Psychological Review
2002, Vol. 109, No. 1, 116–136

0033-295X/02/$5.00 DOI: 10.1037//0033-295X.109.1.116

Understanding the Nature of the General Factor of Intelligence: The Role of Individual Differences in Neural Plasticity as an Explanatory Mechanism

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The nature of the general factor of intelligence, or *g*, is examined. This article begins by observing that the finding of a general factor of intelligence appears to be inconsistent with current findings in neuroscience and cognitive science, where specific connections are argued to be critical for different intellectual abilities and the brain is argued to develop these connections in response to environmental stimuli. However, it is then observed that if people differed in neural plasticity, or the ability to adapt their connections to the environment, then those highly developed in one intellectual ability would be highly developed in other intellectual abilities as well. Simulations are then used to confirm that such a pattern would be obtained. Such a model is also shown to account for many other findings in the field of intelligence that are currently unexplained. A critical period for intellectual development is then emphasized.

Perhaps the most well-known concept that scientific psychology has provided to the wider community is that of IQ. Although few people in the general public are familiar with concepts such as latent inhibition and event schemas, IQ is recognized as an attempt to identify and measure differences in that mysterious characteristic known as intelligence.

However, although many researchers do agree that the characteristic underlying IQ performance is a real one (e.g., Brody, 1992; Jensen, 1998; Mackintosh, 1998; Neisser et al., 1996), substantial differences exist as to its importance (e.g., Horn, 1998; Stankov, Boyle, & Cattell, 1995). In addition, there is general dissatisfaction with current explanations as to what it is that the tests are actually measuring. Indeed, when recent advances in neuroscience and cognitive science are considered, the notion of a general factor of intelligence appears to be incomprehensible.

The purpose of the present article then is to attempt to bridge the gap that currently exists between neuroscience and cognitive science on the one hand and psychometric intelligence research on the other. It is shown that principles derived from neuroscience and cognitive science can be used to account for the general factor of intelligence, but that this also leads to some perhaps unexpected implications for intellectual development.

Current Approaches to Understanding Intelligence

Intelligence may be defined in many ways. One possible definition is the ability to adapt to the environment. In this sense, even bacteria may be said to possess a form of intelligence. If we restrict ourselves to human capacities, characteristics such as musical ability (Gardner, 1983) and practical knowledge (Sternberg, 1985) represent useful skills and may be referred to as different aspects of intelligence (see also Carroll, 1993). However, at the same time, it is often observed that some people seem to possess a characteristic, commonly associated with terms such as “bright” and “gifted,” which makes them better at many tasks that involve reasoning and the understanding of relations.

This relation was first formalized by the work of Spearman (1904). Spearman observed that people highly developed in one intellectual ability tend to be, on average, highly developed at other, different intellectual abilities as well. In other words, intellectual tasks show positive manifold, whereby all tasks are positively correlated with each other to varying extents. Researchers such as Spearman have concluded that this phenomenon indicates that there is a general factor, referred to as *g*, that is common to all tests of intellectual ability. In addition, because some tests have higher correlations with this *g* factor than others, such tests are argued to be more heavily dependent on this general factor (Brody, 1992; Jensen, 1998; Neisser et al., 1996).

In other words, if people who are good at one test are good at other tests as well, it seems reasonable to infer that there is some ability being tested that is common to both tests, hence the correlation. In addition, because some tests are more highly correlated with each other than others, these tests are more dependent on this common factor for determining their performance than the other unspecified abilities or factors that may cause variations in test performance.

Therefore, on the basis of this belief, different tests have been analyzed using factor analysis to determine the extent to which they are correlated with each other. Tests most highly correlated with each other were considered the most heavily *g* loaded, and because *g* is required on all tests of mental ability, the tests most heavily *g* loaded were considered representative of “pure” or “raw” intelligence. IQ tests have then evolved as an attempt to measure this factor (Jensen, 1981; Kaufman, 1990). This then indicates that IQ tests are not intended to represent a crude com-

I thank Richard Roberts, Greg Pettersen, Sabina Kleitman, and Arthur Jensen for comments on earlier versions of this article.

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posite or average of a number of divergent abilities but rather are indicative of a single factor that underlies performance on many different intellectual tasks. IQ tests and many other measures of intelligence are thus designed to assess how a person is likely to perform in many situations.

Changes in Intellectual Performance Over the Life Span

The relationship just discussed is further complicated when people of different ages are considered. This is because performance on intellectual tasks is not constant over the life span but rather increases during the childhood years. Therefore, the IQ was originally based on dividing a person's mental age by their chronological age. Whereas a person's IQ was then argued to be stable over time, this represented their rate of development and their actual intellectual performance would be increasing. Further investigation revealed that mental age or reasoning ability appeared to cease to develop at maturity, or about the age of 16 years. Thus, originally, any person older than 16 years was taken to have a chronological age of 16 when calculating their IQ score.

More recent advances in IQ testing have seen the quotient measure replaced with a norming procedure, whereby a person's IQ indicates their level of intellectual development relative to other people of the same age. However, the intellectual performance of the norming groups has still been observed to increase with age, at least until maturity, and this means that an older child with the same IQ will perform better on a given test of intellectual ability. This then indicates that it is possible to distinguish between what this article refers to as intelligence as opposed to intellectual abilities. Intelligence is used to refer to whatever it is that causes individuals to perform better than others of the same age. On the other hand, intellectual ability refers to a person's actual performance level on intelligence tests. Thus, a person's intelligence is represented by their IQ score and is stable over time, whereas their actual intellectual abilities improve or develop over childhood until maturity (Neisser et al., 1996).

An important further contribution to the area was made by Cattell (1987; see also Horn & Noll, 1994). Cattell observed that not all intellectual abilities stopped developing at maturity, but rather two separate processes could be discerned. One set of abilities, described as fluid intelligence, consisted of tasks that depended heavily on an individual's capacity to reason, manipulate abstractions, and discern logical relationships. Typical tasks assessing fluid intelligence included Raven's Progressive Matrices and Letter Series Completion. Performance on these tasks was observed to stop developing at maturity and, indeed, to decrease somewhat in later life. On the other hand, crystallized intelligence consisted of the application of intelligence to learning acquired through education and experience. Examples of tasks assessing this characteristic included Vocabulary and General Knowledge. It was observed that, unlike fluid intelligence, crystallized intelligence could continue to develop throughout most of the life span.

Typical IQ tests then consisted of subtests that would weight more heavily on either one of these two characteristics. However, fluid and crystallized intelligence were still observed to be correlated, suggesting that a general factor of intelligence did indeed exist. For instance, Carroll (1993) studied more than 400 different data sets and concluded that a general factor would account for approximately 50% of the variance on even quite diverse batteries of tests, although this amount did vary substantially from study to study.

The general factor observed is commonly considered to be most closely related to, and possibly even identical to, the factor causing differences in fluid intelligence (Gustafsson, 1999). It is with this factor that the current article is concerned. Although this only represents a subset of cognitive performance, this factor does have substantial influence on achievements in present society and also contributes to performance on many other cognitive tasks as well (Jensen, 1998).

Causal Influences on Fluid Intelligence

Many researchers have argued that once it is possible to objectively measure a person's level of intelligence through *g*, this can be used to determine the relative contribution of heredity and the environment to this factor. In addition, it may also be determined whether intervention programs designed to boost intelligence do, in fact, accomplish such an objective.

Thus, these researchers have investigated the stability of IQ over the life span and the differences in IQ that occur between different family members such as twins and siblings. In addition, the effect of environmental enrichment programs on IQ has also been examined. From such studies, many researchers have concluded that IQ is relatively immutable, with the heritability of IQ being argued to be as high as .80 for the adult population. Therefore, the conclusion has been made that intelligence is largely fixed by the genes within the present environment and that attempts at increasing intellectual abilities through environmental intervention programs are largely unsuccessful (Bouchard, 1997; Brand, 1996; Jensen, 1998; Loehlin, Horn, & Willerman, 1997; Plomin & Petrill, 1997). This view has also been popularized so that many lay people are also led to believe this research (e.g., Herrnstein & Murray, 1994).

However, attempts at explaining the nature of the cause or causes of *g* have been less successful. For example, Neisser et al. (1996) represented a collaborative review by many of the leading researchers in the field. They concluded that "differences in genetic endowment contribute substantially to individual differences in (psychometric) intelligence, but the pathway by which genes produce their effects is still unknown." (p. 97; see also Hunt, 1997; Sternberg & Kaufman, 1998). Current attempts at explaining *g*, such as speed of information processing or neural efficiency, are also notable for their eschewing of current research on how the brain does in fact process information (e.g., Eysenck, 1994; Haier, 1993; Jensen, 1998; Miller, 1994).

Apparently, though, this lack of knowledge of the underlying basis of *g* does not negate the validity of using highly *g*-loaded tests to determine whether intellectual abilities are determined by heredity or not. However, let us now consider a theory that explains the nature of the phenomenon that is generally referred to as intelligence or fluid intelligence and see just how valid this reasoning is.

Recent Advances in Neuroscience and Connectionist Science

Since Spearman originally proposed the existence of *g*, much has been learned about how the brain processes information. Accordingly, although his notion of "mental energy" may have seemed credible at the time, it now seems antiquated. However, current intelligence research has also failed to incorporate recent advances that have taken place in the understanding of how the brain works. These advances have come about from understanding how neurons process information, observing the properties of artificial neural systems, and examining how the human brain develops. The derivation of this theory comes from a consideration of these advances.

The Properties of Neurons

It is through the action of neurons that intelligent behavior becomes possible. Therefore, an investigation of the properties of neurons is likely to provide some indication as to the method by which the brain can process information. This will then give some suggestion as to the cause of individual differences in the ability to process information.

The properties of neurons have been firmly established through recent procedures such as electrophysiological recording of single neurons and the patch clamp technique. In fact, the precise characteristics of neurons have been specified both mathematically and in computer simulations (Bear, Connors, & Paradiso, 1996; Kandel, Schwartz, & Jessel, 1991; Thompson, 1985). These studies have shown that neurons represent a relatively simple gating mechanism whereby inputs are summed, and if these inputs exceed a certain threshold, an action potential is produced that is propagated to all of the neuron's attendant connections (Beale & Jackson, 1991; Dayhoff, 1990). The critical issue then is how a system consisting of such units may produce meaningful or intelligent behavior.

Given that intelligent responding at the neural level must ultimately consist of the ability to arbitrarily map inputs to outputs, some mechanism is required to allow this mapping. For instance, in a particular situation, stimuli innervating neurons X and Y should lead to the same response, the firing of neuron Z. Alternatively, seeing the same word on a page written by two different people should lead to the same vocalization. Adaptations such as these will then enable the eduction of relations and correlates. They will also facilitate the production of appropriate responses to the environment.

The answer to this issue lies in changing the connections between the neurons. By changing the connections, the pattern of activation through the network can be modified. This would then allow the neural system to produce whatever pattern of firing would represent, in the appropriate context, a meaningful processing of the inputs.

This also appears to be the only way that the neural system is able to do this.[1] A neuron cannot decide to receive inputs from only one neuron and not others to which it is connected. Inputs to the dendritic tree result in changes in electropotentials across the membrane that obey simple laws of conductance. Nor can the neuron choose to send an action potential to only one axonal branch and not another. Similarly, the neuron does not represent a mechanism that can be acted on by external forces; thus, neural activity is not able to shape its pathway through the neural network actively. Rather, the neuron is a relatively simple processing unit that operates independently of other neurons and whose firing is determined by changing the connections between itself and the other neurons (Judd, 1990). Therefore, this argues for a critical role for the connections in the production of meaningful output.

The Properties of Neural Systems

The importance of the connections for processing information has been highlighted in cognitive science with the development of the connectionist approach (McLeod, Plunkett & Rolls, 1998; O'Reilly & Munakata, 2000). This approach uses computer simulations of networks based on units with similar properties to biological neurons. Cognitive scientists have found that, although a neural system with undifferentiated or homogeneous connections does not produce any type of meaningful behavior, by adjusting the connections using a general adaptation mechanism many processing phenomena are able to be modeled. In contrast, other characteristics of the network such as the activation functions of the units and the output functions are observed to be relatively unimportant in determining the network's behavior (Caudill & Butler, 1990; Elman et al., 1996; Rumelhart & McClelland, 1986).

Consider the example of character recognition. Character recognition studies involve teaching artificial neural systems to respond appropriately when presented with different letters or symbols (M. M. Nelson & Illingworth, 1991). In such studies, an initially undifferentiated neural system is presented with a number of training stimuli, such as *A*s and *B*s. Each letter is presented in various forms, such as in different handwriting and typed in different fonts. Initially, when the network is presented with these inputs, its response patterns do not reflect the commonality that exists between the different forms of the letter. Rather, output is just random. However, during subsequent presentations, the neural system is trained to produce particular activations by adjusting the connections within the network. For instance, one output neuron would be trained to fire if and only if an *A* is presented to the network, irrespective of the way the *A* is written. Other output neurons would be trained to represent other letters.

After the training of the network, it is then found that not only can the network correctly respond to letters from the training stimuli, but it can also generalize to other letters that were not part of the original training stimuli but that do share the same features (e.g., two diagonal lines intersected by a horizontal line for the letter *A*). Thus, the artificial neural network has learned to abstract the concepts of the different letters.

A number of additional features are worth noting. For instance, unlike digital computers, which must be programmed, the artificial neural systems learn by experience with the stimuli involved, just as humans learn. Also, once an appropriate rule is determined for changing the connections in response to stimuli, such systems can adapt to any structured stimuli with which they are presented, leading to meaningful processing and output. The responses of the network also generalize to novel instances, again like humans, and they can solve problems such as character recognition in a few computational steps. This is similar to human performance, which is based on as few as a hundred computational steps from asking

[1] Although it could be argued that changes in neuronal physiology could also influence activation patterns, the implications of this would not affect the ultimate conclusions of this article, namely that there is a critical period for intellectual development.

a question to answering and is unlike digital computers, which have difficulty with character recognition despite being able to perform millions of calculations every second. Finally, such neural systems also exhibit gradual deterioration in performance with damage, again similar to human performance (M. M. Nelson & Illingworth, 1991; Rumelhart & McClelland, 1986).

A second, possibly more compelling example is that of NETtalk (Sejnowski & Rosenberg, 1986). This is again an artificial neural system, but this system has been developed to read out loud printed text. NETtalk was presented with various texts such as the continuous informal speech of a child and the 1,000 most common words in English. After training, it was found that NETtalk could produce spoken utterances that were correct up to 98% of the time. During the training of the network, it was also observed that the system went through stages that mimicked the stages infants go through when learning to talk, such as babble. In addition, a number of relations the network had difficulty learning are also relations that humans have difficulty learning (see also Appendix A for a more detailed description of the NETtalk network).

This example is important because speech and reading are characteristics that are very much a hallmark of the development of intelligence, with more intelligent children being able to develop these skills faster and more easily. In fact, people at the lower extreme of the distribution for intellectual ability may never develop the ability to read, and even speech may present a serious difficulty.[2]

Artificial neural systems have had similar success modeling many other behaviors which are generally thought of as being intelligent. For example, pattern classification, language acquisition, decision making, application of rules, game playing, and even musical composition (e.g., Churchland & Sejnowski, 1992; Ellis & Humphreys, 1999; Kasabov, 1996; Levine, 1991; McClelland & Rumelhart, 1986; Waltz & Feldman, 1988).[3] Examples such as these indicate that a neural network with undifferentiated connections will not respond in a manner that is at all intelligent or meaningful. However, by adjusting the connections in response to stimuli, neural systems are able to change their response patterns, thereby extracting meaningfulness from the stimulus array and producing adaptive responses.

Even harsh critics of the connectionist approach do not dispute this point. For instance, Pinker and Prince (1988), in a well-known critique of the connectionist approach, noted that “given what we know about neural information processing and plasticity it seems likely that the elementary operations of symbolic processing will *have* to be implemented in a system consisting of massively interconnected parallel stochastic units in which the effects of learning are manifest in changes in the connections” (p. 183). Similarly, Fodor and Pylyshyn (1988) argued that “there is the route that treats connectionism as an implementation theory. We have no principled objection to this view” (p. 67).

Thus, given the critical importance of particular, specific connections for a neural system to produce meaningful output, the next issue then is, how does the brain develop its connections?

Development of the Human Nervous System

Studies of brain damage have revealed that the cerebral cortex is the brain area responsible for higher intellectual processes. It is also a recent evolutionary development, which is at its most advanced in humans. A histological examination of adult cortical neurons reveals that these cells tend to form very idiosyncratic connections with the other neurons of the cortex (Kritzer & Goldman-Rakic, 1995; Mountcastle, 1998; Szentagothai, 1978). This observed specificity of connections is then confirmed by electrophysiological recordings, which reveal that there is only a 10% probability of two neighboring cortical neurons (within 300 μm) being synaptically coupled (Abeles, Prut, Bergman, & Vaadia, 1994).

This then indicates that the cerebral cortex has evolved to produce very complex connections between the neurons, in contrast to earlier evolved brain areas, which possess simpler and more uniform neural circuits (Glees, 1988). These cortical connections would then largely mold or restrict the patterns of activation through the network and would allow complex relations between input and output. This would, in turn, affect intellectual behavior.

Figure 1 then depicts the development of cortical neurons over childhood. It can be seen that, when the child is born, the connections of the neuron are undifferentiated. However, during childhood the connections the cell makes with adjacent neurons become more and more complex and idiosyncratic up until maturity, coincidentally when fluid intelligence stops developing (Blinkov & Glezer, 1968; Mrzljak, Uylings, Van Eden, & Judas, 1990; Schade & Van Groenigen, 1961). Thus, given the importance of these changes in neural connectivity for the growth or development of intelligence, the next issue is what causes these developments to occur.

Perhaps the first possibility to be considered should be the genes. In other words, the idiosyncratic growth in connections that occurs over childhood represents a wiring diagram that is contained within the genes and that is developed slowly over the 16 years until maturity. However, there are various problems with this interpretation. First, there is not enough genetic material to even attempt to code for all of the possible neural connections. In particular, it is estimated that there are only 10^5 genes in mammals, in contrast to as many as 10^{15} neuronal interconnections (Changeux, 1985; Kandel et al., 1991). Second, even if there was enough genetic information, how could the genes control such precise fine tuning of the neural connections? Third, if the genes were used to code the precise patterns of the neural circuits, one would question the effects of meiosis.

These theoretical objections are then confirmed by the finding that animals with the same genes possess different neural connections and may not even have corresponding neurons (Changeux,

[2] These comments should not be taken as inferring that a failure to acquire either speech or reading is necessarily a reflection of a lack of general intelligence. Other impairments could exist that selectively affect these processes while the individual is still highly intelligent in other respects (e.g., deafness, dyslexia). However, these types of impairments would not affect the broad range of abilities that are observed to be affected by the general factor of intelligence.

[3] This is not intended to suggest that just because an artificial neural system can produce similar performance to humans, then human performance is based on precisely the same neural mechanisms. Rather, it is arguing that only by changing the connections, no matter how complex the neural system, will meaningful output be obtained. For example, a symbolic system would still need such an implementation.

Figure 1. Growth of the dendritic trees and axon branches of cortical pyramidal neurons in the human, from fetus (left) to adult (right). From "Progressive Neuron Differentiation of the Human Cerebral Cortex in Ontogenesis," by G. I. Poliakov in *Development of the Central Nervous System* (pp. 11–26), edited by S. A. Sarkisov and S. N. Preobrazenskaya, 1959, Moscow: Medgiz. Copyright 1959 by Medgiz.

1985; Dayhoff, 1990). Therefore, the hypothesis that the genes manage to precisely determine the fine-tuning of the neural circuits can be rejected.

Perhaps then the development of these connections occurs through an interaction with the environment, with stimuli causing the connections to change so that the neural system can extract regularities out of the stimulus environment. This would then lead to meaningful processing, just as is demonstrated with artificial neural systems that change their connections in response to presented stimuli. Thus, behavior would not be fixed by the genes; rather, the neural system would be able to adapt to any relation or phenomenon with which it is presented.

This would then mean that children would be able to learn to read and write, even though their early ancestors did not possess these skills and such skills were not even required. In fact, such a mechanism would allow the person to adapt and function intelligently no matter what the environmental requirements. Also, because the system is self-organizing, it would be able to cope with various kinds of trauma such as neural loss, which would normally severely disrupt the development of the system. In fact, the brain would be able to develop approximately normally even if one hemisphere was severely damaged in early life (Neville, 1991).

Research has confirmed that this is how the brain does develop (e.g., Kolb & Whishaw, 1998; C. A. Nelson, 1999). The neural system will exhibit both axonal and dendritic plasticity in response to experience (Crutcher, 1986; Katz & Shatz, 1996; Mitchell, 1980; Wiesel & Hubel, 1963).[4] In other words, neurons will change their connections with other neurons based on environmental stimulation. This would then necessarily change the processing characteristics of the neural system and would potentially allow it to respond in a more meaningful way.

However, the time frame during which this process occurs has also been observed to differ based on the brain area in question. The cortical areas responsible for lower level processing such as the primary visual cortex possess this plasticity only until about 5 years of age in humans (Brown, Hopkins, & Keynes, 1991). In contrast, the brain areas responsible for higher abilities such as language and fluid intelligence retain the plasticity process for longer. This would then allow them to adapt based on the adapted output of the lower areas.

For instance, Rakic (1995) examined data from both humans and primates. It was noted that "another critical cellular event that begins before birth but is completed primarily during infancy and adolescence is the establishment of the fine wiring arrangement of neural connections. At that stage, environmental stimulation sculpts the final pattern of neural organization from an initial state of excess cells, axons, and synapses" (p. 127). Huttenlocher (1990) studied specifically human data and argued that these processes stop at 16 years of age, the age at which fluid intelligence is also generally considered to stop developing.[5]

Therefore, consider the possibility that the development of intelligence over childhood is due to this long-term process whereby the brain gradually alters its connections to allow for the processing of more complex environmental stimuli. This would then account for the time frame of the development of intellectual abilities.[6]

[4] Neural plasticity in this article is used to refer to those processes that involve major connectional changes of the nervous system in response to experience and that are observed to cease to operate at maturity in humans. These processes would be long-term in that any such changes would take at least days for the necessary anatomical changes to take place. Therefore, such processes could not directly affect responding on an IQ test that is administered over a few hours (much less the few minutes required for individual questions), but would contribute to the development of intellectual abilities over childhood. This would also reflect the nature of these processes, which is to base changes in specific connections on past environmental input so as to enable more efficient processing of future environmental experiences.

[5] The observation that these processes cease to operate at maturity is not meant to infer that the brain no longer has the ability to change in response to experience after maturity. Indeed, adults continually show examples of learning and memory. However, these processes would likely be due to synaptic changes that involve the modification of existing connections and would also likely be based on different principles to determine whether a connection should or should not be strengthened. Similarly, the adult brain may also show examples of major connectional changes in response to injury, but these processes would likely be due to chemical signals being released that activate previously dormant plasticity processes (Calford, 1995). The lack of some forms of neural plasticity after maturity may at first seem to be unusual, but it should be realized that these processes originated as mechanisms to determine the initial wiring of the nervous system. Natural selection has then led to these processes being operational for longer and longer time periods, as is demonstrated by the evolution from apes to humans. Thus, the human brain is actually much more plastic than other species. Precisely how the different plasticity processes do differ is still very much open to conjecture, however, although the existence of different forms of learning with different developmental periods indicates that different plasticity processes do exist in the human brain.

[6] The decline in fluid intelligence that is observed in later life may be accounted for by the deterioration of the connections that is observed over this same time (Anderson & Rutledge, 1996), although other explanations are also possible (e.g., Li & Lindenberger, 1999). However, such explanations cannot be used to account for individual differences in intelligence because these characteristics would not lead to the same differences as is observed by people who differ in *g*. For instance, *g* is characterized by a

However, this acknowledgment also appears to provide difficulties for intelligence research. On the basis of this evidence, it can be ascertained that different intellectual abilities require different neural circuits and that the brain depends on environmental stimulation to develop these connections. Therefore, one would not expect there to be any such thing as a general ability. However, at the same time, psychometric studies do show a general factor of intelligence. This factor also appears to be largely determined by the genes. Therefore, how is this conundrum to be resolved?

A Supposition

It would be true to say that humans vary in many characteristics—for instance, rate of hair growth, metabolic rate, production of various enzymes, and so forth. It then follows that people may also vary in terms of the plasticity process described previously. In other words, some people would possess brains that are better able to adapt their neural circuitry to environmental stimulation during childhood.

In addition, a basic principle of evolution also argues that those characteristics that have evolved most recently will also show the largest variation across the population. Thus, because the ability to adapt the neural circuits to the environment has evolved relatively recently (Changeux, 1985; Glees, 1988; Killackey, 1995), it is expected that there would be large individual differences in this process. This is in contrast to other brain characteristics such as neural transmission, which would be largely identical across different individuals. Therefore, let us consider the implications if people did vary in neural plasticity or the ability to adapt their neural circuits to the environment.

First, it should be apparent that a person's relative level of intellectual development would be a function of their brain's relative ability to adapt to the environment. In other words, because all people are largely exposed to the same environmental experiences, individuals with more plastic brains would be more highly developed at all intellectual abilities, irrespective of their superficial characteristics. This is because all intellectual abilities would be the result of the same adaptation process.

This is demonstrated in Appendix A, where it is shown that an artificial neural network that is better able to adapt its connections to the environment can learn to read faster, accommodate information from the environment better, and score higher on an actual fluid intelligence test. All of these characteristics are also shown by people who are higher in *g*.

Alternatively, if there were not individual differences in neural plasticity, then idiosyncratic differences in environmental experiences would lead to idiosyncratic differences in different intellectual abilities. Therefore, differences in neural plasticity are required to produce a general factor of intelligence when the brain depends on an adaptation mechanism to develop the appropriate connections.

Consider further what individuals with a very low rate of neural plasticity would be like. Their neural circuits would be unable to adapt appropriately to the environment to which they are exposed. They would then remain childlike, reflecting their poorly developed neural circuits. They may even have difficulty with relatively simple processing tasks such as learning to read. This description would seem to correspond closely to those individuals who are believed to suffer from mental retardation.[7]

In contrast, consider the example of people whose brains are very good at adapting to the environment. They could then develop the appropriate neural circuits to comprehend and understand any phenomenon to which they are exposed. Therefore, these individuals would seem to be advanced for their age and would be able to grasp difficult concepts sooner. Thus, they would be considered to be "bright" or "gifted."[8]

Note, however, that according to this model intellectual abilities are also in no way fixed, especially not by the genes. A person's neural network would possess the capacity to adapt itself to any required tasks, as long as it is exposed to these problems before maturity while the network is still malleable or plastic in this way. However, there is an interesting occurrence when this model is exposed to the current psychometric approach.

Evaluating the Psychometric Approach

As previously noted, an implication of differences in neural plasticity would be that people highly developed in one intellectual ability would be highly developed in other intellectual abilities as well, the phenomenon known as *g*. However, there would not be abilities that are more and less dependent on this process. Rather, all intellectual abilities would develop as a result of the same developmental mechanism.

However, there would still be abilities that would correlate more or less with each other, and this would simply represent the degree to which such abilities have differences in the extent to which they are affected by idiosyncratic experiences in the environment. In

progressive increase in intellectual abilities over childhood, with people developing at different rates. Similarly, as people become older, they do not process information in the same way as people who are younger but less intelligent.

[7] A comment should perhaps be made about the idiot savant syndrome. It is often argued that these individuals demonstrate that people with low intelligence overall can demonstrate high intelligence in some situations, arguing against a general factor mediating intellectual performance. However, even a cursory examination of these abilities reveals that they are very different to what is generally considered to be characteristic of fluid intelligence, or the ability to reason. Instead, they consist of skills such as number calculation and days of the calendar, abilities that do not involve understanding or meaning but can instead be easily programmed into a digital computer to perform (Nettelbeck, 1999). In contrast, the abilities possessed by individuals of high IQ are not easily programmed into a digital computer, and these individuals also cannot perform the feats like number calculation and days of the calendar that idiot savants can.

[8] Although it can be demonstrated using artificial neural network simulations that extremely high levels of neural plasticity can also be disruptive to learning, the slow rate of acquisition of abilities for even high-IQ individuals suggests that the range of plasticity for the human population is considerably less than the optimum level. In addition, it is questionable whether a biological system would ever be able to attain the level of plasticity required to be maladaptive, given that such biological systems are inherently limited in their plasticity because of structural constraints that do not exist with mathematical models. For instance, a biological system does not have the freedom to form connections with every other node in the system after a single trial of learning. The connection pattern must be gradually developed. This is in contrast to a mathematical system in which every node can be hypothetically connected to every other node.

other words, those abilities that most correlate with each other would be those that are a function of environmental experiences that are largely identical across individuals. Thus, abilities with the highest *g* loadings would not be abilities that require more of any given factor; they are simply those that have the lowest environmental variances. An example of this relationship using hypothetical data is given in Appendix B.

Therefore, if one then examined these highly *g*-loaded abilities, it would be found that they do possess relatively little environmental variance. However, this would be because one has specifically chosen to test abilities that statistical analyses have already identified as having low environmental variances. These abilities would also not be representative of intellectual abilities as a whole. Rather, all of the other abilities with lower *g* loadings would have greater environmental variance, and clearly, according to how the brain adapts, all intellectual abilities are actually quite malleable, although the relative ability to develop them is determined by heredity. Therefore, to then use highly *g*-loaded abilities to be representative of intelligence as a whole and use the invariance of such abilities to argue that intellectual abilities in general are immutable would be extremely misleading.[9]

The situation becomes even more confusing when we start to look for evidence to support this view. According to the prior model, it would be predicted that there would be no psychological characteristic of a task that would determine its *g* loading. In contrast, *g* loadings should be directly related to heritability. Therefore, it is worth noting that intelligence research has failed to identify any psychological attribute that determines the *g* loading of a task. In contrast, Jensen (1998) noted that “the relative *g* loadings of various tests predict their relative heritability coefficients” (p. 169).

The Development of Intelligence

Given these very different interpretations of the underlying basis of intelligence, it should be possible to distinguish between them by examining how abilities do, in fact, develop. According to the process argued for here, such abilities are a function of environmental stimulation. In contrast, the geneticist view argues that some other factor is limiting development. Therefore, examining the development of intelligence should provide some insight into this issue.

Piaget (1952; see also Flavell, 1963) performed the most extensive study of the development of childhood intelligence, and current research still supports his main findings. During these investigations, Piaget identified two fundamental processes involved in intellectual development: assimilation and accommodation. Assimilation involves the incorporating of experience into present cognitive structures. However, if new experiences are not compatible with these existing cognitive structures, the cognitive structures are altered to accommodate the new experiences. In other words, the neural connections are adapted to reflect the new experiences. Thus, the plasticity processes described here are consistent with the accommodation processes that are known to be critical for intellectual development (see also Elman et al., 1996; McClelland & Jenkins, 1991).

Piaget went on to argue that cognitive development was typified by various stages of development. For instance, Inhelder and Piaget (1958) evaluated children’s performance on a balance scale task (Figure 2). In this task, children are required to judge which side of the balance scale will go down given various combinations of weight and distance from the fulcrum. The correct solution involves multiplying the weight by the distance on each side of the scale and predicting that the side with the greater magnitude will go down. Siegler (1976) carried out more extensive investigations of this task and identified four rules that may dictate performance. It was found that children would proceed through these four rules as they developed cognitively. These rules could also be used to account for many other developmental phenomena as well. (Siegler, 1981).

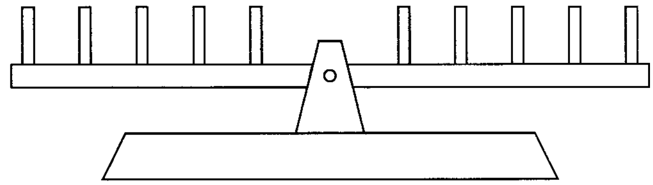

Figure 2. The type of balance scale first used by Inhelder and Piaget (1958) and later by Siegler (1976; 1981).

McClelland and Jenkins (1991) used an artificial neural system to simulate performance on the balance scale task. They observed that as the neural system adapted its connections to the environment, it would proceed through the same developmental stages observed in children. In particular, it was noted that

> The model captures several of the more intriguing aspects of cognitive development. It captures its stage-like character, while at the same time exhibiting an underlying continuity which accounts for gradual change in readiness to move on to the next stage. It captures the fact that behavior can often seem very much to be under the control of very simple and narrow rules, yet exhibit symptoms of gradedness and continuity when tested in different ways. It captures the fact that development, in a large number of different domains, progresses from an initial over-focussing on the most salient dimension of a task or problem—to the point where other dimensions are not even encoded—followed by a sequence of further steps in which the reliance on the initially unattended dimension gradually increases. (p. 69)

Therefore, this indicates that the development of the connections is consistent with the development of intelligence. In addition, it is observed that more intelligent people are more able to and can more quickly accommodate experiences into their cognitive structures, and they also pass through the Piagetian stages faster (Carroll, Kohlberg, & DeVries, 1984; Humphreys & Parsons, 1979; Jensen, 1980). This indicates that their neural systems can adapt better, allowing for the development of structures that are more compatible with environmental stimuli (see also Appendix A, in which it is demonstrated that differences in neural plasticity would lead to differences in the rate at which people would proceed through the stages of the balance scale task described above).

In contrast, no explanation is given as to how current explanations of *g*, such as myelination or neural efficiency, would lead to

[9] Incidentally, it is often remarked that the evidence is unsupportive of a Genotype × Environment interaction for intelligence (e.g., Loehlin et al., 1997). However, this is a different relation to that described in this article. It is concerned with whether the general factor or *g* is due to a Genotype × Environment interaction, a view that is also being argued against in this article.

the stagelike character of intellectual development. Nor does it seem credible to argue that differences in the myriad of different intellectual abilities are all due to a single factor such as myelination, ignoring the connections and the different ontogenies and developmental trajectories of these abilities.

Other Support for a Neural Plasticity Model

It is never possible to prove conclusively that a given theory is correct. There is always the possibility that another theory will be discovered that provides a better explanation of the evidence. Rather, the preferred theory should be the one that can most parsimoniously account for all of the currently observed empirical phenomena. This is particularly the case when the theory makes definite predictions about the evidence that, if contradicted, would lead to a modification or even rejection of the theory itself. Therefore, the validity of a neural plasticity account rests on its relative ability to account for the empirical findings that are observed in intelligence research.

Attempts to Improve Intellectual Abilities

The first issue that may be examined is the effect that intervention studies have on the development of intelligence. According to a neural plasticity model, it is expected that environmental interventions in the form of intellectual training would improve intellectual abilities. This is because environmental interventions would increase exposure to the type of stimuli responsible for normal intellectual development, thereby leading to faster adaptation than would otherwise be the case. However, these same interventions would not affect the underlying differences in neural plasticity. Differences in neural plasticity would likely be determined by differences in the genes. For instance, neural plasticity would need various neural structures to be present, whose existence would depend on particular genetic programs.

Therefore, it is expected that intervention programs would improve the development of intellectual abilities relative to controls as long as the children are part of the program. However, once the intervention is removed, higher plasticity children who were not part of the program would be expected to catch up and overtake children from the program who possessed lower levels of plasticity. Thus, over time, the relative rank of individuals would return to where it was before the intervention.

This phenomenon has been consistently observed in the literature. Intervention programs do affect relative intellectual performance, with the typical effects being between 5 and 20 IQ points. However, at the conclusion of such programs, the IQ gains are gradually lost relative to control groups (Brody, 1992; Neisser et al., 1996). Similarly, schooling can also increase IQ performance (Mackintosh, 1998). It should also be noted that the magnitude of the IQ increase would be a function of the underlying differences in neural plasticity. If there are large differences in neural plasticity, then even relatively large interventions would not be sufficient to overcome differences in this factor. This can be seen from the examples given in Appendix A.

Another well-known phenomenon associated with intervention studies is the lack of transfer from trained intellectual abilities to other abilities (Brody, 1992; Detterman, 1993). This is again consistent with the view that different intellectual abilities are based on different neural circuits. In this case, the intervention would be expected to improve the neural connections responsible for the ability being trained, but this would not influence the level of performance for other abilities. Rather, these other abilities would still be dependent on the normal level of intellectual stimulation for their development. Therefore, the lack of transfer provides evidence that different intellectual abilities are based on different neural circuits.

Finally, because intelligence tests are not measuring any direct property of the brain but rather a characteristic that is due to an interaction with the environment, differences across generations in the amount and quality of environmental stimulation may also be expected to change the mean level of performance on IQ tests. This characteristic has again been observed, with performance on IQ tests increasing by about 3 IQ points per decade (Flynn, 1996), presumably because of changes in educational practices over this time (Mackintosh, 1998). This effect has commonly been referred to as the Flynn effect.

Thus, a neural plasticity model can account not only for the stability of differences between individuals in intellectual performance but also for the finding that the overall level of intellectual performance can be seen to vary under differing environmental conditions.

The Relationship Between Brain Size and Intelligence

Another relation that may be examined is the relationship between brain size and intelligence. Brain mass and volume progressively increase over childhood, again until maturity (Morgan & Gibson, 1991). However, the brain also possesses more neurons shortly after birth than at any time thereafter. In fact, the loss of neurons during early infancy can be quite severe. Therefore, because neurons are being lost over childhood, the increase in brain mass and volume must be due to other factors.

The factor most likely to be the cause of the increase in brain mass is the progressive increase in connection complexity over childhood (Blinkov & Glezer, 1968; Epstein, 1979). The increase in connections not only leads to an increase in volume directly, but concomitant with the increase in connections is an increase in support tissue, including myelination, blood vessels, glial cells, and an elaboration of the nerve cells themselves (Diamond, 1991; Konner, 1991; Sirevaag & Greenough, 1987). This is then supported by the finding that different environments not only lead to the previously noted increase in connection complexity but also increases in brain mass and volume as well (Kolb & Whishaw, 1998).

It could then be postulated that if people did differ in neural plasticity and this was causing the differences in intelligence, it would be expected that more intelligent people would also develop larger brains. This is because a given amount of environmental stimulation would cause more intelligent people's brains to develop more connections. However, it would also not be brain size per se that is causing the differences in intelligence but rather that brain size is an indication of relative connection complexity. Therefore, other factors that influence brain size but that are not indicative of connection complexity would confound the relationship. For instance, people with larger bodies would also be expected to have larger brains, but this would be reflective of them having greater surface area and hence more neurons than other people (Williams & Herrup, 1988). The possession of more neurons would not affect the intelligent processing of information, however. Therefore, one would expect there to be a stronger relationship between intelligence and brain size once body size is controlled for. Similarly, given that the differences in neural plasticity would manifest themselves in differences in connection complexity gradually over childhood, one would expect the correlation between brain size and intelligence to increase over childhood as more intelligent people's brains adapt more to the environment.

Both of these relations have been observed. Advances in magnetic resonance imaging (MRI) techniques have allowed in vivo investigation of brain volume in healthy individuals. It has been found that there is a positive correlation between measures of cortical volume and intelligence and that this relationship increases when body size is controlled for (Jensen, 1998; Wickett, Vernon, & Lee, 1994; Willerman, Schultz, Rutledge, & Bigler, 1991). In addition, the relation between brain size and intelligence increases over childhood (Jensen & Johnson, 1994).

Given the finding that there is a relation between brain size and intelligence, it has also been argued that this is due simply to larger brains possessing more neurons (e.g., Willerman et al., 1991). However, there are a number of difficulties with this view. First, as previously noted, the number of neurons actually decreases over childhood. Therefore, it is difficult to see how a loss of neurons could lead to the development or increase in intelligence over the same time period. Similarly, if brain size was the limiting factor of intelligence, then it would be expected that larger people should, in fact, be more intelligent irrespective of body size, because their brains would still be larger and contain more neurons. Because this is observed not to be the case, it is sometimes argued that larger bodies also have more information to process. However, larger bodies still have similar processing requirements in terms of the number of arms and legs, number of mouths, and many other characteristics. In addition, even if it was acknowledged that the primary processing areas do have more work to do, larger people would also have larger general association areas. Therefore, it would still be expected that they could understand more relations compared with people with smaller brains, if intelligence was simply determined by neuron number.

The view that larger brains are necessarily more intelligent also has difficulties when the properties of neural systems are again considered. The addition of more neurons in itself would not affect the pattern of activation in a network. Also, the NETtalk network shows only minimal increase in performance when the number of elements is increased from 60 to 120 (Sejnowski & Rosenberg, 1986). Therefore, given that even a small human brain would have many millions of neurons for an ability such as speech, increasing the number of neurons by a few percentage points would not seem to be a critical contribution. This is in contrast to the crucial importance of the connections in determining processing output.

Differences in Neural Speed and Neural Efficiency

A brain that is more able to adapt its connections to the environment may also be expected to show other characteristics as well. For instance, a network with stronger and more appropriate connections would be able to process even relatively simple tasks faster and with less error. This has again been observed, with more intelligent people having faster reaction times and showing less variability in reaction times even on simple tasks (Jensen, 1998). This relationship has been confirmed in the simulation work of Anderson (1994; Anderson & Donaldson, 1995), where it has been shown that differences in the number of connections would account for the observed reaction time data, unlike other possible explanations such as differences in the speed of transmission, which cannot explain the reduced variability in reaction times.

A network with better connections would also be more tuned to environmental stimuli. This would result in the brain being less active when processing information as the network has developed the capacity to discriminate between different inputs, leading to only the appropriate relations being activated. This is then confirmed with positron emission tomography (PET) studies that show that the brains of more intelligent people are less active when processing information, as revealed by glucose metabolism (Haier, 1993). Thus, differences in speed and efficiency can be attributed to differences in the connections between more and less intelligent people.

Differences in the Neural Connections

Perhaps the most direct way of establishing whether differences in the neural connections are the cause of differences in intellectual abilities would be to examine the connections themselves. Therefore, it is worth noting that in some cases the only detectable brain difference in mentally retarded individuals as opposed to normal controls is a lack of dendritic branching (Huttenlocher, 1991). In contrast, individuals who have obtained a higher education, and who were presumably more intelligent, have been observed to have greater dendritic complexity (Jacobs, Schall, & Scheibel, 1993).[10] Unfortunately, however, the lack of biographical information that can be obtained from autopsy patients limits the data with which conclusions can be made.

Modularity

Much interest has arisen in the issue of modularity of brain function (Fodor, 1983). Sometimes evidence for modularity has also been taken to be evidence against the notion of a general factor of intelligence. However, such findings are quite compatible with a neural plasticity account of intelligence. The simulations in Appendix A show that neural networks may be completely independent and yet be related to each other through a common adaptive process. In this case, brain localization studies and studies of brain damage will reveal different areas specialized for different tasks, and yet the abilities will be related in the normal population. Incidentally, such a finding also does not provide evidence against some other theories of *g* such as speed of information processing, which would again postulate that there is some widespread quality of brain processing that is beneficial to many different functions.

[10] Note, however, that it is not more connections per se that would lead to superior intelligence. Rather, more connections would be indicative of the brain possessing the capacity to develop connections in response to stimulation. Some individuals may have relatively high connection complexity but poor intellectual abilities because the neurons have formed inappropriate connections.

Thus, the evidence for (or against) modularity is surprisingly weak in its implications for the nature of *g*.

Current Explanations of Intelligence

There have been many attempts at providing an explanation for *g*. Some researchers have used the previously mentioned correlation between performance on simple reaction time tasks and IQ to argue that a characteristic such as speed of information processing is the cause of *g* (e.g., Jensen, 1998; Miller, 1994; Vernon, 1992). Other researchers have argued that *g* is due to greater efficiency of processing (Haier, 1993) or fewer errors in neural transmission (Eysenck, 1994). However, these theories appear to suffer from a number of difficulties. First, they seem to disregard recent research arguing that the connections are critical for intellectual development. This is even though differences in intelligence are characterized by differences in intellectual performance that are characteristic of differences in the connections (see Appendix A). In contrast, no attempt is made to show how increasing the speed of nerve transmission or the efficiency of the brain would result in a better transformation of input, let alone reproduce the differences in performance that distinguish people of differing intelligence. Rather, these theories leave unresolved the issue of how the brain is actually able to solve intellectual problems. It is also not possible to argue that the connections are responsible for normal development and some other factor then leads to individual differences, because individual differences in intelligence are determined by the rate at which abilities are developed.

These issues can be illustrated when the properties of artificial neural systems are observed. These neural systems are mathematical models of biological systems and assume instantaneous and perfect nerve transmission (Rumelhart & McClelland, 1986). Therefore, it would be expected that these models would have immense computational power, in contrast with the human brain, in which these characteristics are supposed to limit the meaningfulness of processing. However, in reality, an artificial neural system with perfect processing and transmission characteristics does not implicitly show any intelligent processing properties. It is only once the connections are adapted that intelligent-like performance occurs (see also Mackintosh, 1986, 1998; Stankov & Roberts, 1997, for criticisms of speed as the underlying cause of intelligence).

Other researchers have argued that differences in *g* are based on differences in working memory capacity (Kyllonen & Christal, 1990). This is based on the observation that more intelligent people can store more complex mental representations and perform more complex transformations on those representations. These characteristics would again be determined by the neural connections. At the same time, a characteristic such as dendritic density or arborization cannot be used to explain *g*, because these attributes in themselves do not determine the validity of the processing of a neural network. For instance, 100 artificial neural networks could be randomly created with the same connection density as the NETtalk network shown in Appendix A, but none of these would perform any better than chance levels. Connectionist science has revealed that a general property of the connections will not lead to meaningful processing, but rather the connections must be specifically adapted to whatever function they are performing. Hence, any theory of *g* must be able to allow for a general factor of intelligence, while at the same time allowing specific adaptations to be made for different intellectual abilities.

Another approach has been to argue that there is not some general process, but rather *g* is due to the sampling of a number of different, but overlapping, modules (Detterman, 1994). However, this account again seems unconvincing. What module would be in common and hence account for the correlation between performance on an inspection time task (Nettelbeck, 1987) and detection of the number of notes in a musical chord (Lynn & Gault, 1986)? Similarly, the tasks with the two highest *g* loadings are typically Raven's Progressive Matrices and Letter Series Completion (Jensen, 1998). By the sampling account, these two tasks must have more components in common with each other than with any other intellectual tasks. However, they would again seem to be based on very different processes for their solution, as would be demonstrated if they were instantiated within network simulations.

Another failing of all current theories of intelligence is that they simply cannot account for all of the observed data about intelligence. For instance, how does speed of information processing account for the Flynn effect, the effect of intervention studies, or differences in the connections between more and less intelligent people? Similarly, how does working memory capacity account for intelligence being related to very simple processing tasks such as inspection time, again the effect of intervention studies, or different stages in the development of intellectual abilities? These limitations in current theory are recognized by current intelligence researchers. For instance, Jensen (1998, p. 257) noted that "we have a number of suggestive neurological correlates of *g*, but as yet these have not been integrated into a coherent neurophysiological theory of *g*. There are still too many missing pieces of the jigsaw puzzle to be able to assemble a complete picture." It is my position that differences in neural plasticity can go some way toward resolving this issue. Differences in neural plasticity can provide an account of many of the findings that have been observed in intelligence research, including differences in reaction time on simple tasks, the Flynn effect, the effect of intervention studies, the stagelike nature of development, the relation between brain size and intelligence, the relation of *g* loadings to heritability, and so on. No other current theory of intelligence is able to account for all of these findings.

The strength of the approach advocated here is that it also moves away from the approach that is reliant on simply observing correlations between performances to determine causation. In other words, because there is a correlation between reaction time on simple tasks and intelligence, or working memory tasks and intelligence, it is concluded that each of the former causes intelligence. However, the observation of a correlation leaves open the possibility that there is a third factor, such as differences in neural plasticity, that leads to better performance on each of these tasks. Similarly, even if we could directly observe neural attributes in the brain, we would still be dealing with correlations between characteristics and intelligence. In order to establish possible causation, it is necessary to be able to independently manipulate the possible causal factor. However, it is unlikely that ethical permission will ever be obtained to manipulate the growth processes of children's brains. Thus, research is likely to become more and more reliant on the use of simulations to evaluate the likely plausibility of mechanisms. Simulations not only allow the independent manipulation of variables that are thought to have a causal influence such as the learning rate, but they also force the model to be specified to the extent that it can actually be shown to be a sufficient account of intellectual processing. Such an account is no longer reliant on speculation as to whether a given characteristic would, in fact, lead to the observed differences in performance. This leads to a more convincing account of the causal factors.

The Existence of a Critical Period

The previous sections have argued that the brain has evolved a remarkable capacity to adapt its connections to the environment. This would then account for intellectual development. However, this capacity of the brain to adapt its connections to the environment also diminishes over time, suggesting the existence of a critical period for intellectual development.

This characteristic has already been established for the visual cortex, where stimulation is required during early childhood if the connections are to be developed correctly. For instance, a cat exposed to only vertical lines during its infancy will then not be able to perceive horizontal lines later on in its life (Mitchell, 1980). The difference with other areas of the cortex is that this adaptation process can last up until maturity (e.g., Huttenlocher, 1990; Huttenlocher & Dabholkar, 1997). This is then confirmed by the finding that fluid intellectual abilities do not develop after this time (Horn & Noll, 1994). Therefore, does this not indicate that there is a critical period for the development of fluid intellectual abilities as well?[11]

In other words, intellectual abilities develop or increase over childhood. This is due to the brain being able to adapt its connections to environmental stimulation. However, intellectual abilities are also observed to stop developing at maturity. Therefore, this indicates that the brain has lost the ability to adapt its connections to the environment; otherwise, intellectual abilities would continue to develop. Therefore, if the appropriate connections are to be developed for a particular intellectual ability, a person would be required to be presented with the appropriate stimulation during childhood, while intellectual abilities are still observed to be able to change.

A Critical Period for Language Development

Consider the example of language. Language proficiency is often used to assess intelligence (Jensen, 1998). However, it has also been established that there exists a critical period for the development of language. For instance, Lenneberg (1967) argued that language acquisition must occur before the onset of puberty in order for language to develop fully. This was based on such evidence as recovery from aphasia by children as opposed to adults and differences in language acquisition by the mentally retarded before and after maturity.

Grimshaw, Adelstein, Bryden, and MacKinnon (1998) also found evidence for a critical period for language. They examined the case of E. M., a young man who had been profoundly deaf since birth and grew up in a rural area where he received no formal education and had no contact with the deaf community. At the age of 15 years, he was fitted with hearing aids that corrected his hearing loss and then he began to learn verbal Spanish. Four years after the acquisition of the hearing aids, it was found that he continued to demonstrate severe deficits in verbal comprehension and production, again supporting the critical period hypothesis for language (see also Pinker, 1994).

Similarly, Johnson and Newport (1989) examined the acquisition of English by Chinese or Korean migrants to America. These individuals were controlled for the number of years of exposure to the second language but differed in age of initial exposure. Johnson and Newport found that ultimate language proficiency in grammar was directly a function of the age of initial exposure. The younger the person was, the higher the level of proficiency obtained. However, this relationship only held until the age of 16 years. After this age, the age of arrival had no further negative impact on ultimate grammar attainment. Thus, this suggests a critical period effect for grammar acquisition in a second language as well.

It is also observed that individuals suffering from localized brain damage are more likely to recover intellectual functions if the lesions occur before maturity (e.g., Stein, Brailowsky, & Will, 1995). This again indicates that the brain is more able to reorganize its connections before maturity. Consider now another situation in which intellectual processing would be dependent on possessing particular neural connections.

Implications for the Development of Genius

It is sometimes observed that particular individuals appear within society whose intellectual abilities are considered to be well in advance of their peers. These individuals are often labeled as geniuses and their capacity to reason and conceptualize problems allows them to make advances when other researchers have failed. For instance, Einstein's conceptual abilities in physics were arguably superior to anyone else not only from his generation but from current generations as well. Similar examples of "geniuses" can be observed in other fields such as economics, mathematics, and cosmology. Given the importance of having individuals who possess such abilities, the issue is how do such people possess the ability to understand such advanced concepts?

Current intelligence research would perhaps argue that these individuals simply possess more *g* than other people in the population. The nature of this *g* is left unspecified. However, because the distribution of *g* is normally distributed, it is doubtful whether such unique individuals would exist. It would be expected that for every person with an extremely high IQ, there would be a number of people whose IQ was only slightly less. Thus, these lower individuals would still have comparable reasoning abilities, and it would not be possible to unequivocally identify the geniuses from the other bright individuals. In addition, the high *g* account can be rejected because such individuals are shown not to possess these outstanding reasoning capabilities in all situations, and they may not even have possessed a high *g*. For instance, observations of

[11] A number of researchers have argued that critical period effects are due to the effect of the learning process itself, whereby changes in the connections themselves limit possible future changes (e.g., Marchman, 1993). However, this view has difficulties once an individual differences perspective is taken. In particular, it is observed that fluid intelligence stops developing at maturity, irrespective of the intellectual level reached at that time (Cattell, 1987). Therefore, this suggests that the mechanism responsible for the critical period is a true maturational effect rather than one based on learning.

Einstein during his youth suggested that he was not an exceptionally gifted child. Instead, he was little more than average (Bernstein, 1973). Therefore, Einstein was able to perform great reasoning without possessing a high *g* factor. Thus, this suggests that geniuses seem to possess something other than simply a high IQ.

This article has argued that reasoning capacities would be a function of the connections of the neural system. These connections then develop over childhood as the neural system adapts itself to the environment with which it is presented. Therefore, to be able to reason like Einstein, one would need a neural system that possesses the correct connections. However, it was also noted that this capacity of the nervous system to change the connections in response to the environment also stops at maturity. This is shown by fluid intellectual abilities ceasing to develop after this time. Therefore, you could present a person with an IQ of 200 with the appropriate phenomena when they are 20 years old, after the critical period, and they would not have the capacity to adapt their brains to the new phenomena. In contrast to this, people are able to develop their connections before maturity, as is shown by their developing intellectual performance over this time. Therefore, if it is desired that people possess these abilities, should not they be exposed to the appropriate stimulation during their childhood while their brains can still adapt in this way?[12]

Unfortunately, this does not then imply that every child would be able to develop these abilities. Children possessing a low rate of neural plasticity would not be able to develop the appropriate connections even when exposed to the appropriate stimulation, as is demonstrated by their lack of attainment of normal intellectual abilities. However, it would still be expected that many children would be able to develop the right connections if given the appropriate experience. In fact, it may be argued that relations like theoretical physics concepts are relatively simpler to learn than something as complex as language. The reason that more children acquire language is that they are extensively exposed to it during the critical period.

This analysis is then supported by the observation that such geniuses are also distinguishable from their peers because they began to investigate their field before maturity, while their neural circuits were still malleable. For example, Einstein began thinking about the universe from the age of 5, and by 12 he was studying advanced mathematical textbooks (Bernstein, 1973). This would then have enabled him to develop the appropriate neural connections that are required to internally conceptualize and process the intellectual problems in such areas.[13]

In contrast to this, consider the current approach to education. The abilities possessed by geniuses such as Einstein are considered to be very valuable to society. However, the educational system then presents these phenomena to people in college when they are past the critical period. It is then surprised when these young adults cannot acquire these abilities. However, given that fluid intellectual abilities are no longer developing at this age and that these individuals cannot learn new languages to native proficiency, it does not seem to be that surprising that they cannot acquire these other intellectual abilities as well.

This is, of course, not intended to mean that early environmental experience is then the only determinant of genius. Indeed, many other factors may also exist, including personality and motivational attributes (see Simonton, 1999). Rather, it is being argued that environmental experience during the critical period is a necessary but not sufficient condition if certain intellectual abilities are to be developed.

Note, however, that this relationship would not hold if intellectual abilities were due to the type of general factor that present intelligence researchers suggest. If reasoning ability was simply determined by a characteristic such as speed of information processing or neural efficiency, then those individuals who were high in this characteristic should be able to perform well at any intellectual problem irrespective of the nature of the problem. Their performance would not be limited by their connections and, therefore, their childhood experience would not play a critical role in determining their intellectual abilities. Thus, contrary to what many intelligence researchers suggest, it is not possible to determine the heritability of intellectual abilities simply by determining the heritability of highly *g* loaded abilities and ignoring the nature of the general factor. It depends on what the nature of the general factor or process is as to whether intellectual abilities are a function of the environment or not. However, intelligence researchers also admit that the nature of the general factor of intelligence has not yet been established. It is also questionable whether theories like neural speed even represent a viable alternative to differences in neural plasticity as a possible explanation of differences in intellectual abilities. Thus, the possibility of there being a critical period for intellectual development should at least be considered to be a possibility, rather than the current approach in which attempts at increasing intellectual abilities are discounted simply because of the lack of variance shown by highly *g* loaded tasks.

Discussion

The present article has attempted to give a plausible account of the nature of the general factor of intelligence. Research in neuroscience and cognitive science has suggested that different intellectual abilities would require different neural connections. The only feasible mechanism whereby the brain could obtain such connections is through an adaptation mechanism in response to

[12] Other characteristics such as crystallized intelligence may continue to develop after maturity. This would be attributed to their dependence on other processes such as synaptic changes, which involve the strengthening or weakening of existing connections and which continue to occur throughout the life span (Toyama, Komatsu, & Tanifuji, 1995). However, these processes would be limited in the extent to which they could overcome more fundamental differences in the connections. Rather, they would allow the forming of associations within the framework set by the presence or absence of connections. Thus, although fluid intelligence would not change after maturity, vocabulary could because it would involve the formation of new associations between existing neural structures.

[13] Einstein's brain has been subjected to histological analysis, and it was found that one area had a significantly smaller neuron to glial ratio than the control population (Diamond, Scheibel, Murphy, & Harvey, 1985). This is consistent with greater connectional complexity, because brains with more connections are also observed to have more glial cells. However, probably more telling is that Einstein's brain did not really differ exceptionally from that of normal controls. Perhaps his neurons were just wired up differently, and this is what enabled him to conceptualize some things better. In contrast, the theory that the glial cells could be responsible for more intelligent processing would have to be shown to be compatible with all of the evidence provided for in this article. However, such a theory would not appear to get past the initial section where it is argued that specific connections would be critical for different intellectual abilities.

environmental input. Such a developmental mechanism has already been established. These findings are not inconsistent with the observation of a general factor of intelligence because if people differed in the ability to adapt their connections to the environment, a general factor of intelligence would result.

This then suggests that connectionist principles are not incompatible with current psychometric findings regarding the distribution of higher order intellectual processes and that the connectionist approach can, in fact, be used to explain the general factor of intelligence. At the same time, this analysis does suggest that IQ tests are measuring a very definite characteristic of intellectual functioning. However, this characteristic is also substantially different than that assumed by current intelligence researchers. In particular, it is argued that the brain does not have the capacity to directly perceive and understand concepts with which it is presented. Instead, intelligent responding is based on past activations leading to changes in the neural connections so that future activations can be processed more meaningfully. This then eliminates the problem of current intelligence theories that lead to an endless recursion whereby intelligent behavior must appeal to some higher order, intelligent, control mechanism to shape activation patterns through the network.

However, the acceptance of such a theory then necessarily argues for the critical role of environmental stimulation in determining intellectual abilities. Given also that some intellectual abilities are observed to stop developing at maturity, this then also argues for a critical period for the development of these abilities. However, current intelligence research is notable for not even mentioning the possibility of a critical period for intellectual development, despite widespread agreement in other research areas that a critical period does exist for at least some intellectual abilities such as language. Instead, current intelligence researchers assess the malleability of intelligence by simply testing abilities that have already been identified by statistical techniques as possessing the lowest possible environmental variances. Given then the predictable result that such abilities do show relatively low environmental variances, it is concluded that intellectual abilities cannot be improved and that interventions during childhood have little effect.

More confusing still is the open acknowledgment by intelligence researchers that it has not yet been established what the nature of *g* is, despite their analysis assuming that it is a type of relation different to that described previously. Nor is there any plausible attempt at providing an alternative explanation of how the connections may develop. For instance, Jensen (1998) noted that “structural, neural-net, or ‘design’ features of the brain have scarcely been investigated in relation to *g* in normal persons and cannot be evaluated in this respect at present” (p. 205). Miller (1994) argued that “it is unlikely that the differences between the gifted and nongifted involve the size of different parts of the gray matter or the anatomy of its neural connections, since it is hard to think of a mechanism that would consistently affect the gifted relative to the normal, while simultaneously having the same effect on university students relative to 7th grade students” (p. 810).[14] Other intelligence researchers are notable for not even mentioning the role of the connections in determining intellectual output (Brody, 1992; Eysenck, 1994; Mackintosh, 1998; Neisser et al., 1996).

In addition, there is widespread agreement that intelligence consists of the ability to adapt to the environment (e.g., Neisser et al., 1996; Sternberg & Detterman, 1986). Therefore, identifying the ability of the neural connections to adapt to the environment with intelligence seems to be the making of a sensible deduction.

Future Directions

A number of avenues for future research would then appear to be suggested from this analysis. First, it is argued that there is a critical period for intellectual development and that many children are not currently developing abilities of which they are capable. This characteristic has already been investigated to some extent for language, but other intellectual abilities have been neglected. Important issues include identifying precisely which abilities are dependent on a critical period for their development, whether any learning of such abilities is possible beyond the critical period, the duration of the critical period, and whether major adaptations are possible even close to the end of the critical period. These issues may be investigated by using the procedure whereby people of different ages are presented with the same environmental stimulation, and determining whether the effect of the stimulation on intellectual performance varies with the age of the participants. This is in contrast to the favored training paradigm of the past, such as in programs like Headstart, in which environmental stimulation was presented to very young children of disadvantaged circumstances in the hope of changing the factor causing differences in IQ (Mackintosh, 1998).

Another interesting prospect is the implication of understanding the cause of differences in intelligence for educating those who are low in intelligence. In particular, the current analysis suggests that people of low IQ perform poorly because their brains do not adapt well to environmental stimulation. However, educational methods may be designed that are more likely to produce the appropriate change in the connections. This may be guided by the work on artificial neural networks and observing the types of stimulation from which networks with low learning rates are most able to learn. For instance, networks with low plasticity tend to learn better if the complexity between input and output is reduced, and the network is taught in stages. This then reduces the dimensionality of the problem and allows the network to concentrate on only adapting the critical connections. Applying these principles to education could, it is hoped, lead to successful outcomes.

At a biological level, much more needs to be understood about the plasticity processes that underlie the changes in the connections. For instance, what algorithm determines whether a connection will or will not be formed between two particular neurons? Does the back-propagation algorithm represent a somewhat close analog of this process, or is it simply a mathematical technique to approach the same final result? Is the difference between people of low and high IQ simply based on quantitative differences in the ability to change the connections, or is it that people of differing intelligence actually change their connections based on differing algorithms? If people of low IQ do adapt their connections on the basis of a different algorithm, are there some situations in which it is advantageous (e.g., consider the idiot savant syndrome)?

[14] Incidentally, the present model can quite easily account for this finding. Differences in performance between people of the same age are due to differences in neural plasticity, whereas differences in average performance between people of different ages are due to differences in the amount of environmental stimulation or experience.

These issues will be difficult to resolve because they require both the examination of the fine detail of the nervous system in a living organism over time and also preparations that are as closely related to humans as possible. Although much of the original research on neural plasticity was done using the rat (e.g., Hebb, 1949; Rosenzweig, 1979), it is questionable just how relevant these processes are to understanding fluid intelligence in humans. For instance, two concepts closely associated with fluid intelligence are consciousness and language, attributes that are sometimes argued to be unique to humans, or at least to the primate species. In addition, even if fluid intelligence does exist in the rat, a characteristic like maze performance is more likely to be a reflection of trial-and-error learning and memory processes than fluid intelligence as such. This then suggests that new procedures for evaluating rat performance need to be established, and there needs to be some validation that these procedures are assessing characteristics that are equivalent to fluid intelligence in humans.

Finally, and perhaps most exciting, once the neural process responsible for differences in intelligence has been identified, this opens the possibility of biological interventions that can improve the intelligence of people suffering from low IQ. Already some knowledge is being gathered as to the biochemical substrates of the plasticity process (Kostovic, 1990), and advanced genetic analysis and gene therapy will provide the option to children who suffer from low neural plasticity of having their plasticity level increased to that of other individuals in the population.

At the same time, the present analysis discounts the view that intelligence can be increased immediately by the taking of some smart drug or medication. Even if a person's level of neural plasticity was greatly increased through the use of such a drug, it would not immediately lead to any change in the person's intellectual performance. Instead, it would allow their brain to adapt better to current stimuli. This would then allow them to process future stimuli more intelligently.

Summary

The present approach has attempted to integrate the findings from neuroscience and cognitive science with that of psychometric intelligence research. These approaches initially seem to be contradictory because neuroscience and cognitive science argue that different intellectual abilities would be based on different neural circuits and that the brain would require environmental stimulation to develop these abilities. In contrast, intelligence research argues that there is a general factor of intelligence and that it is highly heritable. However, it was then observed that if people differed in their ability to adapt their neural circuits to the environment, a general factor of intelligence would result. Such a model can also explain many other phenomena observed with intelligence that are currently unexplained. However, acceptance of such a model then necessarily also argues for a critical period in intellectual development, with the implication that many children are not currently developing abilities that they can attain. This is an issue that needs to be addressed in future intelligence research.

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(*Appendixes follow*)

Appendix A

Demonstration That Differences in Neural Plasticity Would Lead to the Observed Differences in Human Intellectual Performance Using Artificial Neural Networks

This appendix demonstrates how differences in neural plasticity, or the capacity of a neural network to change its connections in response to environmental stimulation, would lead to the observed differences in human intellectual performance.

The Stuttgart Neural Network Simulator from the Institute for Parallel and Distributed High Performance Systems at the University of Stuttgart was used for the simulations. The connections between the neurons for each network were initialized to random values between −1.0 and 1.0 before training. These same initialization values were used for each of the training runs comparing different levels of neural plasticity. The activation of each unit in the network was calculated using

$$\mathrm{net}_j(t) = \sum_i w_{ij} a_i(t)$$

$$a_j(t+1) = \frac{1}{1 + e^{-(\mathrm{net}_j(t))}},$$

where $\mathrm{net}_j\,(t)$ is the net input to unit j at step t, j is the index for some unit in the net, i is the index of a predecessor of unit j, w_{ij} is the weight of the connection from unit i to unit j, and $a_i(t)$ is the activation of unit I at step t.

The connection weights were then updated if the discrepancy between desired and actual output was greater than 0.1. The following back-propagation formula with momentum was used:

$$\Delta w_{ij}(t+1) = \eta \delta_j a_i + 0.5 \Delta w_{ij}(t)$$

$$\delta_j = \begin{cases} f'_j(\mathrm{net}_j)(t_j - a_j) & \text{if unit } j \text{ is an output-unit} \\ f'_j(\mathrm{net}_j) \sum_k \delta_k w_{jk} & \text{if unit } j \text{ is a hidden-unit,} \end{cases}$$

where $\Delta w_{ij}(t)$ is the weight change of the connection from unit i to unit j; η is the learning parameter, values of 0.2, 0.02, and 0.002 were used; δ_j is the error (difference between the real output and the teaching input) of unit j; a_i is the activation of the preceding unit I; i is the index of a predecessor to the current unit j with link w_{ij} from i to j, j is the index of the current unit, and k is the index of a successor to the current unit j with link w_{jk} from j to k.

Each of the three neural network simulations chosen for this study used these same parameters. Two of the simulations, NETtalk and the balance scale task, have already been described in the text. The third task used was the Concealed Words test, an actual fluid intelligence test. Each of these is now described.

NETtalk Simulation

For the NETtalk simulation, a similar neural network to that used by Sejnowski and Rosenberg (1986) was used. This consisted of 7 sets of 29 input units, 120 hidden units, and 26 output units. Each of the 7 sets of input units encoded one letter of the input text, so that up to seven letters were presented to the network at a time. The desired output of the network was the correct phoneme for the center or fourth letter of this seven-letter window. The other six letters were then used to provide a context for the decision. Twenty-three of the 26 output units encoded the required phonemes using a distributed representation. The remaining three output units were used to encode stress and syllable boundaries.

The training stimuli consisted of the 1,000 most common words in the English language, again similar to that used by Sejnowski and Rosenberg (1986). Each word was stepped through the input window until each letter had been presented in the center window. After being exposed to each letter, the discrepancy between the actual and desired outputs was calculated and the error was back-propagated from the output to input layers of the network. The connections between the units were then adjusted to minimize their contribution to the total mean square error between the desired and actual outputs.

To simulate differences in neural plasticity, three different neural network learning rates were used: 0.2, 0.02, and 0.002. Because the network is a mathematical approximation of a biological system, the actual differences in neural plasticity are likely to differ somewhat to this representation, but functionally the results will be similar.

Figure A1 depicts the effect of varying neural plasticity on the ability of the network to learn the phonemic representations of the 1,000 most common words. This task is also similar to the task that children face when first learning to read. As can be seen in Figure A1, the neural network that is most able to adapt its connections to the environmental requirements (represented by 0.2) quickly achieves the task. The neural network with the moderate rate of adaptation (represented by 0.02) takes longer to attain the same level of performance, even though the amount of environmental stimulation (or years of education) is equivalent. Finally, the network with the lowest ability to adapt its connections to environmental demands takes considerably longer again and still has not attained satisfactory performance at the conclusion of the training. Thus, it can be seen that differences in neural plasticity would lead to differences in neural networks (or the brain) being able to learn the task of reading written text. Jensen (1998) also noted that "the acquisition of decoding skill in young children is highly related to mental age (and to IQ in children of the same chronological age). But after word reading skill is fairly mastered, it is only weakly diagnostic of IQ or *g*" (p.280). This description would seem to correspond surprisingly closely to the pattern of results shown in Figure A1.

Balance Scale Task

The next example involves the simulation of the balance scale task, as described in McClelland and Jenkins (1991). As was noted, children's performance on the balance scale task is shown to proceed through four stages or rules (Siegler, 1976). This represents a move away from focusing on only the most salient dimension of a task to a situation in which all information that is relevant to task performance is taken into account.

The neural network used consisted of four groups of five input units, two groups of two hidden units, and two output units. Two of the groups of five

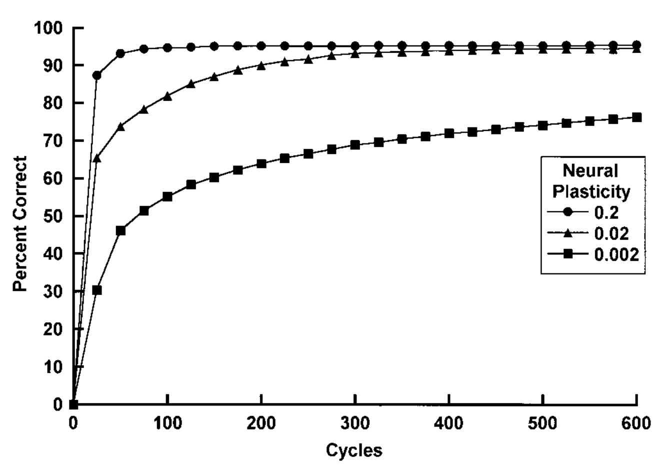

Figure A1. Performance on the NETtalk network as a function of differences in network learning rate or neural plasticity.

input units were used to code weight information, one for each side of the balance scale, and the other two groups of input units were used to code the equivalent distance information. One group of hidden units was connected to the weight input units, whereas the other group was connected to the distance input units. Finally, the two output units were used to code whether the scale would tilt down on either the left- or right-hand side. If the scale was balanced, this was represented by having both output units at half activation.

The training stimuli were also similar to those used in McClelland and Jenkins (1991). They consisted of all 625 possible problems involving the 25 possible weight combinations multiplied by the 25 possible distance combinations. To make weight the more salient dimension, problems in which the distance from the fulcrum was the same on both sides were listed an additional nine times each. Each training cycle consisted of the full set of 1,750 problems, unlike in McClelland and Jenkin's study, in which a random subset of 100 patterns was used. This did not affect the outcome but did make training easier.

Again, Figure A2 shows the results when the same differences in network learning rate were used. It can be seen that, again, the network that is best able to adapt its connections performs the best. In particular, it quickly proceeds through the developmental stages from random responses to appropriately taking into account all relevant information for the task at hand. In contrast, the 0.02 network takes considerably longer to proceed through these same stages, even though it has been exposed to the same environmental input. Finally, the 0.002 network is very much struggling to acquire an understanding of the task. It takes a very long time for it to attain Rule 1, and there is no sign of it progressing to the more complex rules. Thus, in this example, it can be seen how neural networks that differ in their plasticity would differ in their ability to accommodate information from the environment. This would affect their capacity to respond appropriately in many situations in which they are required to process information. Remember also that Piagetian tasks are good indicators of *g*. In other words, more intelligent people pass through the Piagetian stages faster (Humphreys & Parsons, 1979).

Figure A3. An example of the training (left) and test (right) stimuli for the Concealed Words simulation (not taken from the actual test).

Concealed Words Test

The final demonstration consists of training the same neural network simulations on an actual intelligence test. The test chosen was the Concealed Words test, a test taken from French, Ekstrom, and Price (1963; see also Thurstone's Mutilated Words). In this test, people are presented with 26 words that have been largely obscured or hidden (Figure A3). The objective is then to correctly identify as many of these words as possible. The Concealed Words test is a *g* loaded test, indicating that it is a good measure of the characteristic that determines performance on other intelligence tests as well (Jensen, 1980).

The neural network consisted of an input matrix of 240 columns by 80 rows, 100 hidden units, and 26 output units. The input matrix was used to represent the training and test patterns that had been scanned into the computer and converted into "on" and "off" bits of information on a 240×80 grid. This allowed a high-resolution representation of the stimuli. The 26 output units were used to represent the word with which the network had been presented.

The training stimuli consisted of the 26 words that were on the actual test and were printed out in a similar but not identical font to that used for the actual test. The printed words were then scanned into the computer, and nine training patterns were created for each of the words. This was done by using the combination of three different horizontal and three different vertical offsets. This encouraged the network to associate the actual shape of the words with the appropriate response rather than just the firing of specific input units. Eye movements in biological systems would encourage a similar response.

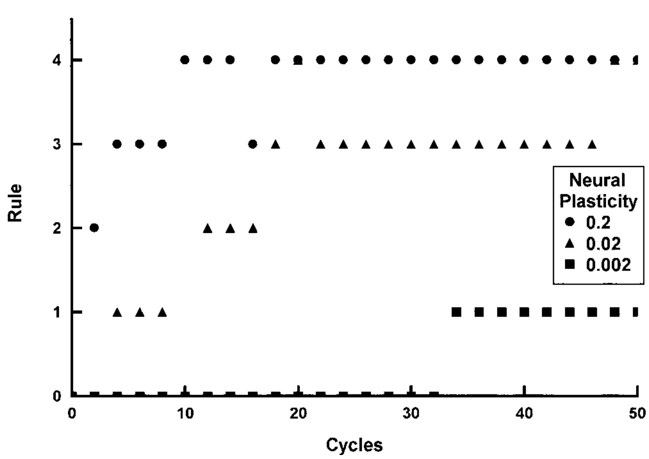

Figure A2. Acquisition of Siegler's (1976) rules on the balance scale task as a function of differences in network learning rate or neural plasticity.

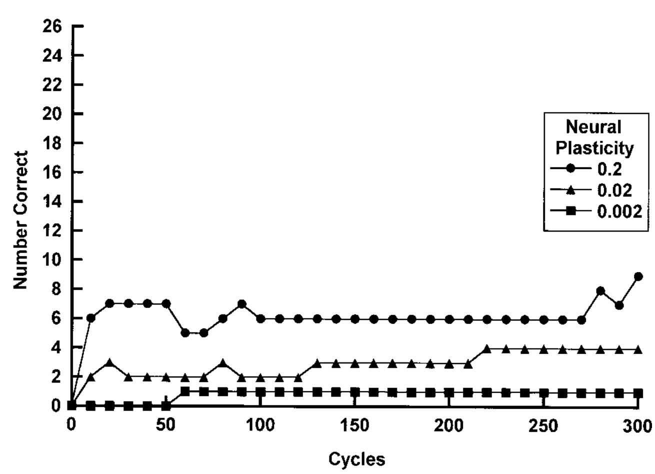

Figure A4. Performance on the Concealed Words test as a function of differences in network learning rate or neural plasticity.

(*Appendixes continue*)

The test stimuli consisted of the actual 26 concealed words on the Concealed Words test. These test patterns were approximately centered in the region of the three vertical and three horizontal offsets used for the training stimuli. Correct performance depended on the correct output unit having the highest activation when presented with the appropriate pattern. Thus, chance performance was 1 out of 26.

Figure A4 shows the performance of the network on the actual Concealed Words test as it was trained on the training patterns. It should be noted that at no point was the network actually trained on the test patterns. Rather, the network was taught to respond appropriately to the completed words and was then required to generalize to the test items. This is a similar situation to that faced by people when they initially learn the unobscured words and are then given the Concealed Words test as a test of their intelligence.

Specifically, it can be seen in Figure A4 that the 0.2 neural network quickly attains a high level of performance on the test. For instance, after 300 cycles of exposure, it is scoring 9 out of 26 for the test. This is comparable to university undergraduate intellectual performance, in which the average score is around 10 correct (the test is quite difficult because many of the words are almost completely obscured). Of course, there are also many differences between the present artificial neural network implementation of the test and human performance. These factors would be both an advantage and a disadvantage to human performance relative to the simulation's performance at the task.

In contrast to the network that is most able to adapt its connections, the 0.02 network takes considerably longer to reach a given level of performance and never attains the level of performance the more adaptable network achieves. After 300 cycles, it is only scoring 4 out of 26. Similarly, the 0.002 network is worse again, and it has difficulty recognizing any of the words on the Concealed Words test, even though it has been exposed to exactly the same training information that the other two networks have been presented with. Thus, again it can be seen that differences in neural plasticity would lead to differences in performance on an intellectual task.

Summary

These examples have shown that a more plastic neural network would perform better in many different situations or tasks. In particular, a neural network that is better able to adapt its connections to the environment is observed to be able to learn to read faster, accommodate information from the environment better, and score higher on an actual intelligence test. It can also be seen how the same factor can show very different characteristics of performance under different situations. In the first task, it shows differences in rate of acquisition but not major differences in final performance. The second task showed qualitative differences in performance, whereas the third task showed simply quantitative differences in performance. Appendix B examines the outcome when results such as these are factor analyzed.

Appendix B

Demonstration That the Factor-Analytic Structure of Human Abilities Is Compatible With a Neural Plasticity Model of Intellectual Development

The purpose of this appendix is to demonstrate how differences in neural plasticity are consistent with the observed results of factor analysis. It also demonstrates how relying on highly *g*-loaded tests will lead to a bias when assessing the relative environmental and genetic contributions to the development of intellectual abilities. Finally, it also shows how differences in neural plasticity can also account for another characteristic of the correlational structure of intellectual abilities.

Defining the Model

In Appendix A, it was shown how equivalent levels of environmental experience would lead to very different levels of intellectual performance if people differed in their brain's capacity to adapt to the environment. However, it is also clear that not all people would be exposed to exactly the same stimuli for each and every ability. Rather, there would also be differences in the amount of environmental stimulation to which people are exposed for each ability through such factors as their own interests, and this can again be seen from Appendix A to influence intellectual development.

A mathematical model was developed to simulate these differences in both neural plasticity and environmental stimulation. The intention was to show how, even though intellectual abilities are determined by both genetic and environmental factors, a reliance on examining highly *g*-loaded abilities would lead to the misleading conclusion that intellectual abilities are highly heritable in general.

Differences in neural plasticity were represented quantitatively as values between 0.002 and 0.200. A normal distribution was created between these limits with a mean of 0.101 and a standard deviation of 0.050. This means that a person with neural plasticity of 0.002 would be two standard deviations below the mean and a person with neural plasticity of 0.200 would be two standard deviations above the mean. A total of 488 values were used to represent the variation in neural plasticity. A normal distri-

Table B1
Differences in the Amount of Variation in Environmental Stimulation for the Five Simulated Intellectual Tasks

Task	Amount of variation in environmental stimulation
A	100 ± 0–20
B	100 ± 0–40
C	100 ± 0–60
D	100 ± 0–80
E	100 ± 0–100

Table B2
Factors Extracted From the Variance of Five Simulated Intellectual Tasks Occurring as a Result of a Neural Plasticity Process

Factor	Eigenvalue	% of variance	Cumulative variance
1	3.350	67.00	67.00
2	0.646	12.92	79.92
3	0.512	10.25	90.17
4	0.341	6.82	96.99
5	0.151	3.01	100.00

Table B3
Factor Loadings of the Five Simulated Tasks on the First Factor Extracted by Factor Analysis

Task	Factor loading
A	.951
B	.880
C	.768
D	.662
E	.546

bution was used because differences in IQ are typically observed to be normally distributed (Jensen, 1980), but the effects of the model would be the same if a uniform distribution was used.

As can be seen in Appendix A, the amount of intellectual development is a function of an interaction between the amount of stimulation and the amount of neural plasticity. A person with lower neural plasticity would require more environmental experience to attain the same intellectual level. The mean level of stimulation for each intellectual task was taken to be a nominal 100 units. Thus, an individual with neural plasticity of 0.200, and the average amount of environmental stimulation for a particular task would be given a score of $0.200 \times 100 = 20$ for that task (an error component could also be added, but this would not affect the overall outcome of the model).

However, as already noted, not all individuals would experience the same amount of environmental stimulation. Different people would receive different amounts of environmental stimulation. The amount of variation in environmental stimulation would also vary across tasks. Some intellectual abilities would have relatively small differences in environmental experience across the population, whereas other abilities would have quite large variations. It could also be argued that the amount of variation in environmental stimulation would be less for less important intellectual skills. This is because individuals would not have an incentive to make a greater effort in attaining these abilities. Thus, each individual would spend approximately the same amount of time attempting to acquire them (such as time in the classroom). In contrast, intellectual abilities that are more important for later success would be characterized by greater differences in environmental exposure across individuals because some children would be more conscientious.

The differences in environmental stimulation across tasks were represented by a random quantity added to or taken away from the mean environmental stimulation of 100 units. For a task characterized by larger environmental variation, the possible values of the random quantity that could be added to or taken away from the mean environmental exposure were extended over a greater range.

Five tasks were chosen with the ranges of environmental stimulation simulated as deviating up to plus or minus 20, 40, 60, 80, or 100 units away from the mean of 100 (see Table B1). Thus, for the first task differences in environmental stimulation were uniformly distributed over the range of 80 to 120, whereas for the fifth task differences extended from 0 to 200. Each individual's performance on each of the five tasks was then calculated, taking into account their relative level of plasticity and the amount of environmental stimulation they had received for each task. This gave each individual a score on each of the five tasks, similar to the scores that are collected on a typical battery of intelligence tests. This datum was then analyzed using maximum likelihood factor analysis.

Results of the Factor Analysis

Table B2 contains the initial results of the factor analysis. Although five factors were extracted, it can be seen that there was only one factor that accounted for more variance than any of the original tasks. This accounted for 67% of the total variance across all five tasks and is consistent with the finding of a general factor influencing performance on the intellectual tasks just mentioned.

Table B3 shows the factor loadings of the prior hypothetical tasks on the general factor extracted. As can be seen, the factor loadings systematically decrease as the amount of environmental variation on the task increases, even though all tasks are determined by the same developmental process. The highly *g* loaded tasks possess high *g* loadings simply because the amount of environmental variation that occurs on these tasks is relatively lower. This is what then enables them to correlate more highly with each other. Of course, the absolute magnitude of the factor loadings would also be determined by the relative amount of variation in the genetic and environmental dimensions.

Thus, the prior demonstration shows that if the development of intellectual abilities was due to a neural plasticity process, then a general factor of intelligence would still be revealed through factor analysis. In addition, even though all intellectual abilities would be dependent on an interaction between this neural plasticity factor and environmental stimulation, factor analysis would identify those abilities whose differences in environmental stimulation within the present population are relatively small. If one then assessed the heritability of these tasks, one would find that they are highly heritable. However, this would purely be a function of having chosen to test tasks that have already been identified statistically as having extremely low environmental variances within the present population. These tasks would be most representative of a person's relative level of neural plasticity, but they would not necessarily be a good indicator of their various intellectual capacities.

Table B4
Correlations Between the Simulated Tasks Separately Analyzed for Low and High Neural Plasticity Groups

	Low neural plasticity					High neural plasticity				
Task	1	2	3	4	5	1	2	3	4	5
1. Task A	—					—				
2. Task B	.797	—				.548	—			
3. Task C	.681	.602	—			.376	.343	—		
4. Task D	.599	.528	.442	—		.337	.216	.245	—	
5. Task E	.527	.444	.344	.406	—	.157	.177	.156	.148	—

(*Appendix continues*)

Thus, the prior analysis demonstrates how the finding of high heritabilities for particular intellectual abilities is not incompatible with abilities developing as a result of environmental experiences. Rather, these particular tasks would be tasks in which environmental stimulation is largely identical across the population. Note also that correlations in environmental stimuli for different abilities would also result in the formation of lower level factors or cognitive abilities, as observed by Carroll (1993).

Differences in Correlations Based on Intellectual Level

Astute readers would also be aware that the development of intellectual abilities according to a neural plasticity model would also reveal another characteristic. Because a given amount of environmental stimulation would have a greater effect on high-IQ than on low-IQ individuals, because their brains are more able to adapt to environmental stimulation, it then follows that high-IQ individuals' intellectual abilities would be more differentiated. In other words, the same differences in environmental stimulation would cause the intellectual abilities of high-IQ individuals to differ more than those of low-IQ individuals. Thus, the correlations between abilities would be expected to be higher for low-IQ than for high-IQ individuals.

Table B4 illustrates the correlations between the five stimulated tasks when the scores were analyzed separately for individuals above and below the mean for neural plasticity. As can be seen, the correlations for the low-IQ group are approximately twice the size of those for the high-IQ group. Thus, if intellectual abilities were due to a neural plasticity process, it would also be expected that the correlations between abilities would be greater for low-IQ than for high-IQ groups. This could again be used as a test to determine whether the prior model is appropriate.

Therefore, it is again worth noting that another basic characteristic of intelligence that has been observed is that the size of the correlations between tests are smaller for high-ability groups than for low-ability groups (Spearman, 1927). For instance, Detterman and Daniel (1989) analyzed the variance from their own studies and that of the Wechsler Adult Intelligence Scale–Revised and Wechsler Intelligence Scale for Children–Revised standardization samples. They noted that "correlations declined systematically with increasing IQ. In both studies, correlations were found to be two times higher in low IQ groups than in high IQ groups" (p. 349; see also Deary et al., 1996; Detterman, 1991, for more recent discussions).

Received January 22, 1999
Revision received October 11, 2000
Accepted June 22, 2001 ■