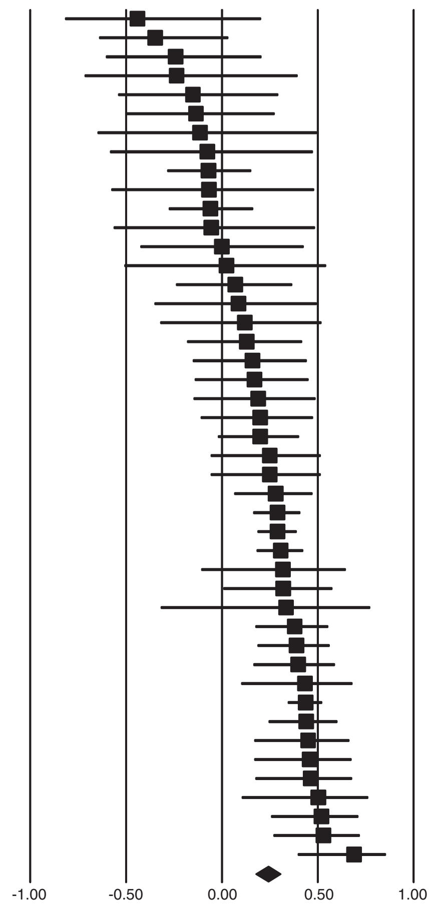
This meta-analysis represents the first attempt to quantitatively synthesize the available evidence for the relationship between cognitive ability and chess skill. Future studies of chess skill should include broad assessments of cognitive ability, and samples with even wider ranges of chess skill and age than in the studies included in this meta-analysis. Adding to the results of this meta-analysis, this work will shed light on the underpinnings of expertise in one of the most fruitful domains for research on expertise.

Appendix A

Fig. A1. Correlations between Gf and chess skill (Model 1).Note: Correlations (squares) and 95% confidence intervals (CIs; lines) are displayed for all effects entered into the meta-analysis. The diamond on the bottom row represents the meta-analytically weighted mean correlation. Multiple measures were adjusted for dependency. For studies with multiple independent samples, the result for each sample (S1, S2, etc.) is reported separately. Similarly, for studies with multiple performance measures, the result for each measure (M1, M2, etc.) is reported separately.

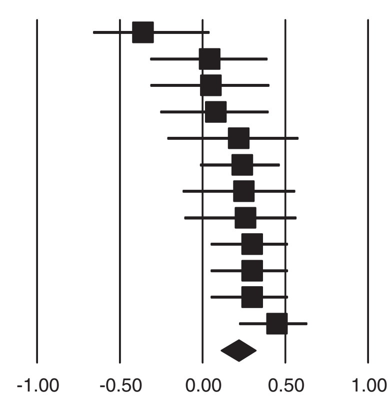
Study name	Statistics for each study				
	Correlation	Lower limit	Upper limit	Z-Value	p-Value
Horgan & Morgan (1990) - M2	-0.440	-0.818	0.204	-1.363	0.173
Bilalic, McLeod, & Gobet (2007) - S1	-0.348	-0.640	0.032	-1.800	0.072
Unterrainer, Kaller, Leonhart, & Rahm (2011) - M1	-0.241	-0.604	0.205	-1.061	0.289
Hanggi, Brutsch, Siegel, & Jancke (2014) - M1	-0.236	-0.716	0.395	-0.716	0.474
Unterrainer, Kaller, Leonhart, & Rahm (2011) - M2	-0.151	-0.541	0.293	-0.657	0.511
Li, Jiang, Qiu, Yang, Huang, Lui, & Gong (2015)	-0.135	-0.503	0.275	-0.637	0.524
Hanggi, Brutsch, Siegel, & Jancke (2014) - M2	-0.114	-0.648	0.496	-0.341	0.733
Unterrainer, Kaller, Halsband, & Rahm (2006) - M1	-0.076	-0.583	0.474	-0.253	0.801
Grabner, Neubauer, & Stern (2007) - M3	-0.070	-0.285	0.152	-0.615	0.539
Unterrainer, Kaller, Halsband, & Rahm (2006) - M2	-0.067	-0.577	0.481	-0.223	0.824
Grabner, Neubauer, & Stern (2007) - M4	-0.060	-0.276	0.162	-0.527	0.598
Campitelli & Labollita (2016) - M2	-0.055	-0.565	0.485	-0.185	0.854
Unterrainer, Kaller, Leonhart, & Rahm (2011) - M4	0.000	-0.425	0.425	0.000	1.000
Campitelli & Labollita (2016) - M1	0.024	-0.508	0.543	0.080	0.936
Frank & D'Hondt (1979) - M10	0.070	-0.239	0.366	0.438	0.661
Unterrainer, Kaller, Leonhart, & Rahm (2011) - M3	0.087	-0.351	0.494	0.376	0.707
Unterrainer, Kaller, Leonhart, & Rahm (2011) - M5	0.120	-0.322	0.519	0.520	0.603
Frank & D'Hondt (1979) - M6	0.130	-0.181	0.417	0.816	0.414
Frank & D'Hondt (1979) - M3	0.160	-0.151	0.442	1.008	0.314
Frank & D'Hondt (1979) - M2	0.170	-0.141	0.451	1.072	0.284
Bilalic, McLeod, & Gobet (2007) - S2	0.190	-0.148	0.488	1.105	0.269
Frank & D'Hondt (1979) - M7	0.200	-0.111	0.475	1.266	0.205
Grabner, Neubauer, & Stern (2007) - M5	0.200	-0.021	0.402	1.778	0.075
Frank & D'Hondt (1979) - M4	0.250	-0.058	0.515	1.595	0.111
Frank & D'Hondt (1979) - M5	0.250	-0.058	0.515	1.595	0.111
Grabner, Neubauer, & Stern (2007) - M1	0.280	0.064	0.471	2.522	0.012
Trinchero & Sala (2016) - S3	0.291	0.164	0.409	4.373	0.000
Sala, Gorini, & Pravettoni (2015) - S1	0.291	0.186	0.390	5.259	0.000
Trinchero & Sala (2016) - S1	0.307	0.181	0.423	4.630	0.000
de Bruin, Kok, Leppink, & Camp (2014)	0.319	-0.107	0.646	1.478	0.139
Ferreira & Palhares (2008) - M2	0.320	0.007	0.576	2.004	0.045
Horgan & Morgan (1990) - M1	0.335	-0.319	0.773	1.006	0.314
Grabner, Neubauer, & Stern (2007) - M6	0.380	0.175	0.554	3.508	0.000
Grabner, Neubauer, & Stern (2007) - M7	0.390	0.186	0.562	3.611	0.000
Sala, Gorini, & Pravettoni (2015) - S2	0.398	0.165	0.589	3.236	0.001
Sala & Trinchero (n.d.) - S1	0.434	0.101	0.680	2.503	0.012
Trinchero & Sala (2016) - S2	0.437	0.344	0.521	8.368	0.000
Grabner, Neubauer, & Stern (2007) - M2	0.440	0.244	0.602	4.141	0.000
Frank & D'Hondt (1979) - M8	0.450	0.169	0.663	3.027	0.002
Ferreira & Palhares (2008) - M1	0.458	0.169	0.675	2.989	0.003
Ferreira & Palhares (2008) - M3	0.463	0.175	0.678	3.028	0.002
Sala & Trinchero (n.d.) - S2	0.503	0.103	0.763	2.412	0.016
Frank & D'Hondt (1979) - M1	0.520	0.257	0.711	3.599	0.000
Frank & D'Hondt (1979) - M9	0.530	0.269	0.718	3.685	0.000
Frydman & Lynn (1992)	0.689	0.396	0.855	3.881	0.000
	0.240	0.176	0.303	7.124	0.000

Correlation and 95% CI



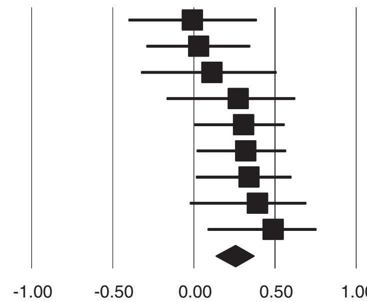
Study name	Statistics for each study				
	Correlation	Lower limit	Upper limit	Z-Value	p-Value
Bilalic, McLeod, & Gobet (2007) - S1	-0.360	-0.661	0.041	-1.768	0.077
Unterrainer, Kaller, Leonhart, & Rahm (2011)	0.043	-0.316	0.391	0.228	0.820
Frank & D'Hondt (1979) - M1	0.050	-0.315	0.402	0.261	0.794
Bilalic, McLeod, & Gobet (2007) - S2	0.080	-0.255	0.398	0.461	0.645
de Bruin, Kok, Leppink, & Camp (2014)	0.219	-0.212	0.579	0.996	0.319
Grabner, Neubauer, & Stern (2007) - M3	0.240	-0.015	0.466	1.848	0.065
Frank & D'Hondt (1979) - M2	0.250	-0.120	0.559	1.332	0.183
Frank & D'Hondt (1979) - M3	0.260	-0.109	0.566	1.388	0.165
Grabner, Neubauer, & Stern (2007) - M1	0.300	0.050	0.515	2.336	0.019
Grabner, Neubauer, & Stern (2007) - M2	0.300	0.050	0.515	2.336	0.019
Grabner, Neubauer, & Stern (2007) - M5	0.300	0.050	0.515	2.336	0.019
Grabner, Neubauer, & Stern (2007) - M4	0.450	0.221	0.632	3.658	0.000
	0.217	0.110	0.318	3.943	0.000

Correlation and 95% CI



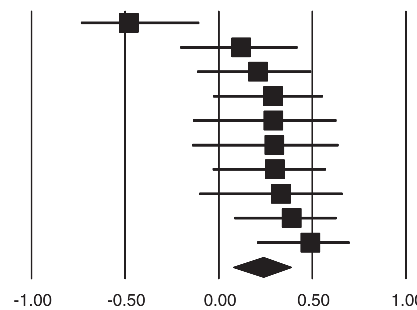
Study name	Correlation	Lower limit	Upper limit	Z-Value	p-Value
	Statistics for each study				
Bilalic, McLeod, & Gobet (2007) - S1	-0.009	-0.403	0.388	-0.042	0.966
Waters, Gobet, & Leyden (2002)	0.030	-0.292	0.346	0.178	0.859
Jastrzembski, Charness, & Vasyukova (2006) - S1	0.111	-0.325	0.509	0.488	0.626
Hanggi, Brutsch, Siegel, & Jancke (2014)	0.274	-0.167	0.624	1.226	0.220
Schneider, Gruber, Gold, & Opwis (1993) - S2	0.307	0.003	0.559	1.979	0.048
Schneider, Gruber, Gold, & Opwis (1993) - S1	0.320	0.018	0.569	2.071	0.038
Bilalic, McLeod, & Gobet (2007) - S2	0.340	0.013	0.601	2.034	0.042
de Bruin, Kok, Leppink, & Camp (2014)	0.392	-0.024	0.692	1.852	0.064
Jastrzembski, Charness, & Vasyukova (2006) - S2	0.489	0.085	0.755	2.333	0.020
	0.254	0.134	0.367	4.073	0.000

Correlation and 95% CI



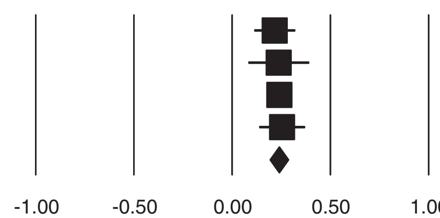
Study name	Correlation	Lower limit	Upper limit	Z-Value	p-Value
	Statistics for each study				
Bilalic, McLeod, & Gobet (2007) - S1	-0.480	-0.736	-0.105	-2.453	0.014
Frank & D'Hondt (1979) - M3	0.120	-0.205	0.421	0.720	0.471
Frank & D'Hondt (1979) - M2	0.210	-0.115	0.494	1.273	0.203
Frank & D'Hondt (1979) - M4	0.290	-0.030	0.556	1.783	0.075
de Bruin, Kok, Leppink, & Camp (2014)	0.292	-0.137	0.629	1.345	0.179
Jastrzembski, Charness, & Vasyukova (2006) - S2	0.298	-0.142	0.639	1.338	0.181
Bilalic, McLeod, & Gobet (2007) - S2	0.300	-0.032	0.572	1.778	0.075
Jastrzembski, Charness, & Vasyukova (2006) - S1	0.332	-0.104	0.661	1.506	0.132
Frank & D'Hondt (1979) - M1	0.390	0.083	0.629	2.459	0.014
Frank & D'Hondt (1979) - M5	0.490	0.205	0.698	3.201	0.001
	0.237	0.077	0.386	2.879	0.004

Correlation and 95% CI



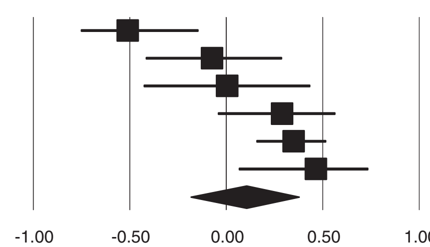
Study name	Point estimate	Standard error	Variance	Lower limit	Upper limit	Z-Value	p-Value
	Statistics for each study						
Gc	0.217	0.053	0.003	0.113	0.321	4.090	0.000
Gs	0.237	0.079	0.006	0.083	0.392	3.007	0.003
Gf	0.240	0.032	0.001	0.177	0.304	7.408	0.000
Gsm	0.254	0.059	0.004	0.138	0.371	4.273	0.000
	0.237	0.024	0.001	0.190	0.284	9.933	0.000

Point estimate and 95% CI



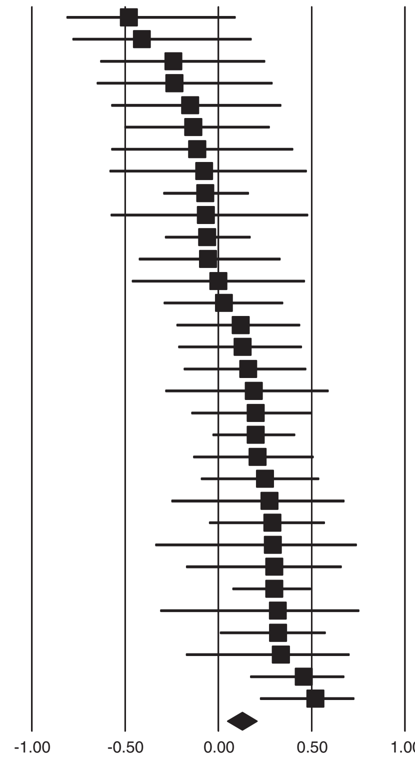
Study name	Correlation	Lower limit	Upper limit	Z-Value	p-Value
	Statistics for each study				
Bilalic, McLeod, & Gobet (2007) - S1	-0.510	-0.753	-0.144	-2.639	0.008
Unterrainer, Kaller, Leonhart, & Rahm (2011)	-0.073	-0.417	0.289	-0.387	0.699
Gliga and Flesner (2014)	0.005	-0.428	0.436	0.021	0.983
Bilalic, McLeod, & Gobet (2007) - S2	0.290	-0.043	0.565	1.715	0.086
Grabner, Neubauer, & Stern (2007)	0.350	0.156	0.518	3.448	0.001
de Bruin, Kok, Leppink, & Camp (2014)	0.465	0.065	0.736	2.252	0.024
	0.104	-0.185	0.376	0.702	0.483

Correlation and 95% CI



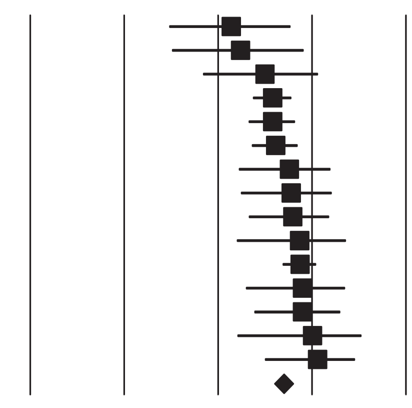
Study name	Correlation	Lower limit	Upper limit	Z-Value	p-Value
Bilalic, McLeod, & Gobet (2007) - S1 - M1	-0.480	-0.814	0.092	-1.666	0.096
Bilalic, McLeod, & Gobet (2007) - S1 - M2	-0.410	-0.782	0.178	-1.388	0.165
Unterrainer, Kaller, Leonhart, & Rahm (2011) - M1	-0.241	-0.633	0.250	-0.961	0.336
Hanggi, Brutsch, Siegel, & Jancke (2014) - M2	-0.236	-0.652	0.289	-0.876	0.381
Unterrainer, Kaller, Leonhart, & Rahm (2011) - M2	-0.151	-0.574	0.336	-0.595	0.552
Li, Jiang, Qiu, Yang, Huang, Lui, & Gong (2015)	-0.135	-0.503	0.275	-0.637	0.524
Hanggi, Brutsch, Siegel, & Jancke (2014) - M3	-0.114	-0.574	0.400	-0.417	0.677
Unterrainer, Kaller, Halsband, & Rahm (2006) - M1	-0.076	-0.583	0.474	-0.253	0.801
Grabner, Neubauer, & Stern (2007) - M2	-0.070	-0.295	0.162	-0.587	0.557
Unterrainer, Kaller, Halsband, & Rahm (2006) - M2	-0.067	-0.577	0.481	-0.223	0.824
Grabner, Neubauer, & Stern (2007) - M3	-0.060	-0.286	0.172	-0.503	0.615
Campitelli & Labollita (2016)	-0.055	-0.426	0.332	-0.270	0.787
Unterrainer, Kaller, Leonhart, & Rahm (2011) - M3	0.000	-0.463	0.463	0.000	1.000
Waters, Gobet, & Leyden (2002)	0.030	-0.292	0.346	0.178	0.859
Frank & D'Hondt (1979) - M4	0.120	-0.224	0.438	0.678	0.498
Frank & D'Hondt (1979) - M1	0.130	-0.215	0.446	0.735	0.463
Frank & D'Hondt (1979) - M7	0.160	-0.185	0.470	0.907	0.365
Bilalic, McLeod, & Gobet (2007) - S2 - M2	0.190	-0.284	0.589	0.778	0.436
Frank & D'Hondt (1979) - M2	0.200	-0.145	0.502	1.139	0.255
Grabner, Neubauer, & Stern (2007) - M4	0.200	-0.031	0.411	1.699	0.089
Frank & D'Hondt (1979) - M3	0.210	-0.135	0.509	1.198	0.231
Frank & D'Hondt (1979) - M8	0.250	-0.093	0.540	1.435	0.151
Hanggi, Brutsch, Siegel, & Jancke (2014) - M1	0.274	-0.252	0.675	1.024	0.306
Frank & D'Hondt (1979) - M5	0.290	-0.050	0.570	1.678	0.093
de Bruin, Kok, Leppink, & Camp (2014) - M1	0.292	-0.338	0.741	0.903	0.366
Bilalic, McLeod, & Gobet (2007) - S2 - M1	0.300	-0.173	0.661	1.253	0.210
Grabner, Neubauer, & Stern (2007) - M1	0.300	0.075	0.496	2.593	0.010
de Bruin, Kok, Leppink, & Camp (2014) - M2	0.319	-0.311	0.754	0.993	0.321
Ferreira & Palhares (2008) - M2	0.320	0.009	0.575	2.014	0.044
Horgan & Morgan (1990)	0.335	-0.174	0.703	1.304	0.192
Ferreira & Palhares (2008) - M1	0.458	0.170	0.674	3.004	0.003
Frank & D'Hondt (1979) - M6	0.520	0.224	0.728	3.238	0.001
	0.126	0.046	0.204	3.093	0.002

Correlation and 95% CI



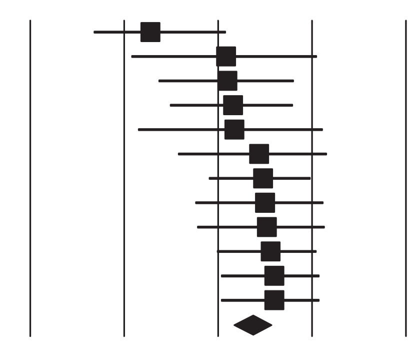
Study name	Correlation	Lower limit	Upper limit	Z-Value	p-Value
Frank & D'Hondt (1979) - M4	0.070	-0.259	0.384	0.410	0.682
Unterrainer, Kaller, Leonhart, & Rahm (2011) - M1	0.120	-0.245	0.455	0.638	0.523
Frank & D'Hondt (1979) - M1	0.250	-0.080	0.530	1.494	0.135
Sala, Gorini, & Pravettoni (2015) - S1	0.291	0.186	0.390	5.259	0.000
Trinchero & Sala (2016) - S3	0.291	0.164	0.409	4.373	0.000
Trinchero & Sala (2016) - S1	0.307	0.181	0.423	4.630	0.000
Grabner, Neubauer, & Stern (2007) - M2	0.380	0.111	0.597	2.717	0.007
Grabner, Neubauer, & Stern (2007) - M3	0.390	0.123	0.605	2.797	0.005
Sala, Gorini, & Pravettoni (2015) - S2	0.398	0.165	0.589	3.236	0.001
Sala & Trinchero (n.d.) - S1	0.434	0.101	0.680	2.503	0.012
Trinchero & Sala (2016) - S2	0.437	0.344	0.521	8.368	0.000
Frank & D'Hondt (1979) - M2	0.450	0.148	0.675	2.835	0.005
Grabner, Neubauer, & Stern (2007) - M1	0.450	0.194	0.649	3.292	0.001
Sala & Trinchero (n.d.) - S2	0.503	0.103	0.763	2.412	0.016
Frank & D'Hondt (1979) - M3	0.530	0.250	0.728	3.451	0.001
	0.349	0.299	0.398	12.656	0.000

Correlation and 95% CI



Study name	Correlation	Lower limit	Upper limit	Z-Value	p-Value
Bilalic, McLeod, & Gobet (2007) - S1	-0.360	-0.661	0.041	-1.768	0.077
Unterrainer, Kaller, Leonhart, & Rahm (2011) - M1	0.043	-0.461	0.526	0.156	0.876
Frank & D'Hondt (1979) - M1	0.050	-0.316	0.403	0.260	0.795
Bilalic, McLeod, & Gobet (2007) - S2	0.080	-0.255	0.398	0.461	0.645
Unterrainer, Kaller, Leonhart, & Rahm (2011) - M2	0.087	-0.425	0.557	0.316	0.752
de Bruin, Kok, Leppink, & Camp (2014)	0.219	-0.212	0.579	0.996	0.319
Grabner, Neubauer, & Stern (2007) - M4	0.240	-0.048	0.491	1.638	0.101
Frank & D'Hondt (1979) - M2	0.250	-0.121	0.560	1.328	0.184
Frank & D'Hondt (1979) - M3	0.260	-0.110	0.567	1.383	0.167
Grabner, Neubauer, & Stern (2007) - M3	0.280	-0.005	0.523	1.925	0.054
Grabner, Neubauer, & Stern (2007) - M1	0.300	0.017	0.539	2.071	0.038
Grabner, Neubauer, & Stern (2007) - M2	0.300	0.017	0.539	2.071	0.038
	0.185	0.084	0.282	3.552	0.000

Correlation and 95% CI



Appendix B. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.intell.2016.08.002.

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Corrigendum

Corrigendum to "the relationship between cognitive ability and chess skill: A comprehensive meta-analysis" [Intelligence 59 (2016) 72–83]

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We adjusted for dependent performance measures using a method based on Cheung and Chan's (2004, 2008) method. Cheung and Chan's method adjusts the sample size to be between the sample N and the cumulative sample N, and applies this to the average of the dependent effect sizes. Their adjustment formula is as follows: adjusted $N = ((N-1)/C) + 1$, where C accounts for the correlation between dependent effect sizes, in addition to the overall average effect size, and the number of dependent effect sizes per sample. We inadvertently used the formula as follows: adjusted $N = (N-1)/(C+1)$ and then applied this formula to each individual effect size (rather than an average). We did not realize this until recently.

Publication bias analyses as originally reported.

Trim and fill analyses estimate the number of missing studies from the meta-analysis due to the suppression of the most extreme results on one side of the funnel plot. The method then imputes the effect sizes for the missing studies based on the observed data's asymmetry to create a more symmetrical funnel plot. The adjusted meta-analytic mean effect size is also reported. This adjusted mean effect size is not necessarily a more valid estimate of the overall effect, but provides information about the sensitivity of the model to publication bias due to suppression. In the present case, these analyses indicated that studies yielding a larger-than-average effect size were missing from the Gf model (10 studies). By contrast, the analyses suggested that studies yielding weaker-than-average effect sizes were missing from the Gsm, Gs, and full-scale IQ models (1 study, 3 studies, and 1 study, respectively). Given that the asymmetry fell on both sides of the means across the models, there is little evidence to suggest a systematic suppression of particular effect size magnitudes.

Publication bias analyses after Cheung and Chan adjustment.

Trim and fill analyses estimate the number of missing studies from the meta-analysis due to the suppression of the most extreme results on one side of the funnel plot. The method then imputes the effect sizes for the missing studies based on the observed data's asymmetry to create a more symmetrical funnel plot. The adjusted meta-analytic mean effect size is also reported. This adjusted mean effect size is not necessarily a more valid estimate of the overall effect, but provides information about the sensitivity of the model to publication bias due to suppression. In the present case, these analyses indicated that studies yielding a larger-than-average effect size were missing from the Gf model (1 study) and Gc model (3 studies). By contrast, the analyses suggested that studies yielding weaker-than-average effect sizes were missing from the Gsm, Gs, and full-scale IQ models (1 study, 2 studies, and 1 study, respectively). Given that the asymmetry fell on both sides of the means across the models, there is little evidence to suggest a systematic suppression of particular effect size magnitudes.

The overall conclusion that cognitive ability contributes meaningfully to individual differences in chess skill is unchanged; most important, the meta-analytic average of correlations between chess skill and broad cognitive abilities is similar to the originally reported value and still statistically significant (0.24, $p < .001$, in the original analyses, vs. 0.22, $p < .001$, in the corrected analyses). However, as shown below in Table 1, there are changes in some specific conclusions. Most notably, while the correlations of chess skill with fluid intelligence (Gf) and short-term/working memory (Gsm) are unaffected, the correlations of chess skill with crystallized intelligence (Gc) and processing speed (Gs) are no longer statistically significant. See Table 1 for a complete list of our reported results compared with the results using Cheung and Chan's approach, and see Fig. 1-9 for updated funnel plots. Questions can be directed to Alexander P. Burgoyne at burgoyn4@msu.edu.

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Table 1
Results as Reported Compared with Results with Cheung and Chan's Adjustment Method.

Results description	Reported results	Results with Cheung and Chan adjustment
Model 1: Meta-analytic average correlation between Gf and chess skill	$\bar{r}$ = 0.24, 95% CI [0.18, 0.30], p < .001. I^2 = 56.94	$\bar{r}$ = 0.23, 95% CI [0.16, 0.31], p < .001. I^2 = 68.62
Model 2: Meta-analytic average correlation between Gc and chess skill	$\bar{r}$ = 0.22, 95% CI [0.11, 0.32], p < .001	$\bar{r}$ = 0.13, 95% CI [−0.05, 0.30], p = .153
Model 3: Meta-analytic average correlation between Gsm and chess skill	$\bar{r}$ = 0.25, 95% CI [0.13, 0.37], p < .001	$\bar{r}$ = 0.25, 95% CI [0.13, 0.37], p < .001
Model 4: Meta-analytic average correlation between Gs and chess skill	$\bar{r}$ = 0.24, 95% CI [0.08, 0.39], p = .004. I^2 = 50.36	$\bar{r}$ = 0.19, 95% CI [−0.03, 0.41], p = .097. I^2 = 64.96
Model 5: Meta-analytic average correlation of Models 1 through 4	$\bar{r}$ = 0.24, 95% CI [0.19, 0.28], p < .001	$\bar{r}$ = 0.22, 95% CI [0.16, 0.28], p < .001
Meta-analytic average correlation of full-scale IQ and chess skill	$\bar{r}$ = 0.10, 95% CI [− 0.19, 0.38], p = .483. I^2 = 75.13	$\bar{r}$ = 0.10, 95% CI [− 0.19, 0.38], p = .483. I^2 = 75.13
Meta-analytic average correlation of visuospatial ability and chess skill	$\bar{r}$ = 0.13, 95% CI [0.05, 0.20], p = .002	$\bar{r}$ = 0.08, 95% CI [−0.03, 0.20], p = .143
Meta-analytic average correlation of numerical ability and chess skill	$\bar{r}$ = 0.35, 95% CI [0.30, 0.40], p < .001	$\bar{r}$ = 0.34, 95% CI [0.30, 0.39], p < .001
Meta-analytic average correlation of verbal ability and chess skill	$\bar{r}$ = 0.19, 95% CI [0.08, 0.28], p < .001	$\bar{r}$ = 0.12, 95% CI [−0.04, 0.28], p = .131
Skill level (ranked vs. unranked) moderator of correlation of Gf and chess skill	$Q(1)$ = 8.37, p = .004	$Q(1)$ = 9.71, p = .002
Correlation between Gf and chess skill for ranked samples	$\bar{r}$ = 0.14, 95% CI [0.02, 0.25], p = .018	$\bar{r}$ = 0.10, 95% CI [−0.01, 0.21], p = .089
Correlation between Gf and chess skill for unranked samples	$\bar{r}$ = 0.32, 95% CI [0.27, 0.38], p < .001	$\bar{r}$ = 0.33, 95% CI [0.24, 0.43], p < .001
Skill level (mean rating < 2000 vs. ≥ 2000) moderator of correlation of Gf and chess skill	$Q(1)$ = 1.99, p = .159	$Q(1)$ = 0.21, p = .647
Correlation between Gf and chess skill for higher-rated samples	$\bar{r}$=-0.10, 95% CI [−0.34, 0.14], p = .411	$\bar{r}$=-0.11, 95% CI [−0.41, 0.20], p = .495
Correlation between Gf and chess skill for lower-rated samples	$\bar{r}$ = 0.10, 95% CI [−0.04, 0.23], p = .147	$\bar{r}$=-0.02, 95% CI [−0.22, 0.18], p = .842
Age (adult vs. youth) moderator of correlation of Gf and chess skill	$Q(1)$ = 9.83, p = .002	$Q(1)$ = 10.65, p = .001
Correlation between Gf and chess skill for adult samples	$\bar{r}$ = 0.11, 95% CI [−0.01, 0.22], p = .071	$\bar{r}$ = 0.04, 95% CI [−0.11, 0.18], p = .628
Correlation between Gf and chess skill for youth samples	$\bar{r}$ = 0.32, 95% CI [0.25, 0.38], p < .001	$\bar{r}$ = 0.31, 95% CI [0.22, 0.39], p < .001
Rank by age (ranked adult vs. ranked youth) moderator of correlation of Gf and chess skill	$Q(1)$ = 0.932, p = .334	$Q(1)$ = 1.00, p = .317
Correlation between Gf and chess skill for ranked adult samples	$\bar{r}$ = 0.11, 95% CI [−0.01, 0.22], p = .071	$\bar{r}$=-0.01, 95% CI [−0.25, 0.22], p = .916
Correlation between Gf and chess skill for ranked youth samples	$\bar{r}$ = 0.27, 95% CI [−0.04, 0.53], p = .092	$\bar{r}$ = 0.18, 95% CI [−0.11, 0.47], p = .232
Skill level (ranked vs. unranked) moderator of correlation of visuospatial ability and chess skill	$Q(1)$ = 6.39, p = .011	$Q(1)$ = 2.84, p = .092
Correlation between visuospatial ability and chess skill for ranked samples	$\bar{r}$ = 0.05, 95% CI [−0.07, 0.16], p = .420	$\bar{r}$ = 0.03, 95% CI [−0.10, 0.16], p = .630
Correlation between visuospatial ability and chess skill for unranked samples	$\bar{r}$ = 0.25, 95% CI [0.14, 0.35], p < .001	$\bar{r}$ = 0.25, 95% CI [0.03, 0.47], p = .027
Age (adult vs. youth) moderator of correlation of visuospatial ability and chess skill	$Q(1)$ = 8.85, p = .003	$Q(1)$ = 5.16, p = .023
Correlation between visuospatial ability and chess skill for adult samples	$\bar{r}$ = 0.03, 95% CI [−0.06, 0.12], p = .491	$\bar{r}$=-0.01, 95% CI [−0.14, 0.12], p = .905
Correlation between visuospatial ability and chess skill for youth samples	$\bar{r}$ = 0.24, 95% CI [0.14, 0.33], p < .001	$\bar{r}$ = 0.22, 95% CI [0.07, 0.37], p = .003
Skill level (ranked vs. unranked) moderator of correlation of verbal ability and chess skill	$Q(1)$ = 0.01, p = .945	$Q(1)$ = 0.29, p = .593
Correlation between verbal ability and chess skill for ranked samples	$\bar{r}$ = 0.18, 95% CI [0.01, 0.33], p = .039	$\bar{r}$ = 0.06, 95% CI [−0.20, 0.32], p = .646
Correlation between verbal ability and chess skill for unranked samples	$\bar{r}$ = 0.17, 95% CI [0.00, 0.33], p = .052	$\bar{r}$ = 0.16, 95% CI [−0.10, 0.42], p = .226
Age (adult vs. youth) moderator of correlation of verbal ability and chess skill	$Q(1)$ = 2.13, p = .144	$Q(1)$ = 0.66, p = .418
Correlation between verbal ability and chess skill for adult samples	$\bar{r}$ = 0.25, 95% CI [0.12, 0.38], p < .001	$\bar{r}$ = 0.20, 95% CI [−0.06, 0.47], p = .136
Correlation between verbal ability and chess skill for youth samples	$\bar{r}$ = 0.09, 95% CI [−0.09, 0.27], p = .340	$\bar{r}$ = 0.06, 95% CI [−0.15, 0.28], p = .569

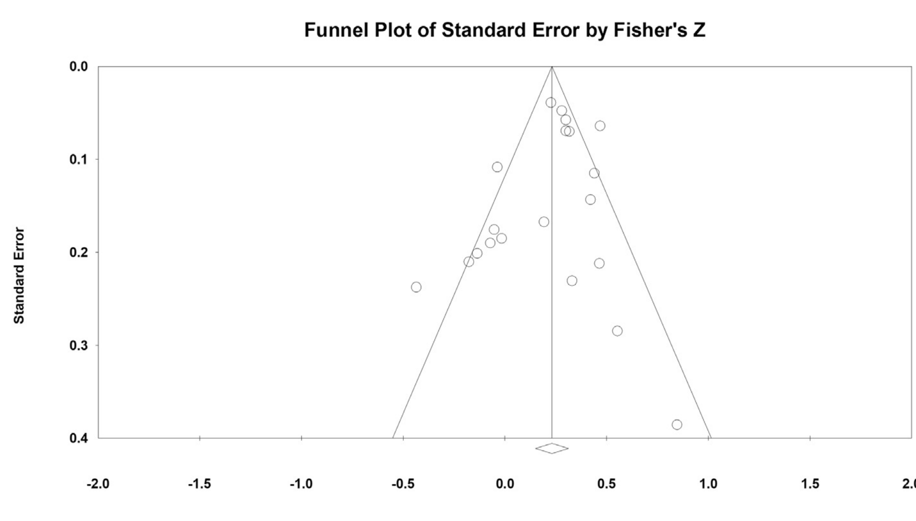

Fig. 1. *Funnel plot for Model 1 (Gf) after Cheung and Chan adjustment.*

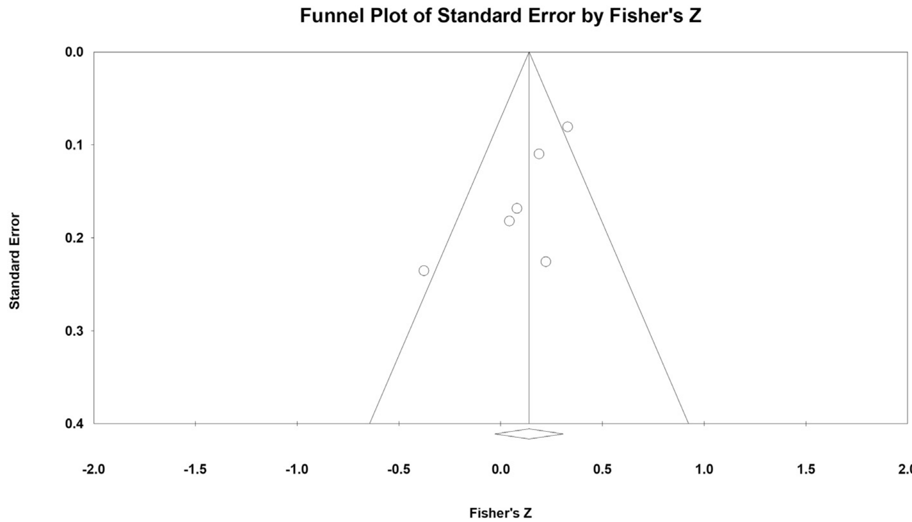

Fig. 2. *Funnel plot for Model 2 (Gc) after Cheung and Chan adjustment.*

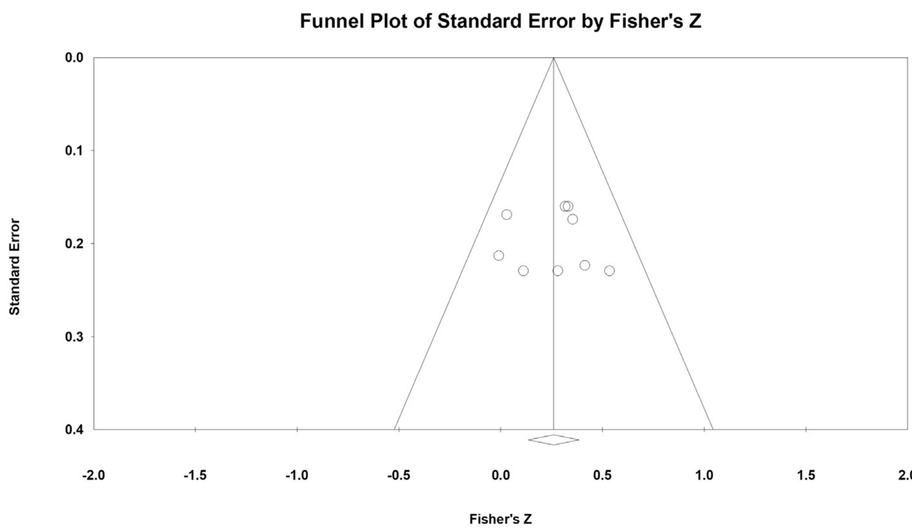

Fig. 3. *Funnel plot for Model 3 (Gsm) after Cheung and Chan adjustment.*

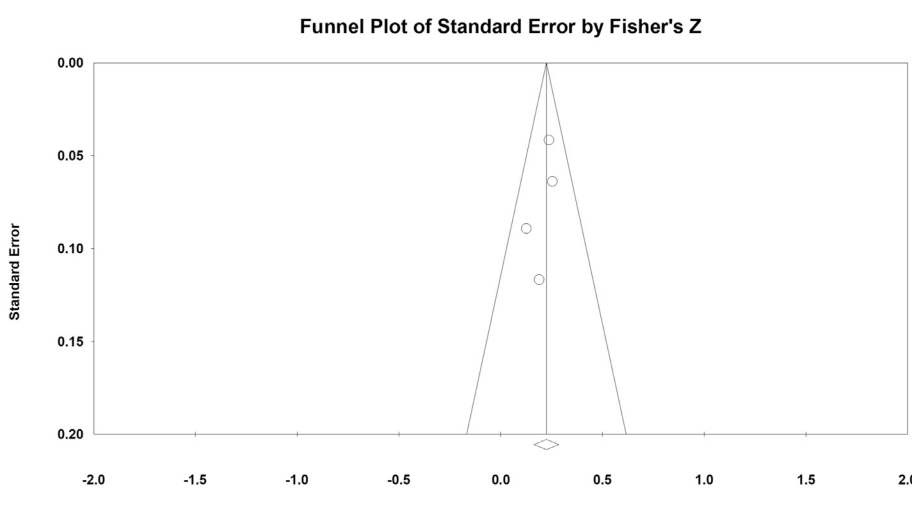

Fig. 4. *Funnel plot for Model 4 (Gs) after Cheung and Chan adjustment.*

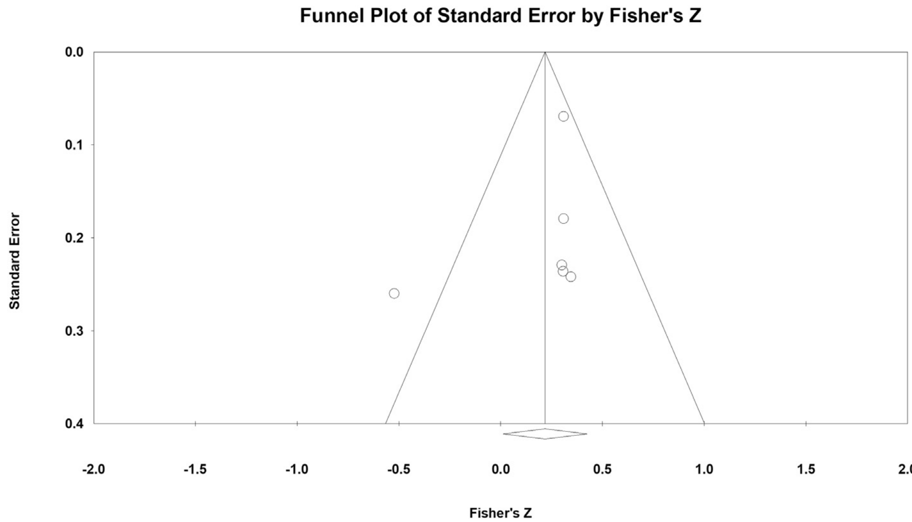

Fig. 5. *Funnel plot for Models 1–4 after Cheung and Chan adjustment.*

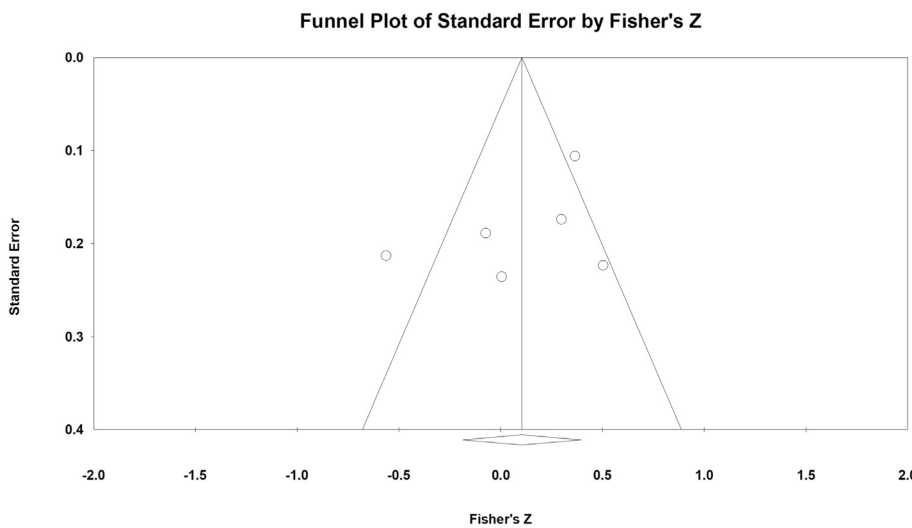

Fig. 6. *Funnel plot for Model 6 (Full-Scale IQ) after Cheung and Chan adjustment.*

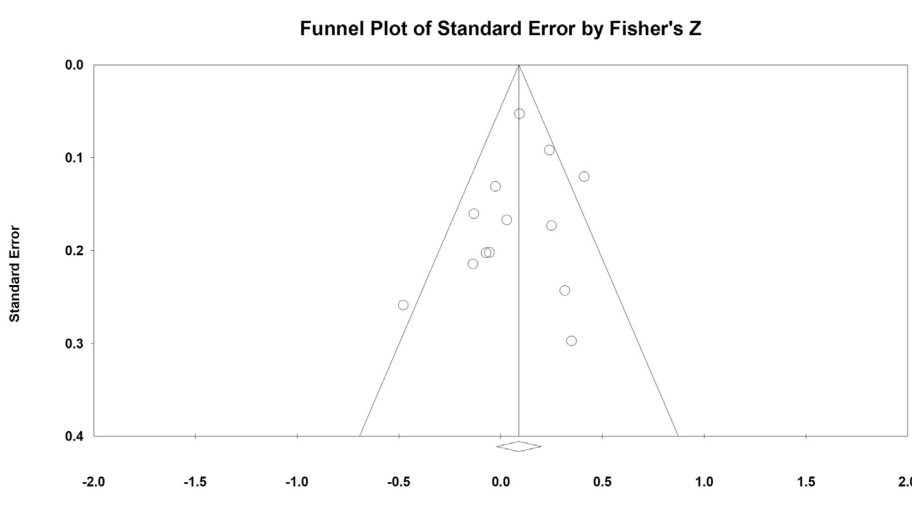

Fig. 7. *Funnel plot for Visuospatial Ability after Cheung and Chan adjustment.*

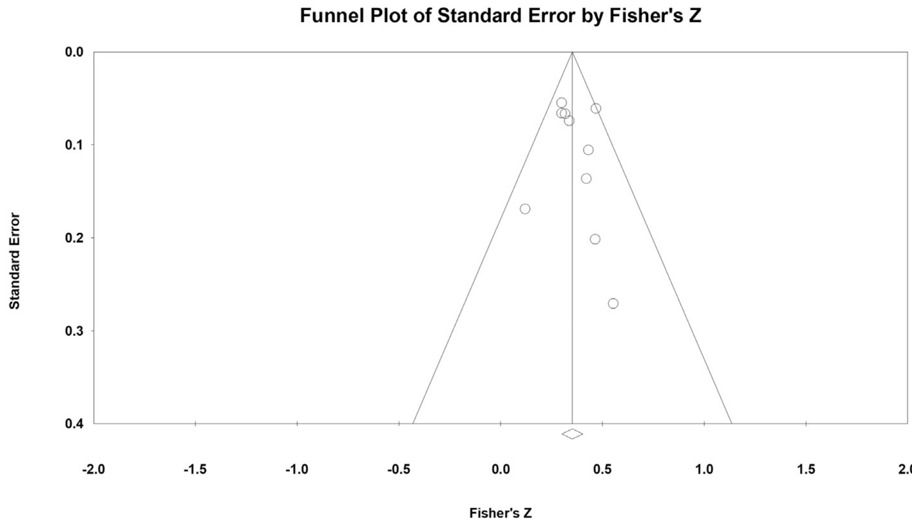

Fig. 8. *Funnel plot for Numerical Ability after Cheung and Chan adjustment.*

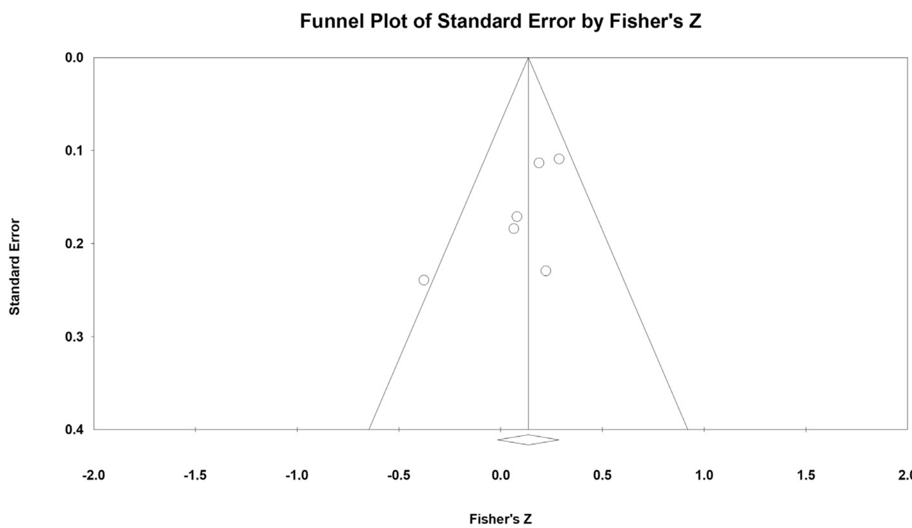

Fig. 9. *Funnel plot for Verbal Ability after Cheung and Chan adjustment.*

References

Cheung, S. F., & Chan, D. K.-S. (2004). Dependent effect sizes in meta-analysis: Incorporating the degree of interdependence. *Journal of Applied Psychology, 89*, 780–791.

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