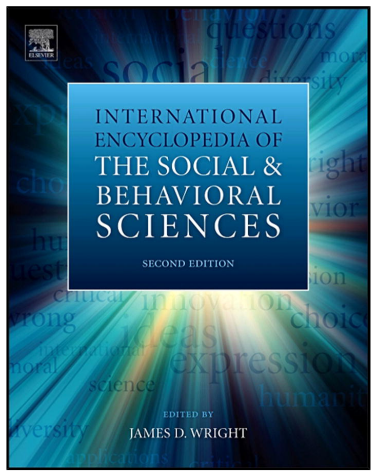

From Stern, E., 2015. Intelligence, Prior Knowledge, and Learning. In: James D. Wright (editor-in-chief), International Encyclopedia of the Social & Behavioral Sciences, 2nd edition, Vol 12. Oxford: Elsevier. pp. 323–328.
ISBN: 9780080970868

Intelligence, Prior Knowledge, and Learning

Elsbeth Stern, ETH Zürich, Zürich, Switzerland

Abstract

Intelligence test scores can account for achievement differences in many content areas to a considerable extent. An individual's intelligence quotient results from complex interactions between genes and environmental stimulation, foremost schooling. The amount of variance in intelligence to be explained by genes is the higher the more successful a society is in providing cognitively stimulating environments for everybody. Intelligence can be understood as a start-up resource of information processing which has to be invested in knowledge in order to enable competencies in a domain. Teacher's professional competencies have a major impact on how learners exploit their intelligence for learning particular subjects.

Intelligence: A Valid Predictor of Achievement Differences

Individuals with similar cultural, social, and educational backgrounds differ from one another in the time they need to process certain information, in their ability to understand complex ideas, in the efficiency with which they can deal with novel, transfer demanding tasks, and in the learning outcome that results from attending certain instructional environments. The construct of psychometric intelligence attempts to clarify what is behind such achievement variations that cannot be explained by differences in learning environments or in amount of practice.

Measuring Intelligence

About a century ago Alfred, Binet constructed problems designed to determine whether children who did not meet certain school requirements suffered from mental retardation or from behavioral disturbances. Since then many psychologists have been quite successful in developing reliable verbal and nonverbal intelligence tests for children and adults. Intelligence tests contain items composed of verbal, numerical, and pictorial material, and they require various mental operations, among them inductive and deductive reasoning, pattern recognition, and memorization. So-called speed tests contain items that are comparably easy for everybody; individual differences in the numbers of correctly solved problems only occur because of time limitations. In power tests, the items are ordered according to their difficulty, and limits in intelligence become apparent if people do not solve all problems despite having sufficient time. The distribution of achievement scores in all intelligence test scales follows the bell curve (normal distribution). This reflects the fact that the majority of people resemble each other quite a lot with respect to their cognitive capabilities, and only a few people show extraordinarily low or high competencies. Normal distribution is the statistical prerequisite for measuring intelligence on interval level by indicating deviations from the mean score. To determine the intelligence quotient (IQ), test scores are converted to a scale in which by convention the mean is 100 and the standard deviation is 15. The reliability of IQ tests, revealed either by correlation coefficients based on repeated measurement or by figuring out internal consistency, is between 0.80 and 0.90, which is higher than for most other psychometric measures. Nonetheless, a reliability lower than 1.0 only allows us to interpret a range rather than a single value. For example, if a person's tested IQ is 110, and if the reliability of the test is 0.90, the IQ of this person is between 101 and 119 with a probability of 95%. A test reliability of 0.80 reveals a range of 97–123.

Despite broad variations in the content and the form of presentation of intelligence test items, all tests have in common that they do not presuppose knowledge that can only be acquired in particular learning environments not accessible to everybody. Moreover, differences in test scores within a group only reflect differences in intelligence between these persons if all of them have had access to comparable learning environments. In other words, each member of the group must have had, in principle, the opportunity to acquire the knowledge necessary to solve the problems. Intelligence test scores can be raised considerably by practicing the respective types of items, while individual differences do not disappear but rather remain quite stable at a higher level. The Flynn effect, named for its discoverer, is the observation that modernization of a nation goes along with massive IQ gains over time. In the meantime, many highly developed countries have reached an asymptote, while nations where modernization began later still gain around three IQ points per decade. Reasons for the Flynn effect are manifold and still under debate, but it is undisputed that better schooling as well as widespread exposure to tasks which resemble intelligence test items in various media are major causes.

Individual differences in intelligence test scores between persons can only be interpreted as differences in general cognitive resources if similar amounts of practice can be presupposed. Attempts to construct so-called culture-free or culture-fair tests, which were supposed to be unaffected by prior experience, have failed because it turns out that different cultures are not prepared in the same way even for dealing with nonverbal material and mental operations that are not part of institutional schooling. Although some studies reveal ethnic differences in mean IQ, hitherto there is no convincing

International Encyclopedia of the Social & Behavioral Sciences, Second Edition, 2015, 323–328

evidence that these differences are genetically affected. There is rather overwhelming evidence that all ethnic groups gain IQ points as a consequence of better schooling. Within a fairly homogenous cultural context, intelligence can be considered as a personality trait mainly for two reasons. First, performance on intelligence items that are based on different contents and mental operations show significant correlations. For instance, correlations between tests on inductive reasoning with pictorial material and with verbal material are around 0.50, and correlations between tests that measure basic visual–spatial competencies such as mental rotation and tests of verbal fluency are about 0.30. In numerous studies run all over the world, multivariate statistical methods such as factor analysis have revealed that a single factor, called factor *g*, can account for 40–50% of the variance in IQ test batteries composed of various scales covering a range of content knowledge and mental operations. Second, longitudinal studies have revealed that IQ is a fairly stable measure across the life span. Long-term stability of IQ for adolescents and adults comes close to the reliability of the tests, as, among others, a once-in-a-century study from Scotland has shown (Deary, 2012). Even cognitive measures of attention gained in early childhood reveal long-term correlations are around 0.50 for both verbal and nonverbal tests. Overall, intelligence test scores predict academic performance fairly well: the correlations between IQ and grades in school and university are about 0.50. The correlations between intelligence test scores and measures of outside-school success such as income or professional status are lower but still significant. That intelligence cannot account for a larger amount of achievement variation is not at all surprising, given the importance of numerous other factors, among them social background, motivation, and effort. A longitudinal study by Duckworth et al. (2011) revealed that standardized achievement test scores were stronger related to intelligence than to motivational factors, while grades determined by teachers were determined more by factors like self-control than by intelligence.

Given that verbal and nonverbal intelligence tests are good predictors of how well an individual will succeed in school and university, they are quite helpful for making recommendations for different educational trajectories. They allow educators to identify children who cannot be expected to gain sufficiently from standard schooling and therefore need extra support adapted to their special needs, or children who might benefit from an advanced learning environment. The validity of intelligence tests can be further increased by the dynamic testing approach (Sternberg and Grigorenko, 2002), which means that all test-takers practice the items in several trials by getting feedback and thinking hints so that individual differences in familiarity with tests are compensated for. Particularly for children from disadvantageous social environments, learning tests are a more reliable and valid measures of intelligence than conventional IQ tests. Attempts to extend the construct of intelligence by including social and emotional competencies as well as striving for success are controversial because the theoretical background of these concepts is still vague, and, more importantly, because the tests designed to measure these aspects do not meet the strong diagnostic criteria that have been established in psychometric research (Neubauer and Freudenthaler, 2005).

What Is Behind Intelligence: Factor *g*, Working Memory, and Specific Abilities

What cognitive capabilities are behind factor *g* is still under debate, although in the past decade major insights could be seen to emerge. This is also due to the fact that much has been learned about the neural underpinnings of human intelligence. The substantial negative correlations between IQ and reaction times in solving simple problems that had been found in numerous studies can now be interpreted in the light of brain imaging research. A constant finding is that more intelligent individuals show less brain activation (measured by electroencephalography (EEG) or functional magnetic resonance imaging (fMRI)) when completing intelligence test items. The more intelligent a person is, the less neural resources he or she needs for solving the problem (Neubauer and Fink, 2009). Particular progress has been made in localizing the brain areas which indicate differences in intelligence: the prefrontal cortex, an area which plays a major role in dealing with complex and novel problems as well as in working memory functions. Considerable progress has been made in bringing together research on working memory and intelligence (Oberauer et al., 2008). Working memory is understood as a central cognitive function of human beings which is responsible for temporarily maintaining and manipulating knowledge during cognitive activity. Working memory functions are measured by tasks that require the goal-oriented active monitoring of incoming information or reactions under interfering and distracting conditions. Performance variations in these tasks have been found to be highly related (average correlations of 0.70 are reported) to differences in intelligence test scores. Psychologists agree that although there is more to IQ than working memory functions, the latter should be regarded as an explanatory construct for reasoning abilities.

Although factor *g* can be extracted from different intelligence tests, many correlations between intelligence subtests, though significant, are low, indicating the involvement of independent mental resources. Even between tests on inductive reasoning which are based on different forms of representation (i.e., pictures, numbers, words), only medium correlations are revealed, suggesting that cognitive processes are to a large extent guided by specific verbal, visual–spatial, or numerical abilities, among others. Since the 1960s, concerted attempts have been made to integrate general and specific abilities into broader theories of intelligence in a hierarchical model which is now known as the Cattell–Horn–Carroll theory, which has been recently discussed in light of modern IQ tests by Kaufman (2009). Psychologists now agree that the abilities which contribute to intelligence tests scores are best classified on three levels. Narrow abilities on level one either refer to speed of sensory processes or specific competencies acquired through learning (e.g., reading skills). The broad abilities on level two go on from the distinction between fluid intelligence (Gf) and crystallized intelligence (Gc). Gf mainly describes logical reasoning, measured by content-poor nonverbal tests, and Gc, which is particularly revealed in content-rich verbal tests, represents the accumulation of reading and writing skills as well as higher-order knowledge over the life span of an individual. Level three describes a unified component of cognitive competencies which corresponds to the general factor.

The distinction between Gf and Gc is important in light of age-related changes of intelligence. While both kinds of intelligence are closely interrelated in childhood, from the age of about 25 years on, however, Gf and Gc take different developmental trajectories. While Gf starts to decrease at the age of 25, first slightly and from about 50 years on more quickly, Gc is unaffected by age and even has good chances to increase until the age of around 70. It is worth noticing that because of the large individual differences, the given age information is only a rough estimation. Developmental changes also occur with respect to the structure of intelligence. The prominence of Gf decreases during childhood while Gc as a function of repeated enlargement and rearrangement of knowledge becomes more useful.

Intelligence as the Result of Gene–Environment Interactions

The question of heritability of intelligence can still cause quite a stir in the broader public. In science, however, the controversy on whether genes have an impact on the development of intelligence is a thing of the past. To make a long story short, it is no longer the question of nature *versus* nurture but nature via nurture (Ridley, 2003). Every aspect of human behavior is embodied in genes but it is the environment which triggers gene expression. Particularly the comparison between identical and fraternal twins shed light on the impact of genes on intelligence. The correlation between the intelligence test scores of raise-together identical twins almost ties up with the reliability coefficient of the respective test. At the same time, the correlation between fraternal twins rarely exceeds the correlation found between regular siblings, although the latter group due to their age differences had been sharing less experience than twins. Other studies revealed that the IQ of young adults who had been adopted shortly after birth was more similar to their biological than to their adoptive parents.

Altogether, twin and adoption studies suggest that 50–80% of the IQ variation is due to genetic differences. This relatively large range of percentage across different studies is due to the population dependence of heritability. It is namely the case that the amount of variance in intelligence test scores explained by genes is higher as more members in a society have access to school education, health care, and sufficient nutrition. Several studies revealed lower heritability of intelligence for children raised in lower socioeconomic status (SES) families (Turkheimer et al., 2003). It turned out that lower SES fraternal twins resembled each other more than higher SES ones, indicating a stronger impact of shared environment under the former condition. Or, in other words, because of the less stimulating environment in lower SES families, the expression of genes involved in the development of intelligence is liable to be hampered.

The complex interaction between genes and environment is also founded on the fact that heritability of intelligence increases during the life span. To understand this very well-established finding, one has to realize that societies which provide access to a broad variety of cognitive activities in professional as well as in private life enable adults more than children to actively select special environments which fit their genes. People who have found their niche can perfect their competencies by deliberate learning. Although, however, it is beyond any shadow of doubt that in developed societies, genes can explain a huge amount of IQ differences, the search for the genes responsible for the expression of cognitive capabilities has not at all met with much success, despite the money and effort invested in human genome projects. Given, however, that even for height less than 20% of the variance can be traced back to already identified genes, it is far from surprising that it is almost impossible to track down the genes that are involved in intelligence (Deary, 2012). It is entirely plausible that very large numbers of genes are spread out across the entire genome and have their share, and moreover these genes seem to interact in very complicated ways with each other as well as with environmental cues. In the foreseeable future, biologists will not be able to predict a baby's cognitive capabilities from his or her DNA. Personalized education, which means that a child gets the education that fits his or her genome, is nothing but a pipe dream. What can, however, be said for sure is that in societies which provide a cognitively stimulating environment for everybody, intelligence differences will not decrease but rather increase on a high level.

Genes, however, not only indirectly guide learning and knowledge acquisition via general and specific abilities. There is rather growing evidence that during evolution, the human mental architecture has been equipped with quite specific knowledge structures, for instance, about visual or auditory patterns, numbers and magnitudes, physical objects, language use, and social situations. Such knowledge structures, typically labeled as core knowledge or privileged knowledge (Spelke and Kinzler, 2007), allow human beings appropriate cognitive and behavioral functioning from the very beginning almost without effort. Such kind of fast learning sharply contrasts with the huge difficulties human beings may encounter when it comes to learning at school. For better understanding the obstacles and often even the severe difficulties that can occur when youngsters are supposed to acquire academic skills and competencies as there are reading, writing, or mathematical and scientific reasoning, one has to take into consideration the evolution of these fields in a cultural context during the past millenniums if not centuries or even decades. A today's child, equipped with a DNA comparable to the one of a stone-age person, is expected to acquire knowledge within few years which took mankind millenniums to develop. The core knowledge human beings have been equipped with during evolution can be the starting point for building more advanced knowledge structures in different domains. In the case of mathematics, it is entirely plausible that nature has equipped human beings with intuitive number knowledge and sensitivity for magnitude. As a consequence, to the best of our knowledge, all cultures have numbers words, even illiterate ones. However, having specific symbols for numbers is even not common among all cultures with script. The Arabic place value number system, which is now common in most parts of the world, was only developed a few hundred years ago. Only after the number '0' had made its way from India via the Arabic countries to Europe that the preconditions for developing our decimal system were given. It was the Arabic number system which opened up the pathway to academic mathematics.

Cultural transformations based on invented symbol systems were the key to advanced mathematics. Central content areas in mathematics curricula of high schools, such as calculus, were only developed less than three centuries ago. What makes school a real challenge is the fact that within a few years young people have to acquire knowledge which has been developed over centuries by genius minds with tremendous effort. While intuitive quantification seems to be a universal cognitive resource almost unaffected by differences in intelligence, correlations of $r = 0.50$ and higher are found between IQ and achievement in mathematics. Discovering principles that underlie the relationships between numbers and understanding how some of these principles can be described in verbal, numerical, and graphical representations required general cognitive resources. This leads to the more general question of how domain-specific knowledge has to be represented in order to allow reasoning and drawing inferences. In the past decades, cognitive scientists have developed theories of knowledge representation which enable higher-order reasoning and academic competencies. Moreover, educational science has worked our frameworks for learning environments that can foster the acquisition of usable knowledge.

Knowledge Construction

Intelligence can be understood as a start-up cognitive resource which has to be invested in the construction of knowledge in order to enable behavioral and cognitive functioning, including problems solving and decision making. How well such activities work out particularly depends on the quality of knowledge representations in the particular content domain. Knowledge has a multifacet nature, among them knowledge about facts or abstract concepts, about how to efficiently solve routine problems, and knowledge about more generally applicable learning strategies. These different facets of knowledge all interact in contributing to a person's competence, and they can differ in their functional characteristics. Elements of knowledge can be isolated or interrelated, context-bound or context-general, abstract or concrete, implicit or conscious, inert or accessible with different degrees. Just having a high accumulation of factual knowledge in a domain is usually not at all enough for cognitive and behavioral functioning. To characterize this situation, the term 'inert knowledge' has been invented. An example of inert knowledge is vocabulary of a foreign language which has been learned and stored in memory in a dictionary style, but cannot be retrieved during natural communication.

Cognitive scientists have agreed on distinguishing between declarative (knowing that) and procedural (knowing how) knowledge, a differentiation that can be applied to a broad variety of subject areas. Declarative knowledge can be communicated because it is represented on the basis of symbol systems (language, script, mathematical, or visual–spatial representations). Declarative knowledge can be applied to concrete instances and facts, or to general and abstract knowledge of the core principles and their interrelations in a domain. It is assumed to be stored mentally in some form of relational representation, for example, schemas or semantic networks which allow for its flexible transformation through processes of inference and elaboration. Declarative knowledge is therefore not bound to specific problem types and it is, in principle, transferable to other problems.

Procedural knowledge, in contrast to declarative knowledge, is usually seen as knowledge of operators and the conditions under which they can be applied to reach certain goals. It can be automated to different degrees, depending on the extent of practice. Automated procedural knowledge can be used with minimal conscious attention and few cognitive resources. This efficiency, however, has the drawback of inflexibility. Because automated knowledge is only partly open to conscious inspection, it can hardly be verbalized or transformed by higher mental processes. As a consequence, it is often tied to specific problem types. Both kinds of knowledge are involved in reasoning and problem solving in any domain, but they are acquired in different pathways. Procedural knowledge results from practice and repetition. The more often we conduct an action in the correct way, the less attention and control will be needed.

Declarative knowledge can be subdivided into factual and conceptual knowledge. While facts can be acquired by rote-learning, conceptual knowledge, in contrast, results from conscious elaboration and reasoning with progressively focusing on defining rather than on characteristic features. This transition was studied for a great variety of concepts from different domains. Younger children, for instance, associate the concept of 'parents' with 'caring for young children,' whereas older children focus on 'having offspring.' Younger children in elementary school will agree that a pile of rice has weight, but deny that an individual grain of rice has weight as well. This seemingly implausible answer turns out to be highly plausible if one realizes that for younger children, 'weight' and 'being heavy' are still equivalent. When being asked whether a grain of rice has weight if it is put on the back of an ant, their answer is yes with deep conviction (for an overview, see Stern, 2005).

Research on learning science and mathematics has shed light on numerous differences in conceptual understanding between experts and novices. This is a particular challenge for schools in general and for teachers in particular. Particularly in subjects like science and mathematics, many teachers are disappointed about their student's scant learning gains despite the effort they put into preparing and structuring the lessons. They strictly keep to a logical sequence, and they present very clear and precise definitions, preferably based on mathematical formulas. As long as tests require students to reproduce definitions and to figure out quantitative information, performance often seems satisfactory. However, a serious lack of conceptual understanding remains, as even the most intelligent students often cannot transfer the insights they should have gained to problems that differ from those dealt with in the classroom. What has gone wrong? Often teachers hold the 'direct transmission' view of learning (Staub and Stern, 2002), according to which successful classroom practice is seen as teachers' providing of information that students memorize and retell. Such learning environments, however, may, at best, help students accumulate facts or acquire simple skills but will not support them in building up the conceptual knowledge they need to model new and complex situations, as required in science and mathematics.

The main barrier that keeps students from learning science and mathematics is not so much what they lack, but what they have – namely, naïve scientific knowledge that often works well in everyday life but largely differs from and even contradicts scientific explanations. Thus, to support students' learning, teachers must diagnose students' initial understanding of the content at hand. Knowledge not conforming to scientific views should not be dismissed as the sad result of deficiencies in previous instruction but, rather, be recognized as an inevitable step in learning. Effective teaching requires presenting students with questions and problems that stimulate processes of knowledge reorganization and thereby help them overcome their bounded or deficient beliefs. Thanks to concerted efforts in educational research, we nowadays know very well that it is the cognitively stimulating classroom environment created by the teachers which is crucial for meaningful learning at all achievement levels. In John Hattie's book *Visible Learning*, more than 800 meta-analyses dealing with factors that might influence school-related achievement were analyzed and synthesized. Obviously accessible factors like class size, methods of instruction, or use of computers were of negligible impact. What counts for student's meaningful learning, however, are teachers who are able to transform student's errors into learning opportunities by providing tasks and tools which make the difference in light of what the students already understand and misunderstand. By presenting their students with challenging but solvable tasks and problems, competent teachers support the construction of a knowledge base where abstract concepts, facts, and procedures are integrated and enable mutual activation.

Prior Knowledge: The Best Predictor of Learning Outcome but Not a Substitute for Intelligence

When entering new learning settings, students often differ from one another. Domain-specific knowledge and intelligence have been identified as the two major sources of difference. Research on cognitive development suggests that variations in prior domain-specific knowledge can often better account for achievement differences between younger and older children than general cognitive capabilities. Moreover, longitudinal studies, such as the Munich Longitudinal Study LOGIC, revealed that within-age level achievement, differences in core elementary school subjects are to a remarkable extent determined by domain-specific prior knowledge obtained in the preschool years. Early numerical competencies could account for achievement variations in mathematics after partialing out general intelligence, and early indicators of letter identification and phonological awareness predicted later performance in reading and writing (Schneider and Bullock, 2009). The reported results are important because they show that at least in complex knowledge domains a high IQ cannot compensate for a lack of prior knowledge, and moreover, that there is no direct connection between intelligence and achievement in content domains based on rich specific knowledge. However, regression analyses based on longitudinal studies reveal that the confounded variance of prior knowledge and intelligence predicts differences in learning outcome better than each single variable. If more intelligent children are placed in stimulating learning environments, they will acquire usable knowledge which will increase their lead.

There is, however, overwhelming evidence for the pivotal role of prior knowledge for further learning and advanced performance. Studies in different areas, among the mathematics, science, and chess, have revealed much better outcomes for persons with high prior knowledge levels (experts) and somewhat lower IQ than for persons with little prior knowledge (novices) and high IQ (Grabner et al., 2007). Note, it were novices and not laypersons who were considered in these studies. In contrast to laypersons novices possess the necessary domain-specific knowledge in terms of rules and core concepts but differ from experts in their lack of practice.

For individuals who grow up in a cognitively stimulating environment, prior knowledge and intelligence are to a certain extent inextricably linked with each other. Intelligence may guide the selection of learning environments and thereby determine the acquisition of prior knowledge. A person with a low IQ will hardly follow courses on theoretical physics even if he or she is credited with extra time. Moreover, intelligence may affect the number of content areas in which a person is able to acquire a profound amount of prior knowledge. This view has been clearly confirmed by the Study of Mathematically Precocious Youth, in which individuals were identified on the basis of very high reasoning abilities before the age of 13. Thirty-five years later, these individuals achieved occupational success comparable to that of individuals attending world-class mathematics, science, and engineering graduate training programs. A remarkable result was that the ratio of very successful people in the upper quarter of this highly selected sample (percentile >99) was higher than in the lower quarter (Lubinski and Benbow, 2006).

Intelligence and Learning: Educational Implications

Comparisons between schooled and unschooled groups reveal a strong effect of education on intelligence test scores even on nonverbal tests. Only by systematic education can individuals' intelligence emerge and approach an optimum. However, given that a basic level of education has been encountered, schooling in general and special training programs in particular increase intelligence only very modestly, if at all. IQ differences remain quite stable over time in groups who have been attending stimulating learning settings. Education highlights individual differences in intelligence rather than compensating for them. Broad variance in intelligence is a challenge for designing educational environments. The question arises whether learners of different intelligence levels gain more if they are assigned to different learning environments. On a first glance, it sounds plausible that less intelligent students gain more from structured than from open instruction, while more intelligent learners show the reverse pattern. This was the hypothesis when so-called aptitude–treatment interactions were investigated. However, most studies have failed to reveal interactions between intelligence and educational treatment, some of them probably because they lacked the statistical power necessary for revealing interaction effects (Hattie, 2009). In general, when assigning learners to different learning treatments according to their intelligence, one must remember that IQ follows the normal distribution. This means that 68% of the people in a population do not differ by more than one standard deviation in either direction from the mean – they are quite similar. Therefore, assigning an unbiased group of learners to two different learning environments by median split of IQ scores is basically problematic.

While attempts to reveal aptitude–treatment interactions have not met with much success with intelligence as indicator for aptitude, it has been shown in many contexts that learners gain from different inputs depending on their prior knowledge. For instances, for areas in science and technology, it has been shown that visual–spatial representations do help novices in understanding complex situations while they are either needless or distracting for experts (Mayer, 2009). Similar results have been shown for including means of focused processing, as there are self-explanations or metacognitive questions. While they help novices to develop a deeper understanding of a subject matter by becoming aware of their misunderstandings and wrong conclusions (Atkinson and Renkl, 2007), experts would be unnecessarily detained by such aids. Such results are not surprising because when being presented with a problem, experts and novices differ in whether they already can fall back on established procedural and conceptual knowledge structures or whether they first have to build them up. Therefore there are better reasons to assign learners to different treatments based on their prior domain-specific knowledge than based on their intelligence. Given the relationship between intelligence and efficiency in learning and information processing, a higher IQ facilitates the exploitation of learning environments, leading to the acquisition of knowledge that is broad as well as deep enough to be prepared for mastering as yet unknown demands of the future. As a consequence, the knowledge gap between more and less intelligent students will increase in the course of time. More intelligent learners who have invested their intelligence in the construction of broad and deep knowledge will be prepared for entering demanding and abstract subjects which will remain closed for those who started under less advantageous conditions. Providing different educational tracks for learners with a vocational focus and for those who are qualified for an academic path is part of the educational system of most countries. There are, however, remarkable differences concerning the age of the students at which the separation starts. While this is around 15 in many countries, in Germany and Austria, for instance, the separation starts as early as 10 years. Meta-analyses, as they are reported by Hattie (2009), revealed almost no impact of ability grouping on student's achievement growth. It rather seems to be the case that professional teachers, who are aware of their student's thinking and knowing and who provide meaningful experience in light of this knowledge, are able to boost different student's potential.

See also: Cognitive Development: Mathematics Learning and Instruction; Developmental Behavioral Genetics and Education; Education for the Gifted and Talented; Instructional Psychology; Learning Theories and Educational Paradigms; Metacognitive Development: Educational Implications; Piaget's Theory of Human Development and Education; School Learning for Transfer.

Bibliography

Atkinson, R.K., Renkl, A., 2007. Interactive example-based learning environments: using interactive elements to encourage effective processing of worked examples. Educational Psychology Review 19, 375–386.

Deary, I., 2012. Intelligence. Annual Review of Psychology 63, 453–482.

Duckworth, A., Quinn, P., Tsukayama, E., 2011. What no child left behind leaves behind: the roles of IQ and self-control in predicting standardized achievement test scores and report card grades. Journal of Education Psychology. http://dx.doi.org/10.1037/a0026280. Advance online publication.

Grabner, R., Stern, E., Neubauer, A., 2007. Individual differences in chess expertise: a psychometric investigation. Acta Psychologic 124, 398–420.

Hattie, J., 2009. Visible Learning: A Synthesis of Over 800 Meta-analyses Relating to Achievement. Routledge Chapman & Hall.

Kaufman, Alan S., 2009. IQ Testing 101. Springer Publishing, New York.

Lubinski, D., Benbow, C., 2006. Study of mathematically precocious youth after 35 years: uncovering antecedents for the development of math–science expertise. Perspectives on Psychological Science 1, 316–345.

Mayer, R.E., 2009. Multimedia Learning, second ed. Cambridge University Press, New York.

Neubauer, A., Fink, A., 2009. Intelligence and neural efficiency. Neuroscience and Biobehavioral Review 33, 1004–1023.

Neubauer, A., Freudenthaler, H., 2005. Models of emotional intelligence. In: Schulze, R., Roberts, R.D. (Eds.), Emotional Intelligence: an International Handbook. Hogrefe, Göttingen, pp. 31–50.

Oberauer, K., Sü, H.-M., Wilhelm, O., Wittmann, W.W., 2008. Which working memory functions predict intelligence? Intelligence 36, 641–652.

Ridley, M., 2003. Nature via Nurture: Genes, Experience, and What Makes Us Human. Harper Collins, New York.

Schneider, W., Bullock, M. (Eds.), 2009. Human Development from Early Childhood to Early Adulthood. Lawrence Erlbaum, Mahwah, NJ.

Spelke, E.S., Kinzler, K.D., 2007. Core knowledge. Developmental Science 10, 89–96.

Staub, F., Stern, E., 2002. The nature of teachers' pedagogical content beliefs matters for students' achievement gains: quasi-experimental evidence from elementary mathematics. Journal of Educational Psychology 93, 144–155.

Stern, E., 2005. Knowledge restructuring as a powerful mechanism of cognitive development: how to lay an early foundation for conceptual understanding in formal domains. In: Tomlinson, P.D., Dockrell, J., Winne, P. (Eds.), Pedagogy – Teaching for Learning. British Psychological Society, Leicester, pp. 153–169.

Sternberg, R., Grigorenko, E., 2002. Dynamic Testing. Cambridge, New York.

Turkheimer, E., Haley, A., D'Onofrio, B., Waldron, M., Gottesman, I.I., 2003. Socioeconomic status modifies heritability of IQ in young children. Psychological Science 14 (S), 623–628.