# The nature of nurture: the role of gene-environment interplay in the development of intelligence

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# CHAPTER 1

## INTRODUCTION

### 1.1 The Difficulty of Intelligence

This thesis stresses the importance of the development of better theory in intelligence research. In addition, it illustrates that taking explicit scientific philosophical standpoints (e.g. realist or nonrealist) with respect to intelligence, and the variables that relate to it, helps to understand empirical results. Without adequate theory and without researchers' philosophical standpoints, it is extremely difficult to make sense of the intelligence literature, as the author of this thesis experienced. The aim of this introduction is first to illustrate why this is so difficult.

Intelligence relates to how well systems process information, for example how well they solve complex problems, how well they can store and retrieve information, how fast they process information, but also how much information these systems contain. In addition, when we restrict ourselves to the intelligence of human information processing systems - people - it should be noted that the level of intelligence is usually not determined on a quantitative scale (interval or ratio scale), but on a relative one (ordinal scale). Without commitment to any specific theory that relates intelligence to a quantitative property (or multiple quantitative properties), intelligence is thus most appropriately expressed in terms of a rank order (Bartholomew, 2004). However, as we will show below, different rank orders of the level of information processing (henceforth cognitive functioning) can be made. This is what makes the detailed interpretation of intelligence surprisingly difficult. Consider the question whether intelligence changes during development. Based on the same data, one researcher can legitimately conclude that it grows, hence changes, while another can legitimately conclude that it is stable and does not change at all. The conclusion largely depends on the scientific perspective.

In line with a developmental perspective, we can make a rank order on the basis of a within individual comparison. Imagine a typical human newborn, call her Anne. Anne it is not yet able to speak, does not have a vocabulary, and shows no sign that she is able to solve any problem that is stated verbally. Provided Anne's cognitive development takes place normally, by the time she is 7, she has developed and improved many abilities that relate to information processing (e.g. speech), and has gained a wealth of knowledge, including a vocabulary. At this point in development, she is well able to solve certain problems that are stated verbally. Once Anne has reached adolescence, she has gained even more knowledge and is able to solve many more (and more complex) problems, both verbal and nonverbal. Given that such cognitive growth occurs in most people, the within-subjects perspective can be translated to a between group ranking: Adolescents, have a higher level of information processing than 12-year olds, for example, and 12-year olds a higher level than 7-year olds; 7-year olds a higher level than newborns. Adopting this developmental perspective, one can argue that throughout the course of development people become more intelligent, because cognitive functioning increases.

Notably, in this developmental perspective people are treated as interchangeable, so that this perspective will not provide an answer to the question of why 7-year old Anne processes information better or worse compared to other 7-year olds. This requires an inter-individual perspective. In line with this perspective, we can make a rank order based on a between individuals comparison instead of a within individual (or between age group) comparison. Theoretically, the between individuals rank order can be completely stable throughout development. Imagine three healthy newborns, Anne, John, and Neil. Anne processes information better than John, and John better than Neil. By the time they are 7, cognitive functioning has improved in all three, but Anne still processes information better than John, and John better than Neil. By the time they are adolescents, cognitive functioning has improved even further, but Anne processes information better than John, John better than Neil, etc., etc. On the basis of this inter-individuals comparison, and in contrast to the developmental perspective, one can maintain that Anne's intelligence has not changed at all. In the light of the above, it is important to note that the cause(s) of inter-individual differences in cognitive functioning can be entirely different from the causes(s) of intra-individual differences in cognitive functioning (cognitive growth). To illustrate this, consider Figure 1.1, which shows the hypothetical developmental trajectories of a certain cognitive ability, say verbal comprehension. Within each individual, verbal comprehension grows, but the rank order among individuals stays the same. Imagine now that within each individual the growth is purely the result of learning and practice, hence of experience. Next, imagine that every individual has the exact same experience, but that the individuals differ in genetic makeup. The between subjects rank order might reflect purely these genetic differences.

In reality, the between subjects rank order on cognitive functioning is not stable throughout development. For example, it has been found that full scale IQ at age 3 correlate less than 0.5 with full scale IQ at age 12 (Sternberg, Grigorenko, & Bundy, 2001). Also, not one, but many variables, influence cognitive growth (Sameroff, Seifer, Baldwin, & Baldwin, 1993). Interventions (e.g. adoption) and other events (e.g. illness) that occur throughout development can have a profound effect on cognitive growth, and thus on the ultimate level of cognitive functioning (Sternberg, Grigorenko, & Bundy, 2001). In order to fully understand why one individual processes information better than another, we need to take into account their life histories. This requires a developmental perspective. On the other hand, cognitive growth is not unlimited, which implies that inter-individual differences in limited resources or capacities will give rise to individual differences in the developmental trajectories and the ultimate level of information processing. In order to understand why the one individual develops differently than the other, one needs to take into account inter-individual differences in these capacities.

So, in order to understand and model human intelligence, we need both the developmental perspective and the inter-individual differences perspective. The majority of the discussions, theories, and models in the field of intelligence (as measured by psychometric tests) lack the developmental perspective. Discussions and theories are mainly concerned with individual differences in hypothesized limiting capacities (e.g. Spearman, 1904; Carroll, 1993; Jensen, 1998), either indirectly, via the history of factor-analysis, or directly. The discussions have led to many different factor models of intelligence (see, e.g. Jensen, 1998). In the next section, we give a brief overview of the most well-known factor models and their history.

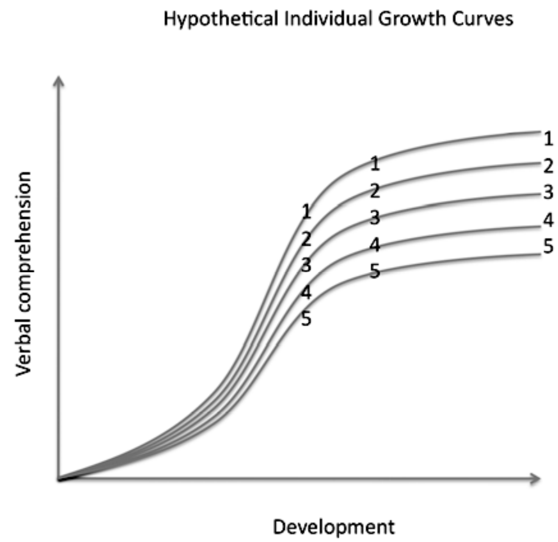


**Figure 1.1** Hypothetical developmental trajectories of verbal comprehension. Within each of 5 individuals, verbal comprehension grows, but the rank order among the individuals stays the same. Individual growth can be purely the result of experience, while the between subjects rank order can reflect purely genetic differences.

## 1.2 Factor Modeling of Individual differences in Intelligence

Factor modeling of individual differences in intelligence started in the early twentieth century, when Spearman (1904) aimed to explain the finding that 22 pupils' ratings on pitch discrimination and 5 different school subjects (English, French, classics, mathematics, and music) were positively intercorrelated. He hypothesized that the individual differences in these ratings reflected in large part individual differences in exactly one (unobserved) variable that the scores had in common. Spearman called this common variable the general factor of intelligence (general intelligence or *g*, for short). Furthermore, he considered the correlations among the ratings to be imperfect due to the influence of other (unobserved) variables that were unique to each rating. These specific variables (*s*, for short) were assumed to be uncorrelated across the observed variables (i.e., the ratings). They were also assumed to be uncorrelated with the common variable. Spearman was aware that correlations among variables are attenuated by measurement error (*e*).

We can depict Spearman's ideas graphically, as in the path diagram in Figure 1.2. Here, the observed ratings (or test scores in general, *x*) are symbolized by squares; the unobserved, hypothetical variables by circles. As mentioned, without any commitment to a theory, intelligence, as measured by intelligence tests, is most appropriately expressed in terms of a rank order. The path diagram illustrates that a higher position on the unobserved variable *g* results (somehow) in a higher position on all observed *x* variables, while a higher position on a specific variable *s* results (somehow) in a higher position on only 1 observed *x* variable. Obviously, the diagram itself does not explain how these individual differences arise, nor if or how intra-individual differences in cognition (cognitive growth) arise, nor whether the relations among the variables are linear or nonlinear. This requires theory, for example Spearman's theory.

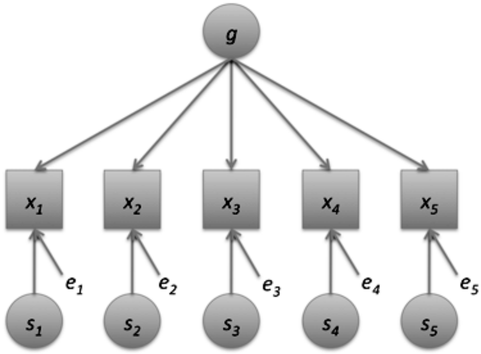


**Figure 1.2** Spearman's (1904) account for the finding that cognitive test scores (*x*) are positively intercorrelated. Individual differences in these scores reflect in individual differences in exactly 1 (unobserved) common variable (the quantitative variable *g*) and other (unobserved) unique variables that were unique to each test *i* (of which the total is $s_i$). Correlations among variables are attenuated by measurement error (*e*).

Spearman's theory appears specific enough about the nature of the common variable *g* to draw certain conclusions in the light of a developmental perspective: He maintained that *g* is a single quantitative variable that is innate and immalleable, hence fixed. It implies that *g* is solely a source of inter-individual differences and not any cause of cognitive development within a person. Cognitive growth must be due to other influences. One way to conceive *g* is as a limiting capacity that constrains this growth. Any individual differences in the other influences cause the relation between *g* and the test scores to be imperfect.

To test whether positive correlations among people's intelligence test scores are indeed due to a single quantitative common source of individual differences, Spearman pioneered the statistical technique factor analysis. His statistical one-common factor model represented his theory formulated in linear equations. The mathematical formulation of the theory is thus stricter than the theory itself, because the relations among the variables are taken to be linear. Because the means of the unobserved quantitative variable *g* and the specific factors are unknown, Spearman's model is usually written in the form of a regression model:

$$x_{ij} = \beta_0 + \lambda_j g_i + \varepsilon_{ij}$$

The symbol $x$ denotes person $i$'s test score on test $j$, $g$ represents the (fixed) inter-individual quantitative variable general intelligence, and $\varepsilon_j$ the total effect of other influences ($s$) on test $j$, including the measurement error ($e$). Parameters $\lambda_j$ denote weights (regression coefficients). Usually, it is assumed that variable $g$ and $\varepsilon_j$ have means of 0 (means have been virtually subtracted). In the interpretation of this regression model as the true data generating mechanism, $\beta_0$ does thus not represent simply a scaling parameter, but includes the subtracted means of $g$ and $\varepsilon_j$. In principle, it also reflects any influences that show no inter-individual differences (of which the variance is 0).

With respect to causation, the mathematical equation is conceptually weaker than the theory and the path diagram. Mathematically, provided $\lambda_j$ is not zero, $x_{ij} = \beta_0 + \lambda_j g_i + \varepsilon_{ij}$ is the same as $g_i = [-\beta_0 + x_{ij} - \varepsilon_{ij}]/\lambda_j$, whereas the hypothesis 'differences in $g$ give rise to differences in $x$' is different from the hypothesis 'differences in $x$ give rise to differences in $g$'. In the statistical testing procedure, it is investigated, albeit indirectly, whether a higher position on the hypothesized variable $g$ corresponds to (rather than results in) a higher position on all observed $x$ variables, while a higher position on unobserved variable $\varepsilon_j$ corresponds to a higher position on only one observed variable ($x_j$).

Spearman's theory has been criticized for a variety of reasons (see Jensen, 1998). First of all, researchers have questioned the robustness of the positive correlations (e.g. Guilford, 1964). However, positive correlations among cognitive tests have been replicated in hundreds of datasets (Carroll, 1993). The finding, which is often called the positive manifold of intelligence, is thus robust and is now regarded as an empirical fact. Second, researchers came up with valid alternative explanations of the positive manifold (Thomson, 1951; Bartholomew, Deary and Lawn, 2009; van der Maas et al., 2006; Dickens, 2008). The consensus is now that Spearman's theory is in line with the positive manifold, but that factor analysis cannot prove a theory, including Spearman's, to be correct. Factor analytical results are statistical summaries of the data; this because although factor analysis does involve goodness-of-fit testing, different mechanisms can lead to the same factorial structure. Therefore theory is required in order to attach a meaning to the factors, for example as representing a true, causal underlying variable (e.g. Borsboom, Mellenbergh, & van Heerden, 2003).

Although factor analysis cannot prove a theory is correct, it can falsify a theory, namely when the theory is formulated as a statistical model, and this model does not fit the data adequately. Eventually this happened to Spearman's theory. It was rejected because one-factor models are usually too simple to explain the data: After partialling out the variable $g$, certain test scores remain positively intercorrelated, which means that certain specific factors in Spearman's model are not statistically independent across tests, as was hypothesized.

Because one-factor models do not give adequate explanations for the patterns of the positive intercorrelations among IQ test scores, scientists developed factor models that include multiple factors. The pioneering researchers often published in all the fields of statistics, test theory, and intelligence, so that these fields were closely connected. Later these fields started to diverge, with the consequence that the connection between theories of intelligence and statistical models of intelligence is nowadays less clear. The consequence is that it is also unclear whether factors should be taken as mere statistical variables or as representing true causal sources of variance (e.g. limiting capacities).

One of the pioneers of (psychometric) intelligence, Thurstone (1938), advanced a model that describes intelligence as existing of multiple (7) statistically independent cognitive abilities. These comprised Word Fluency, Verbal Comprehension, Spatial Visualization, Number Facility, Associative Memory, Reasoning, and Perceptual Speed. Each cognitive ability can be measured by a number of tests (see Figure 1.3); test specific factors attenuate the relation between the cognitive ability and the test scores. Thurstone's model explains the (strong) intercorrelations among tests of (say) Verbal Comprehension on the one hand, and those among tests of Associative Memory, on the other. However, it does not explain (the weaker) positive intercorrelations among tests of Verbal Comprehension and tests of Associative Memory. Multiple solutions have been proposed (see Jensen, 1998). One can propose that IQ tests are not uni-dimensional, for example, by assuming that tests always tap multiple of the statistically independent cognitive abilities, but to different extents (consistent with the model displayed in Figure 1.4), or by assuming that each test measures a general ability in addition to a specific cognitive ability (see Figure 1.5). Assuming that test constructors aim (and succeed) to devise uni-dimensional tests, a theoretically more satisfactory solution is to allow for positive intercorrelations among the cognitive abilities (see Figure 1.6). Of course, it can be hypothesized these intercorrelations are due to a common variable (see Figure 1.7).

More precisely than before, intelligence can now be defined as a weighted average of the cognitive abilities measured by IQ tests. In addition to the problem of how to determine the weights, this definition suffers from the same problems as those mentioned above. Without any further theorizing about the cognitive abilities, intelligence still refers to a rank order, and its interpretation is difficult because the cognitive abilities are not observed directly. Again, on the basis of the same factor analytical results, the one researcher can maintain that there is growth in intelligence, while the other can maintain there is not. We can theorize, for example, that there is growth in the cognitive abilities, which would explain why people's test scores increase during development. Alternatively, we can theorize that the observed knowledge and skills to solve the tests items increase, but that the cognitive abilities represent fixed capacities that constrain the growth of the knowledge and skills, so that performance, rather than underlying intelligence, changes. Factor analysis of individual differences cannot discriminate between those alternatives (to do so latent growth modeling can be used). In any case, in order to interpret psychometric intelligence and individual differences in full scale IQ, one needs theory.

One such theory is Cattell's (1963, 1987) investment theory of fluid and crystallized intelligence. This is one of the few theories of intelligence that aims to account for both the development of cognitive abilities and the factorial structure of intelligence. In the theory, one factor of intelligence, fluid intelligence (Gf), represents an underlying reasoning capacity, which is connected to the maturation of the brain. Individual differences in this capacity are largely due to individual differences in genetic makeup. The acquisition of knowledge and skills, called crystallized abilities, depends on this capacity. Hence individual differences in crystallized abilities reflect in part individual differences in fluid intelligence. Another factor of intelligence, crystallized intelligence (Gc), summarizes the common variance among these crystallized abilities. Because Gc depends on Gf, factors Gf and Gc are modeled as positively correlated.

Like Spearman's *g* model, Cattell's Gf-Gc model was shown to be too simple (e.g. Carroll, 1993). Nowadays, it is assumed that human intelligence comprises about 70 positively inter-correlated specific cognitive abilities (represented by first order factors) (McGrew & Flanagan, 1998). If one would factor analyze in turn the intercorrelations among these abilities, factor solutions including about 8 to 10 correlated factors would give statistically satisfactory results (Cattell, 1987; Carroll; McGrew, 2009; Horn & Blankson, 2005). At this (second-order) level, the two most widely accepted models of intelligence, the extended Gf-Gc factor model of Cattell and Horn and the three-stratum model of Carroll, are nearly identical (McGrew, 2009). The interpretation of the second order factors in these models is often casted in terms of separate cognitive or biological systems (e.g. Carroll). Also, individual differences in the factors of intelligence are considered to be due to both genetic and environmental influences (Plomin et al. 2008).

Because the second-order factors of intelligence are all positively intercorrelated, it is possible to factor analyze their intercorrelations. Carroll (1993) did so, and posited a (third-order) general factor. The model can be regarded as a model in which Spearman's *g* is reintroduced, while allowing for correlations among certain specific factors. Carroll hypothesized the general factor to represent individual differences in a cognitive system separate from the systems represented by the second order factors. Horn and Cattell did not extract a general factor. Horn (Horn & Noll, 1997) regarded such factor as nothing more than a statistical summary of the second order factors; Cattell (1987) believed that the general factor and fluid intelligence represented the same variable (hence cognitive system). Over the last decades, researchers have been trying to synthesize the Gf-Gc and the three-stratum model into one (Cattell-Horn-Carroll) model of intelligence (see McGrew, 2009). The question whether or not to extract a general factor remains a topic of discussion. This discussion is based on theoretical arguments rather than statistical ones. In this light, alternative explanations of the positive manifold are important.

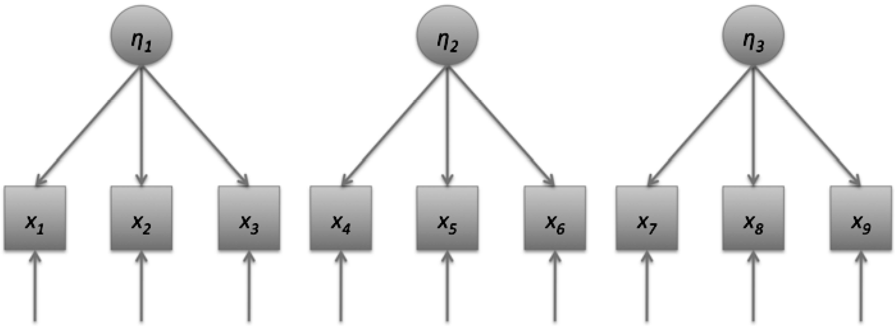


**Figure 1.3** Multiple factor model of psychometric intelligence. Each human cognitive ability ($\eta$) can be measured by a number of tests ($x$). Test specific factors attenuate the relation between the cognitive ability and the test scores. The model explains the (strong) intercorrelations among tests that measure the same ability, but does not explain the (weaker) correlation among tests that measure different cognitive abilities.

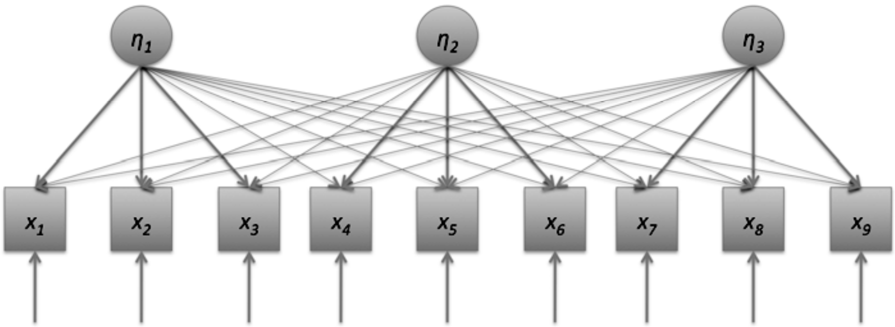


**Figure 1.4** Multiple factor model of psychometric intelligence. Intelligence tests always tap from multiple statistically independent cognitive abilities, but to different extents. The model explains strong and weaker intercorrelations among intelligence tests. Test specific factors attenuate the correlations.

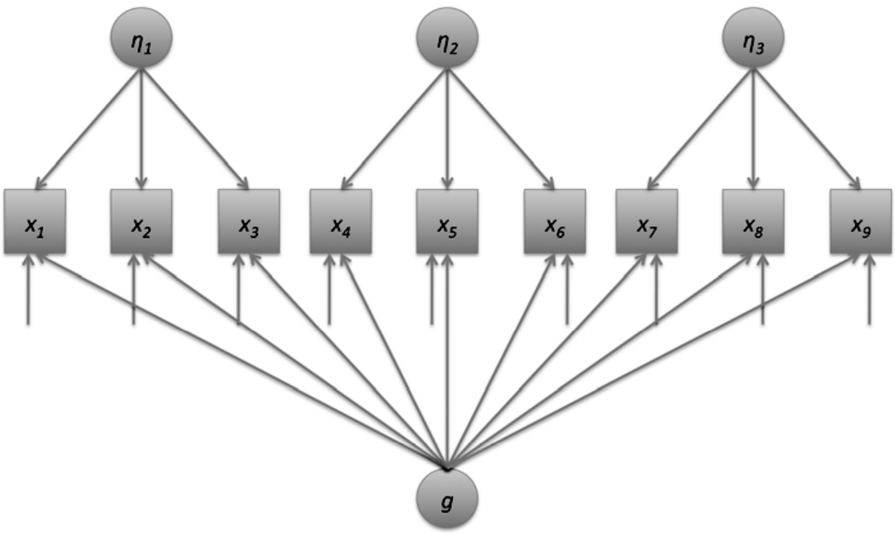


**Figure 1.5** Multiple factor model of psychometric intelligence. Each intelligence test does not only measure a specific cognitive ability but also a general ability. The model explains strong and weaker intercorrelations among intelligence tests. Test specific factors attenuate the correlations.

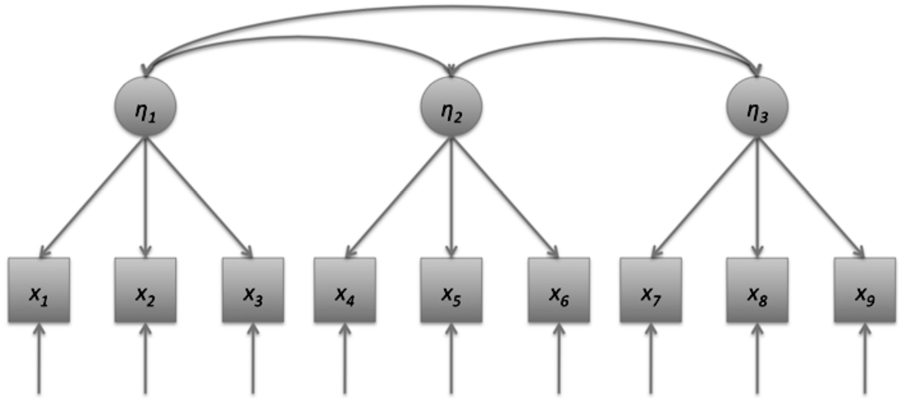


**Figure 1.6** Multiple factor model of psychometric intelligence. Each human cognitive ability can be measured by a number of tests. Test specific factors attenuate the relation between the cognitive ability and the test scores. The model explains the (strong) intercorrelations among tests that measure the same ability as well as the (weaker) correlation among tests that measure different cognitive abilities. The causes of the latter are unknown. Tests are uni-dimensional.

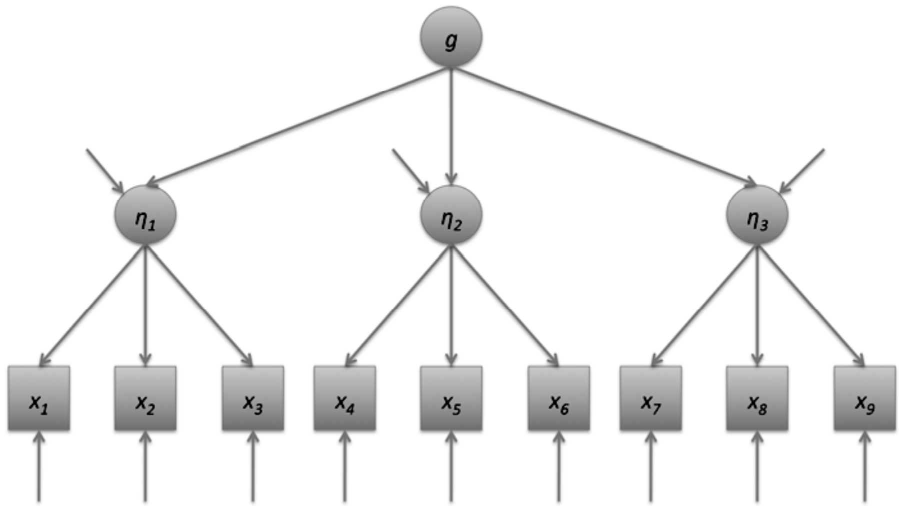


**Figure 1.7** Hierarchical factor model of psychometric intelligence. Each cognitive ability can be measured by a number of tests. Test specific factors attenuate the relation between the cognitive ability and the test scores. Each cognitive ability is influenced by variable *g*. Influences specific to cognitive abilities attenuate the relation between *g* and the cognitive abilities. The model explains the (strong) intercorrelations among tests that measure the same ability as well as the (weaker) correlations among tests that measure different cognitive abilities. Tests are uni-dimensional.

### 1.3 A Dynamical Systems Model of Intelligence

When variables are positively intercorrelated, a statistical general factor can be extracted, but it does not necessarily imply that a true, causal general variable is present. The positive manifold of intelligence, hence the presence of a general factor of intelligence, can be the result of the development itself for example, as in the mutualism model of general intelligence of van der Maas et al. (2006). In this thesis the ideas behind the mutualism model play an important role in the conceptualization of intelligence. Here we give a brief summary of these ideas. More detailed descriptions of the mutualism model and the underlying assumptions are provided and discussed elsewhere in this thesis (in Chapter 6 in particular).

In the mutualism model it is assumed that growth in cognitive processing is largely autonomous and self-regulating, but that it is constrained by heritable limited resources or capacities. However, different cognitive processes exist, each of which is constrained by unique limited resources. Another assumption is that the cognitive processes influence each other during their development and that the effects are largely mutually beneficial. That is, the growth of one cognitive process stimulates the growth of the other cognitive process and vice versa. As a result, the limiting capacity that constrains the growth of the one process, say working memory, has an indirect effect on the growth of other cognitive processes. On the other hand, the limiting capacities of these other processes have an indirect effect on working memory.

Mathematically the mutualism model is formulated as follows:

$$\frac{dx_i}{dt} = a_i x_i (1 - \frac{x_i}{K_i}) + a_i \sum_{\substack{j=1 \\ j \neq i}}^{W} \frac{M_{ij} x_j x_i}{K_i} \text{, for } i, j = 1 \ldots W.$$

Where the $K$'s represent the ($W$) limited resources that constrain the growth of the ($W$) cognitive processes. Parameters $a_i$ are growth parameters associated with each cognitive ability $x$. Weight $M_{ij}$ determines the influence of cognitive process $x_j$ on cognitive process $x_i$. Genetic and environmental influences can be introduced, for example via the limited resources. Simulations showed that even if all underlying variables ($a$'s, and $K$'s) are initially uncorrelated, the observed variables ($x$'s) become intercorrelated over time. That is, individual differences in the cognitive processes eventually show a positive manifold.

### 1.4 Overview

The aims of the thesis are twofold. The first aim is to reinvigorate the development of an adequate theory of intelligence by providing a model that accounts for both cognitive growth and (heritable) interindividual differences in intelligence. The integrated model must be able to explain salient findings in intelligence research, such as a correlation between intelligence subtests' heritability coefficients and their loadings on the (statistical) general factor of intelligence. While developing the theory, we encountered theoretical issues that are not fully addressed in the literature. The second aim is to address these issues. They concern mostly the interpretation of the heritability of intelligence.

In this thesis, we provisionally accept the Cattell-Horn-Carroll (CHC) model as a working hypothesis. We hypothesize that the second order factors in this model (including Gf and Gc) represent individual differences in unique cognitive systems, constrained by genetically and environmentally influenced capacities. We do not posit a substantive underlying general factor, because we believe the positive intercorrelations among the cognitive systems are due to reciprocal interactions among those systems (see Figure 1.8), which occur throughout cognitive development, as in the mutualism model. We also assume that in principle individual differences in these systems can be measured by intelligence tests, although we maintain that in practice intelligence tests are likely not uni-dimensional.

Chapter 2 (published as Kan, Ploeger, Raijmakers, Dolan & van der Maas, 2011) concerns difficulties with the interpretation of the latent genetic and environmental variables in (behavior genetic) statistical models in general. Obviously, this has consequences for the interpretation of the latent genetic and environmental variables in factor models of intelligence. The genetic and environmental variables in these behavior genetic models are not measured, but inferred, using genetically informative research designs (e.g. twin studies). Furthermore, the underlying variables are modeled as acting linearly. We investigate what the estimated relative contributions of the linearly modeled genetic and environmental variables to the total variance in the observed variables are, when in reality the underlying mechanisms are non-linear. We hypothesized that the estimates are then not correct. We aimed to corroborate this with a reciprocal dynamical systems model. We could not use the mutualism model, because this model does not contain nonlinear terms.

Instead we used the two-cell model of van Oss & van Ooyen (1997) (this model is described in Appendix A). The two cells in the model are interpreted as subsystems of working memory capacity (e.g. Gsm in the CHC model). We provide results that are in line with empirical findings in intelligence research: First, the underlying causes are hard to detect, if at all. Second, the estimated relative contribution of the hypothesized genetic variables to the total variance increases (hence the estimated relative contribution of the hypothesized environmental variables decreases). We conclude that caution is required in interpreting high heritability coefficients as meaning 'highly genetically influenced'. Heritability coefficients can be overestimated due to nonlinear developmental effects (e.g. stage transitions).

Further caution is required when interpreting high heritability. As we explain in Chapter 3, a relatively high estimated heritability of a cognitive ability relative to another does not mean environmental and cultural influences are relatively less important. On the contrary, the more cultural aspects differentiate between people, the higher the subtests' heritability coefficients. We show the highly contra-intuitive finding that in IQ tests the highest heritability coefficients are generally of tests that measure highly culturally dependent knowledge and skills, rather than tests that measure less cultural dependent cognitive processing. In terms of investment theory, this means that crystallized abilities are more heritable than tests that measure fluid abilities. The original theory predicted the opposite, namely that fluid abilities are more heritable than crystallized abilities. We suggest that the explanation may lie in gene-environment correlation. Also, crystallized ability tests happen to display the highest loadings on the general factor of intelligence. 'General intelligence' (as a statistical construct) appears to be more like 'crystallized intelligence' than 'fluid intelligence'.

Chapter 4 concerns the relation between fluid and crystallized abilities and group differences. We investigate the claim that when group (e.g. racial or ethnic) differences are the most pronounced on the most heritable and the most *g* loaded subtests it implies the origin must be genetic. This claim is based on Jensen's (1998) method of correlated vectors. Even if researchers accept this (methodologically weak) method, the claim cannot be made, because it involves invalid reasoning, namely affirming the consequent. We show analytically that group differences can be the most pronounced on the most heritable and the most *g* loaded tests when the origin is entirely environmental. In addition, we show empirically that group differences are the most pronounced on the most culturally loaded subtests (crystallized abilities). These results conflict with mainstream theories, because they predict the opposite: group differences are most pronounced on the least cultural loaded tests (fluid abilities).

Chapter 5 (of which parts are published as Kan, Kievit, Dolan, & van der Maas, 2011) concerns the further interpretation of fluid and crystallized intelligence. From a review of investment theory, we conclude that crystallized intelligence must be interpreted as a constructivist variable, i.e., a statistical summary (of the amount of knowledge). This interpretation differs from the interpretation of the CHC factors as representing individual differences in underlying cognitive capacities. We propose to remove factor Gc from the CHC model. We showed that this can be done legitimately, because in a reanalysis of a representative dataset on which the CHC model is based, the factor Gc was redundant, as was predicted; it was statistically equivalent to verbal comprehension. In the dataset, *g* was also redundant, because it was statistically equivalent to fluid intelligence (Gf). We propose that *g* can also be removed from the CHC model as an explanatory variable. The magnitude of the correlation between Gf and *g* is likely a function of sample heterogeneity due to developmental differences.

In Chapter 6 we address whether current theories of general intelligence (*g* theory, fluid-crystallized theory, sampling theory, and reciprocal interaction theories) explain the intriguing finding that the most cultural dependent cognitive abilities (crystallized abilities) are the most *g* loaded and most heritable. It is concluded that (in isolation) they cannot. By implication, the reviewed theories do not explain how group differences become the most pronounced on the most culturally dependent, most heritable, most *g* loaded subtests.

The thesis ends with a general discussion (Chapter 7), in which we present an integrated model of general intelligence. It is a mutualism model (van der Maas et al., 2006) that incorporates the main idea of investment theory (individual differences in cognitive processes - fluid abilities - give rise to differences in knowledge and skills - crystallized abilities) and Dickens & Flynn's (2001;

Dickens, 2008) social multiplier. In line with the mutualism theory (van der Maas et al., 2006), we assume that cognitive processing benefits from knowledge acquisition. In the integrated theory, an underlying *g* (Spearman, 1904; Carroll, 1993; Jensen, 1998) is absent. Genetic correlations among limiting capacities can be present, but are taken to be the result of what we denote genetic sampling (Thompson, 1951; Bartholomew et al. 2009; Anderson, 2001; Penke et al., 2007; see Chapter 6) and not as due to general genetic effects (Kovas & Plomin, 2006). The integrated theory accounts for the fact that individual differences (hence group differences) are the most pronounced on the most culturally dependent subtests, which are the most heritable and the most *g* loaded. The effect is due to differences in gene-environment effects across cognitive abilities.

The main points of this thesis are as follows. First, although it is still not possible to determine whether a realistic, underlying *g* is present or not, we can conclude that current *g* theories are inadequate in explaining certain salient empirical findings. Next to the individual differences perspective they have, they need a developmental perspective. The role of the dynamic interplay between genetic and environmental variables that occurs during development needs to be explicated. Second, formal modeling is important in intelligence research. Using the mutualism model can help researchers to study combined effects, such as the investment hypothesis of fluid and crystallized intelligence and the correlation among subtests' *g* loadings, cultural loadings and heritability coefficients. The concluding chapter provides an example of this kind of formal modeling. The main advantage of the mutualism model is that it can combine the developmental and individual differences scientific perspectives on intelligence. Formal modeling is challenging and may seem difficult, but, as the author of this thesis has experienced, it is considerably less difficult than trying to make sense of the intelligence literature while adequate theory is lacking.

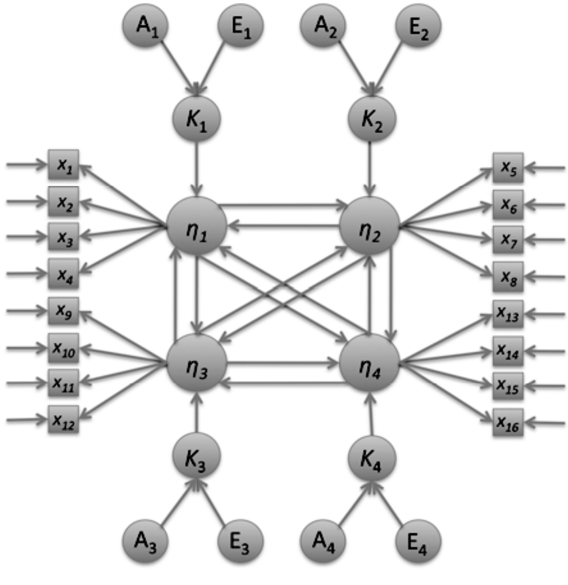


**Figure 1.8** Interpretation of the broad factors in the Cattell-Horn-Carroll model of intelligence. These factors represent information processing systems. The development of the functioning of each system is constraint by genetically (A) and environmentally (E) influenced limiting capacities (*K*), which are assumed to be uncorrelated. Individual differences in the functioning of the systems (cognitive abilities, *η*) can be measured by a number of tests (*x*). Test specific factors attenuate the relation between the cognitive abilities and the test scores. Correlations among test scores that measure different cognitive abilities are due to mutual beneficial interactions among the systems, which are assumed to take place throughout development. Tests are modeled as uni-dimensional.