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Chapter 1 : g factor (psychometrics) - Wikipedia

components from a cognitive model of task performance. An attribute is a description of the procedural or declarative knowledge needed to perform a task in a.

Received Apr 20; Accepted Aug This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited. This article has been cited by other articles in PMC. Abstract Spatial ability predicts performance in mathematics and eventual expertise in science, technology and engineering. Spatial skills have also been shown to rely on neuronal networks partially shared with mathematics. Understanding the nature of this association can inform educational practices and intervention for mathematical underperformance. These findings call for further research aimed at identifying specific environmental mediators of the spatialâ€"mathematics relationship. Research highlights About a third of the variation in spatial ability at age 12 is explained by genetic factors; a little less than half of the variation in mathematics at this age is genetic. We find no sex differences in the genetic and environmental influences either in magnitude or type on mathematical and spatial variation at age Little is known about the aetiology of the associations between spatial abilities and mathematics. The only genetically sensitive study to date suggested that the moderate. Studies, mainly involving elementaryâ€"middle school students, suggest that at a cognitive level, several mechanisms are likely to underlie the spaceâ€"mathematics association e. Performance on a number line task correlates with later mathematical performance, suggesting that precision of symbolic number representation may bootstrap further mathematical learning e. Mathematical relations may be mentally spatially represented, such as the translation of word problems into equations Geary, Recent research has begun to identify brain mechanisms involved in the numberâ€"space cognitive processes. Genetically sensitive studies address the nature of these behavioural, cognitive, and neural associations. The present study is the first adequately powered investigation to evaluate the relative contribution of genetic and environmental factors to individual differences in spatial ability and to its relationship with different aspects of mathematics. However, the twin method explores the sources of individual variation, which can be unrelated to those of average sex differences. We had data for at least one twin in twin pairs MZ, DZ for spatial ability and mathematics; of these, complete pairs MZ, DZ provided data on all measures. More than 10, pairs of twins were recruited to the longitudinal study.

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Chapter 2 : Psychology of reasoning - Wikipedia

In other words, if training on the perceptual-cognitive task could lead to an improvement in abilities that were very different from the training itself. An example of 'far transfer', for instance, could be if an individual starts playing chess and consequently improves his or her mathematical reasoning abilities.

What Are Cognitive Skills, Anyway? Brain training trains the cognitive skills the brain uses to think and learn. Cognitive skills are the core skills your brain uses to think, read, learn, remember, reason, and pay attention. Working together, they take incoming information and move it into the bank of knowledge you use every day at school, at work, and in life. Each of your cognitive skills plays an important part in processing new information. That means if even one of these skills is weak, no matter what kind of information is coming your way, grasping, retaining, or using that information is impacted. In fact, most learning struggles are caused by one or more weak cognitive skills. Enables you to stay focused and on task for a sustained period of time Common problems when this skill is weak: Enables you to stay focused and on task despite distractions Common problems when this skill is weak: Enables you to remember information while doing two things at once Common problems when this skill is weak: Enables you to recall information stored in the past Common problems when this skill is weak: Enables you to hang on to information while in the process of using it Common problems when this skill is weak: Enables you to reason, form ideas, and solve problems Common problems when this skill is weak: Enables you to analyze, blend, and segment sounds Common problems when this skill is weak: Struggling with learning to read, reading fluency, or reading comprehension Visual Processing What it does: Enables you to think in visual images Common problems when this skill is weak: Enables you to perform tasks quickly and accurately Common problems when this skill is weak: Most tasks are more difficult. Taking a long time to complete tasks for school or work, frequently being the last one in a group to finish something We call it brain training. Our clients and their families call it life changing. Find out if cognitive training can make life easier for you or someone you love. The first step is to call a LearningRx center near you and schedule an initial brain skills Assessment. The Assessment takes about an hour and is very reasonably priced. Even better, it will give you a world of information about cognitive strengths and weaknesses, as well as insights into the next best step. Call us today and get the answers you need.

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Chapter 3 : Developmental cognitive neuroscience of arithmetic: implications for learning and education

The cognitive demand of a task is the level of cognitive engagement needed to complete the task (Stein et al.). You could think of a problem that requires only memorization as being at the low end of cognitive demand, whereas a task that requires students to make connections between and among mathematical ideas in new ways is a high.

Specific domains assessed by tests include mathematical skill, verbal fluency, spatial visualization, and memory, among others. This finding has since been replicated numerous times. Spearman referred to this common factor as the general factor, or simply g. By convention, g is always printed as a lower case italic. These correlations are known as g loadings. Full-scale IQ scores from a test battery will usually be highly correlated with g factor scores, and they are often regarded as estimates of g. Tests of vocabulary and general information are also typically found to have high g loadings. For example, in the forward digit span test the subject is asked to repeat a sequence of digits in the order of their presentation after hearing them once at a rate of one digit per second. The backward digit span test is otherwise the same except that the subject is asked to repeat the digits in the reverse order to that in which they were presented. The backward digit span test is more complex than the forward digit span test, and it has a significantly higher g loading. Similarly, the g loadings of arithmetic computation, spelling, and word reading tests are lower than those of arithmetic problem solving, text composition, and reading comprehension tests, respectively. Tests that have the same difficulty level, as indexed by the proportion of test items that are failed by test takers, may exhibit a wide range of g loadings. For example, tests of rote memory have been shown to have the same level of difficulty but considerably lower g loadings than many tests that involve reasoning. Several explanations have been proposed. However, he thought that the best indicators of g were those tests that reflected what he called the eduction of relations and correlates, which included abilities such as deduction , induction , problem solving, grasping relationships, inferring rules, and spotting differences and similarities. Spearman hypothesized that g was equivalent with "mental energy". However, this was more of a metaphorical explanation, and he remained agnostic about the physical basis of this energy, expecting that future research would uncover the exact physiological nature of g. According to Jensen, the g factor represents a "distillate" of scores on different tests rather than a summation or an average of such scores, with factor analysis acting as the distillation procedure. Wechsler similarly contended that g is not an ability at all but rather some general property of the brain. Jensen hypothesized that g corresponds to individual differences in the speed or efficiency of the neural processes associated with mental abilities. Thorndike and Godfrey Thomson , proposes that the existence of the positive manifold can be explained without reference to a unitary underlying capacity. According to this theory, there are a number of uncorrelated mental processes, and all tests draw upon different samples of these processes. The intercorrelations between tests are caused by an overlap between processes tapped by the tests. Similarly, high correlations between different batteries could be due to them measuring the same set of abilities rather than the same ability. Based on the sampling theory, one might expect that related cognitive tests share many elements and thus be highly correlated. Another problematic finding is that brain damage frequently leads to specific cognitive impairments rather than a general impairment one might expect based on the sampling theory. Thus there is no single process or capacity underlying the positive correlations between tests. During the course of development, the theory holds, any one particularly efficient process will benefit other processes, with the result that the processes will end up being correlated with one another. Thus similarly high IQs in different persons may stem from quite different initial advantages that they had. Each small oval is a hypothetical mental test. The blue areas correspond to test-specific variance s , while the purple areas represent the variance attributed to g. Factor analysis is a family of mathematical techniques that can be used to represent correlations between intelligence tests in terms of a smaller number of variables known as factors. The purpose is to simplify the correlation matrix by using hypothetical underlying factors to explain the patterns in it. When all correlations in a matrix are positive, as they are in the case of IQ, factor analysis will yield a general factor common to all tests. The general factor of IQ tests is referred to as the g factor, and it typically accounts for 40 to 50 percent of the variance in IQ test batteries. Initially, he developed a model of intelligence in which variations in all intelligence test scores are explained by only two kinds of variables: Later research based on more diverse test batteries than those used by Spearman demonstrated that g alone could not account for all correlations between tests. Specifically, it was found that even after controlling for g, some tests were still correlated with each other. This led to the postulation of group factors that represent variance that groups of tests with similar task demands e. The broad abilities recognized by the model are fluid intelligence Gf , crystallized intelligence Gc , general memory and learning Gy , broad visual perception Gv , broad auditory perception Gu , broad retrieval ability Gr , broad cognitive speediness Gs , and processing speed Gt. Carroll regarded the broad abilities as different "flavors" of g. Through factor rotation , it is, in principle, possible to produce an infinite number of different factor solutions that are mathematically equivalent in their ability to account for the intercorrelations among cognitive tests. These include solutions that do not contain a g factor. Thus factor analysis alone cannot establish what the underlying structure of intelligence is. In choosing between different factor solutions, researchers have to examine the results of factor analysis together with other information about the structure of cognitive abilities. These include the existence of the positive manifold, the fact that certain kinds of tests generally the more complex ones have consistently larger g loadings, the substantial invariance of g factors across different test batteries, the impossibility of constructing test batteries that do not yield a g factor, and the widespread practical validity of g as a predictor of individual outcomes. The g factor, together with group factors, best represents the empirically established fact that, on average, overall ability differences between individuals are greater than differences among abilities within individuals, while a factor solution with orthogonal factors without g obscures this fact. Moreover, g appears to be the most heritable component of intelligence. These include exploratory factor analysis, principal components analysis PCA , and confirmatory factor analysis. Different factor-extraction methods produce highly consistent results, although PCA has sometimes been found to produce inflated estimates of the influence of g on test scores. At the lowest, least general level there are a large number of narrow first-order factors; at a higher level, there are a relatively small number â€" somewhere between five and ten â€" of broad i. Any test can therefore be used as an indicator of g. Following Spearman, Arthur Jensen more recently argued that a g factor extracted from one test battery will always be the same, within the limits of measurement error, as that extracted from another battery, provided that the batteries are large and diverse. Thus a composite score of a number of different tests will load onto g more strongly than any of the individual test scores, because the g components cumulate into the composite score, while the uncorrelated non-g components will cancel each other out. Theoretically, the composite score of an infinitely large, diverse test battery would, then, be a perfect measure of g. Thurstone argued that a g factor extracted from a test battery reflects the average of all the abilities called for by the particular battery, and that g therefore varies from one battery to another and "has no fundamental psychological significance. This can be done within a confirmatory factor analysis framework. The second study found that g factors derived from four of five test batteries correlated at between. They attributed the somewhat lower correlations with the CFIT battery to its lack of content diversity for it contains only matrix-type items, and interpreted the findings as supporting the contention that g factors derived from different test batteries are the same provided that the batteries are diverse enough. The results suggest that the same g can be consistently identified from different test batteries. The distributions of scores on typical IQ tests are roughly normal, but this is achieved by construction, i. It has been argued[who? In particular, g can be thought of as a composite variable that reflects the additive effects of a large number of independent genetic and environmental influences, and such a variable should, according to the central limit theorem , follow a normal distribution. More specifically, SLODR predicts that the g factor will account for a smaller proportion of individual differences in cognitive tests scores at higher scores on the g factor. SLODR was originally proposed by Charles Spearman , [54] who reported that the average correlation between 12 cognitive ability tests was. Detterman and Daniel rediscovered this phenomenon in

The most common approach has been to divide individuals into multiple ability groups using an observable proxy for their general intellectual ability, and then to either compare the average interrelation among the subtests across the different groups, or to compare the proportion of variation accounted for by a single common factor, in the different groups. Tucker-Drob [58] extensively reviewed the literature on SLODR and the various methods by which it had been previously tested, and proposed that SLODR could be most appropriately captured by fitting a common factor model that allows the relations between the factor and its indicators to be nonlinear in nature. He applied such a factor model to a nationally representative data of children and adults in the United States and found consistent evidence for SLODR. A recent meta-analytic study by Blum and Holling [59] also provided support for the differentiation hypothesis. As opposed to most research on the topic, this work made it possible to study ability and age variables as continuous predictors of the g saturation, and not just to compare lower- vs. Results demonstrate that the mean correlation and g loadings of cognitive ability tests decrease with increasing ability, yet increase with respondent age. SLODR , as described by Charles Spearman , could be confirmed by a g-saturation decrease as a function of IQ as well as a g-saturation increase from middle age to senescence. Specifically speaking, for samples with a mean intelligence that is two standard deviations i. The question remains whether a difference of this magnitude could result in a greater apparent factorial complexity when cognitive data are factored for the higher-ability sample, as opposed to the lower-ability sample. It seems likely that greater factor dimensionality should tend to be observed for the case of higher ability, but the magnitude of this effect i. Practical validity[edit] The practical validity of g as a predictor of educational, economic, and social outcomes is more far-ranging and universal than that of any other known psychological variable. The validity of g is greater the greater the complexity of the task. The correlation between test scores and a measure of some criterion is called the validity coefficient. One way to interpret a validity coefficient is to square it to obtain the variance accounted by the test. For example, a validity coefficient of. This approach has, however, been criticized as misleading and uninformative, and several alternatives have been proposed. One arguably more interpretable approach is to look at the percentage of test takers in each test score quintile who meet some agreed-upon standard of success. For example, if the correlation between test scores and performance is. This is apparently because g is closely linked to the ability to learn novel material and understand concepts and meanings. At more advanced educational levels, more students from the lower end of the IQ distribution drop out, which restricts the range of IQs and results in lower validity coefficients. In high school, college, and graduate school the validity coefficients are. The g loadings of IQ scores are high, but it is possible that some of the validity of IQ in predicting scholastic achievement is attributable to factors measured by IQ independent of g. According to research by Robert L. Thorndike , 80 to 90 percent of the predictable variance in scholastic performance is due to g, with the rest attributed to non-g factors measured by IQ and other tests. The correlations ranged from. The correlation between g and a general educational factor computed from the GCSE tests was. In a study of , students at 41 U. At the level of individual employees, the association between job prestige and g is lower â€" one large U. Mean level of g thus increases with perceived job prestige. It has also been found that the dispersion of general intelligence scores is smaller in more prestigious occupations than in lower level occupations, suggesting that higher level occupations have minimum g requirements. The average meta-analytic validity coefficient for performance in job training is. Research also shows that specific aptitude tests tailored for each job provide little or no increase in predictive validity over tests of general intelligence. It is believed that g affects job performance mainly by facilitating the acquisition of job-related knowledge.

Chapter 4 : Strengthen Cognitive Skills | LearningRx

The relationship of math success to visual-spatial abilities is strongly supported by research, and the correlation actually appears to increase as the complexity of the mathematical task increases. The important aspect of visual-spatial processing is not just remembering the shape, size, color and number of objects, but their relationships to.

Specialized Cognitive Taxonomies and General Student Intellectual Development Around the same time as [1], several papers appeared that used taxonomies specialized to mathematics, e. These have the two-dimensional nature of [1], with the columns or verbs replaced by labels that are specific to mathematics, while the rows or nouns simply correspond to different topics in mathematics. In , Andrew Porter [14] explained it this way: Unfortunately, defining content in terms of topics has proven to be insufficient at least if explaining variance in student achievement is the goal [9]. For example, knowing whether or not a teacher has taught linear equations, while providing some useful information, is insufficient. What about linear equations was taught? Were students taught to distinguish a linear equation from a non-linear equation? Were students taught that a linear equation represents a unique line in a two space and how to graph the line? For every topic, content can further be defined according to categories of cognitive demand. In mathematics cognitive demand might distinguish memorize; perform procedures; communicate understanding; solve non-routine problems; conjecture, generalize, prove. More details about this taxonomy of levels of cognitive demand can be found in [15]. A comparison of various such taxonomies can be found in [15]. Similarly, several papers of Mary Kay Stein and various co-authors [19, 20, 21] analyze mathematical tasks and how they are implemented, focusing on middle school, using four levels of cognitive demand: There are also broad models for student intellectual development across not only individual topics but their entire college experience. One of the first such models is due to William Perry, and it can be overly simplified into the following description. Most college students will begin with the belief that there are right and wrong answers to questions, and that professors hold the knowledge of which these are. In the final stages of intellectual development, students recognize that different areas of intellectual inquiry have different standards and some students develop a balance between intellectual independence and commitment to the discipline. The Perry model has been refined and revised by many psychologists to account for diverse student experiences with respect to gender and other factors; an excellent survey of these developments, with pedagogical implications, has been given by Felder and Brent [6,7]. As Thomas Rishel points out [16], students in the early stages of the Perry model or one of its variants often enjoy mathematics precisely because all the answers are perceived as known, and they frequently value mathematical problems that focus on verification of these truths. As these students begin to encounter complicated modeling problems, or as they are first asked to seriously participate in proof-based mathematical reasoning, the cognitive load of such tasks can be much higher than for students who have developed further along this model. Thus, the intellectual stage of development for a given student can impact the level of cognitive demand for various tasks and problems they will encounter in mathematics courses. Level Identification and Task Assessment Given these theoretical frameworks for both cognitive engagement and intellectual development, a practical challenge for instructors is to use these frameworks effectively to increase the quality of teaching and learning in the classroom. With any of the cognitive taxonomies, it can be hard to assess precisely which level s a given student task is hitting. The taxonomy tables discussed in previous sections provide instructors with tools to produce reasonable cognitive demand analysis of the tasks they give students. Engagement with all cognitive levels is necessary for deep learning to take place, so it is important that mathematics faculty identify and provide students with tasks representing a range of levels. Since lower-level tasks are typically already most prevalent, and easiest to assess both in terms of time and resources, faculty have to make the effort to bring in the higher levels. As a result, three challenges for instructors are to identify high-quality mathematical activities for students at higher levels of cognitive demand, to develop methods for assessing student work on such activities, and to create or make use of institutional programs, culture, and resources to support the use of high-quality activities. We will comment on the third issue in our next article in this series. Some mathematics problems afford a wide range of cognitive engagement. These are activities that can give students practice in lower levels of cognitive demand, but also are open-ended enough to eventually lead to grade-appropriate mathematical investigations with high-cognitive demand. When students are working on LFHC problems, they have flexibility in how they navigate through the problem. Unless explicit guidance is given regarding how students should investigate a LFHC problem, it is possible for them to spend most of their time working inside a small range of cognitive demand. Consequently, it is important for instructors to provide some pathways or scaffolding for students to use when first engaging with such problems. Though they are not as common as they deserve to be, mathematicians have developed a wide range of techniques for assessing high-cognitive demand tasks, including written assignments, group work, projects, portfolios, presentations, and more [3, 4, 10, 12, 13]. However, task-appropriate techniques for assessing a given high-cognitive demand task can be challenging to identify and put in practice. It is important that the method for assessing specific tasks be selected in the context of overall course assessment. Some mathematicians have been experimenting with grading schemes that more directly support high-cognitive demand assignments, such as specifications grading and standards-based grading. Unfortunately, the fact remains that there is much to be learned about the efficacy of different methods of assessment [17]. Active Learning and Theories of Learning Implicit in our discussion has been an important point that should be made explicit: Thus, it is not possible to discuss the cognitive level of a mathematical proof itself, though proofs certainly vary in level of sophistication. Rather, one focuses on the cognitive level of what a student is asked to do with the proof: These tasks are all different from the perspective of cognitive demand, hence they are not interchangeable from the perspective of student learning, yet they exhibit superficial similarities and would each generally be considered valuable for students to complete. It is worth remarking that the verbs used in describing each of the tasks are helpful indicators of level of cognitive demand, as the taxonomies suggest. This observation brings us back to active learning, which by definition has as a primary goal to engage students through explicit mathematical tasks in the classroom, in view of peers, instructors, and teaching assistants. One major effect of active learning techniques is that the mathematical processes and practices of students, which are tightly interwoven with high-cognitive achievement, are brought into direct confluence with peer and instructor feedback. Active learning techniques are also well-aligned with contemporary theories of learning, for example constructivism, behaviorism, sociocultural theory, and others [18, 22]. As one example of this alignment, constructivism is based on the idea that people construct their own understanding and knowledge through their experiences rather than through the passive transfer of knowledge from one individual to another. This is a prominent theory of learning among mathematics education researchers with many refinements, e. Conclusion As research regarding the teaching and learning of postsecondary mathematics and science matures and becomes more well-known, both inside the mathematics community and beyond, significant evidence is building that active learning techniques have a strong impact on student achievement on high-cognitive demand tasks. Our main purpose in writing this survey of concepts related to levels of cognitive demand is to introduce mathematicians to the rich and complex set of ideas that have been developed in an attempt to distinguish different types of student activities and actions related to learning. Given the current evidence supporting the positive impact of active learning techniques, mathematics faculty will have an increased need for a refined language with which to discuss both the successes and failures of our students and the efficacy of the large variety of active learning techniques that are available. In our next post in this series, we will discuss the most prominent of these active learning techniques and environments with an eye toward both institutional constraints as discussed in Part I of this series and student learning in the context of levels of cognitive demand. References [1] Anderson, L. A taxonomy for learning, teaching, and assessing: Taxonomy of Educational Objectives: Personal, Expository, Critical, and Creative: Using Writing in Mathematics Courses. Writing Projects for Mathematics Courses: Crushed Clowns, Cars, and Coffee to Go. Mathematical Association of America, Notices of the American

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Mathematical Society. Active learning increases student performance in science, engineering, and mathematics. Upgrading high school mathematics instruction: Improving learning opportunities for low-achieving, low-income youth. Educational Evaluation and Policy Analysis, 19 4 , Assessment Practices in Undergraduate Mathematics. Mathematical Association of America Notes 49, Exploring Cognitive Demand in Instruction and Assessment. Analytic writing assignments in advanced mathematics courses. Writing in the Teaching and Learning of Mathematics. MAA Note 48, Curriculum Assessment, In J. American Educational Research Association, Porter and John L. Defining, Developing, and Using Curriculum Indicators. A Guide for New Mathematicians. Theories of mathematics education. Grover, and Marjorie Henningsen. American Educational Research Journal, Vol. From Research to Practice. Selecting and Creating mathematical Tasks: Master class in mathematics education: International perspectives on teaching and learning.

Chapter 5 : Why do spatial abilities predict mathematical performance?

The purpose of the present study is to investigate the learning effects of practicing mathematical tasks through AR and CMR on task-solving performance while adopting the creative mathematical reasoning framework (Lithner, , Lithner, , Lithner,) and an individual variations perspective of cognitive proficiency (Alloway et al.,

See other articles in PMC that cite the published article. Abstract In this article, we review the brain and cognitive processes underlying the development of arithmetic skills. This review focuses primarily on the development of arithmetic skills in children, but it also summarizes relevant findings from adults for which a larger body of research currently exists. We integrate relevant findings and theories from experimental psychology and cognitive neuroscience. We describe the functional neuroanatomy of cognitive processes that influence and facilitate arithmetic skill development, including calculation, retrieval, strategy use, decision making, as well as working memory and attention. Building on recent findings from functional brain imaging studies, we describe the role of distributed brain regions in the development of mathematical skills. We highlight neurodevelopmental models that go beyond the parietal cortex role in basic number processing, in favor of multiple neural systems and pathways involved in mathematical information processing. From this viewpoint, we outline areas for future study that may help to bridge the gap between the cognitive neuroscience of arithmetic skill development and educational practice. What are the changes that occur in the brain as children begin to develop more complex and quantitative ways of thinking? Why do children show marked individual differences in mathematical abilities, and what factors contribute to these differences? Now, with advancements in quantitative brain imaging and the use of targeted cognitive experiments, we are uniquely positioned to answer these questions. Neural mechanisms underlying the development of these core numerical systems are reviewed elsewhere Ansari, ; here, we focus on the development of brain systems involved in arithmetic. The approach taken here is to highlight major findings related to key component processes involved in arithmetic problem solving and reasoning. We first review core cognitive and brain processes involved in arithmetic processing and discuss the implications of relevant studies in adults for understanding the neural basis of arithmetic skill development. Recent studies have focused on various aspects of arithmetic processing, including 1 retrieval, 2 computation, 3 reasoning and decision making about arithmetic relations, and 4 resolving interference between multiple competing solutions interference resolution. They help to clarify which brain areas are critically and consistently engaged during arithmetic tasks, which regions provide a supportive role in arithmetic, and which brain areas contribute to arithmetic learning. We then discuss recent brain imaging studies of arithmetic in children and examine how they inform our understanding of skill development. We also highlight areas for future study that will help bridge the gap between cognitive neuroscience and educational practice in this domain. In this section, we summarize the relevant findings from lesion and brain imaging studies in adults and discuss their implications for developmental studies of arithmetic. We first clarify some of the key cognitive processes contributing to accurate arithmetic task performance Fig. Comprehension of numerical properties i. Beyond this foundation, fact retrieval and calculation are two core functions mediating arithmetic proficiency. Memory retrieval based on prior learning allows for fast access of learned arithmetic facts. Working memory resources i. In conjunction with these memory processes, attentional resources, sequencing mental operations and decision making also influence the speed and accuracy of performance. These domain-general cognitive resources are as vital as core numerical knowledge in classroom settings when a child is learning to improve arithmetic skills. In this article, we address the contributions of both core and auxiliary components underlying arithmetic. An important aspect of this inquiry relates to how the role of these auxiliary processes changes with the maturation of problem-solving skills Fig.

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Chapter 6 : Can Cognitive Training Really Improve Sports Performance?

tasks. Others are mathematical models of more complex tasks that appear important in their own right outside the laboratory. Some take the form of computer programs for complex tasks that reach a level of detail far more explicit than most mathematical models (Anderson, , ; Newell & Simon,).

True cognitive training role models, however, stand out due to their quality of science and how they train people. In a recent study , a group of sports scientists put different perceptual-cognitive training interventions to the test. A clear finding emerged; that not all cognitive training programs are created equal. Evaluating Cognitive Training In the study, Dr. Zentgraf and his team conducted a meta-review of studies in perceptual-cognitive training in sports. The aim of the review, carried out at the Institute for Sport and Exercise Sciences in Germany, was to evaluate the effectiveness of perceptual-cognitive training interventions with professional athletes. The researchers explained that in interactive sports there are a couple of key factors that equate performance success. One, perceiving and predicting the motion of the ball, and actions of teammates and opponents is paramount. Two, is the need to execute the correct action based on those perceptions and predictions. Sports science research shows that perceptual-cognitive abilities play a major role in differentiating elite athletes from amateurs. Findings have revealed that this is even more so the case in team sports. Examining Positive Transfer Effects Under rigorous benchmarks for methodological quality, the researchers narrowed down 16 perceptual-cognitive training studies from an initial total of 1, Two NeuroTracker studies were selected from the sixteen, with one of these being the only study to have an ideal sample size of athletes. All of the studies were then evaluated by four independent expert reviewers. They examined the studies for evidence of training and transfer effects, according to strict criteria. In other words, if training on the perceptual-cognitive task could lead to an improvement in abilities that were very different from the training itself. This included both NeuroTracker studies. Other recent meta-reviews have revealed that there is often an absence of far transfer in sports, which also includes novice athlete populations. In this context, NeuroTracker is leading the Holy Grail in cognitive sports science research. A common belief is that for positive transfer to occur, practice conditions should closely recreate key situations of sports performance. Positive transfer would occur if they successfully shoot a 3-pointer in a competitive game, thanks to all that practice. The researchers suggested, however, that the NeuroTracker soccer study may provide evidence to the contrary. Namely that effective training does not necessarily need a high degree of task similarity to in-game performance. NeuroTracker, for example, uses a 3D multiple-object training method to increase decision-making abilities. As previously mentioned, NeuroTracker training improved passing decision-making accuracy in soccer players. Consequently, NeuroTracker research is not only setting the standard for evidence-based far-transfer , but also may be defining the boundaries of training athletic performance. Explore more about its use in athletic, medical and learning applications.