10 Information processing approaches to intelligence: Progress and prospects

Peter G. Caryl[1], Ian J. Deary[1], Arthur R. Jensen[2], Aljoscha C. Neubauer[3], and Douglas Vickers[4]
University of Edinburgh[1]; University of California, Berkeley[2]; Karl-Franzens-University, Graz[3]; University of Adelaide[4].

What are the basic cognitive and psychobiological processes that underlie individual differences in mental abilities? Answers to this question have been sought by experimental psychologists since Galton and with the increased research effort over the last 25 years, it is time to make an assessment of this important research area. The symposium reported in this chapter offered a broad survey of reductionist research into human intelligence. In common with most present-day psychologists, the contributors accepted the reliability and validity of cognitive ability test measures. They also accepted that human mental abilities display a hierarchical structure with general intelligence (Spearman's *g*) at the peak and with successively more specific cognitive abilities as one descends to lower levels (Carroll, 1993), and they shared a curiosity about the origins of differences in intelligence in terms of brain function and structure.

Researchers may take different lines in pursuing this curiosity. Individual differences in brain function may reflect the building up over a lifetime, especially in individuals who obtain high IQ-type test scores, of neural networks whose activation implements various high level mental strategies and algorithms. However, many researchers have suspected that differences in more basic aspects of brain function might account for some of the variance in IQ-type test scores. But what is meant by a basic aspect of brain function? Different answers have been offered from the beginnings of differential psychology. Galton and Spearman thought that sensory discrimination was the simplest, most fundamental, psychological property and that individual differences in this function formed the basis for individual differences in intelligence (Deary, 1994). For others, reaction time performed this explanatory function, as a measure of basic "mental speed" (Deary, 1996). Some researchers adopted explanatory variables that clearly measured a specific construct, e.g., performance in sensory discrimination tasks could be explained using very few parameters, perhaps just one. Other researchers selected variables that were only loosely tied to psychological constructs: A good example is brain size. This measures something about the brain, and appears to correlate modestly and reliably with IQ-type test scores, but it is not obvious which causes or consequences of high or low brain size underlie individual differences in mental functioning (Deary & Caryl, 1997). When one surveys in detail the range of efforts that could be broadly categorised

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as reductionist approaches to human intelligence it becomes clear how heterogeneous a group they are.

Under the banner of the information processing approach to human intelligence it has been traditional to lump together diverse techniques, tests and measures such as brain size, nerve conduction velocity, functional brain scanning techniques (e.g., positron and single photon emission tomography), brain event related potentials, reaction times (including the Hick procedure, the Posner letter matching task, and the Sternberg memory scanning task), and inspection times and other psychophysical measures (Matarazzo, 1992; Neisser et al., 1996; Deary & Caryl, 1997). These diverse approaches all require the assumption that work in another domain will yield tasks or measures that reliably index variance in basic, biological, information-processing parameters, and that these tasks will account for a substantial amount of the variance in cognitive ability test scores—the differential psychologist expects a lot of colleagues in other areas.

Table 1. An assessment of some biological/information processing approaches to intelligence.

	Criterion of Assessment			
MEASURE	Correlation with intelligence	Theoretical tractability	Cause or consequence of IQ	Comments
Brain size	.4 to .5	Poor: several proposed constructs	Probably cause	
Nerve conduction velocity	.2 or less	Good: simple biological measure	Probably cause	Too few studies to date
ERP string Length	Contradictory	Poor[a]	Ambiguous[b]	One of many ERP measures
Hick reaction Time	< .25 for single parameters	Poor: not well understood[c]	Ambiguous[d]	R^2 improved when several parameters are combined
Inspection time	.4 to .5	Problematic	Probably cause, but disputed	

Note. [a] Parameters governing variance speculative.

[b] Could be response characteristic secondary to intelligence level.

[c] Rate of gain of information has not proved a robust correlate of IQ.

[d] Slope could be due to learning.

One might assess the contribution of representative information processing measures to our current understanding of differences in human intelligence in

terms of the following criteria: How well does the measure correlate with psychometric intelligence? Has the measure a good theoretical basis, such that its parameter structure is understood? Is the measure a cause or a consequence of intelligence differences? The criteria in Table 1 reflect desiderata suggested by Deary and Stough (1996). Their fourth consideration—the extent to which the mechanism of the correlation between the "basic" measure and intelligence was understood—is omitted here because it overlaps with the degree to which the measure is theoretically tractable. Brain size—as assessed using magnetic resonance imaging—and inspection time have produced the strongest and most consistent correlations for any single index (Table 1).

As might be anticipated, contributors to this symposium differed in their assessment of the progress and prospects for reductionist approaches to intelligence. The structure of this chapter reflects this diversity of opinion, as well as differences in the methods of analysis and in the information processing or biological measures they considered. The first section presents a very positive overview of progress towards understanding the biology of *g*. The subsequent contributions, which look in more detail at the conceptual and methodological scaffolding required to reach that goal, present a more cautious assessment. While all contributors would agree that biological/information processing measures provide important evidence about the nature of individual differences affecting intelligent behaviour, and that such measures can show substantial correlations with IQ-type test scores, the difficulties of interpreting these measures become apparent on closer inspection. So the schoolteacher's report-card might be marked: Progress—substantial; prospects—still some way to go.

THE LOCUS OF BIOLOGICAL G – A GOAL FOR REDUCTIONISM

Since its discovery by Spearman in 1904, the *g* factor has become so firmly established as a major psychological construct in terms of psychometric and factor analytic criteria that further research along strictly psychometric lines is most unlikely either to disconfirm the construct validity of *g* or to add anything essentially new to our understanding of it. In fact, *g*, unlike any of the primary, or first-order, factors revealed by factor analysis, cannot be described in terms of the knowledge content of mental test items, or in terms of skills, or even in terms of theoretical cognitive processes. It is not essentially a psychological or behavioural variable, but a biological one. It reflects certain properties of the brain, as shown by its correlations with individual differences in brain variables such as size, glucose metabolic rate, nerve conduction velocity, and the latency and amplitude of evoked electrical potentials (Jensen, 1993, 1997; Miller 1994).

The frontier of *g* research now faces the discovery of the anatomical and physiological features of the brain that cause *g*. Research on *g* has finally reached a stage at which the only direction left to go is that presaged by Spearman himself, who wrote that the final understanding of *g* "must come from the most

profound and detailed direct study of the human brain in its purely physical and chemical aspects" (1927, p. 403).

Besides being an end in itself, the aim of achieving a physiological explanation of *g* may be regarded as a strategic necessity for the formulation of a theory of *g*, not only because there is good reason to believe that the ultimate basis of *g* is physiological and largely "hard-wired," but because the facts of neurophysiology provide constraints on the great variety of plausible cognitive processing models and computer simulations that can be formulated to account for the mass of empirical knowledge that psychologists have established at the behavioural level about information processing and its relation to psychometric *g*, as measured by IQ or other highly *g*-loaded tests. The body of empirically established phenomena in this field greatly exceeds our theoretical understanding of them. The properties of neural processes, brain organisation, and localisation of functions can serve to narrow all the possible hypotheses to those that are most likely to prove fruitful for integrating all of the disparate facts revealed by research on individual differences in information processing at the behavioural level. At the same time, this approach would help to establish psychometric *g* in the mainstream of human biology.

But why *g* in particular, rather than just any reliably measurable mental ability? There are three main reasons that *g* seems the most promising variable for beginning research aimed at the explanation of individual differences in ability.

First is the fact that *g* accounts for more of the reliable variance in all psychometric abilities than does any other linearly independent factor (or source of variance).

Second is the fact that, in deriving the *g* factor from a large and highly diverse battery of mental tests, the algorithm for a hierarchical factor analysis in effect "sifts out" virtually all of the sources of variance associated with any particular acquired knowledge or skill; hence *g* reflects mostly variance in information *processing* rather than in *achievement*. The highly varied knowledge and skill content of various tests merely serve as the medium from which factor analysis, so to speak, distils the *g* factor. And just as ethanol cannot be described in terms of any of the characteristics of the particular substances from which it is distilled (e.g., wheat, rye, corn, potatoes, molasses, sugar), *g* cannot be described in terms of any of the particular tests from which it is derived by means of factor analysis.

Third is the evidence that *g* has stronger genetic and physiological correlates than any other known psychometric factor independent of *g*. (See Jensen [1993, 1997], Jensen & Sinha [1993] and Miller [1994] for more detailed discussion of these results). This can be shown most definitively by the *method of correlated vectors*. The *g* factor is extracted from a number of diverse psychometric tests (e.g., the subtests of the Wechsler battery); also, each of the tests is correlated with some non-psychometric variable (e.g., brain volume). Thus we have a column vector of

the various tests' *g* loadings, V*g*, and a corresponding column vector of the tests' correlations with the non-psychometric variable, V*x*. The correlation between these two vectors, then, indicates whether the tests are correlated with the non-psychometric variable by virtue of their loadings on the *g* factor. (The effect of different test reliabilities is controlled by correction of the tests' *g* loadings for attenuation or by partialling out the column vector of the tests' reliability coefficients [Jensen, 1983]). When the method of correlated vectors is applied to several non-psychometric variables, it reveals significant correlations (shown here in parentheses) between V*g* and V*x*, where X is: *heritability* of individual differences in test scores (.60 to .80 in different studies), degree of *inbreeding depression* (.80), habituation of the amplitude of the *evoked potential* (.80), waveform complexity of the evoked potential (.95), cerebral *glucose metabolic rate* (-.79), *head size* [as a proxy for brain size] (.60-.70), the intracellular *pH level* of the brain (.63), and various measures of choice and discrimination *reaction time*. When *g* variance is removed from a battery of psychometric tests by regression, the remaining non-*g* variance (i.e., verbal, spatial, and memory factors, along with test specificity, which together are about equal to the *g* variance) shows zero correlation with reaction times measured in a variety of elementary cognitive tasks (ECTs). This implies that *g* is the factor solely responsible for the many chronometric studies of ECTs that show correlations between reaction time and various psychometric tests. The results of these studies can be generalised across all psychometric tests to the extent that they are *g*-loaded, but they probably can not be generalised to a test's non-*g* components of variance.

A conceptual obstacle to research on the neurophysiological basis of *g* is the failure to make a crucial distinction between the constructs of *intelligence* and of *g*. It can be argued that the term *intelligence* should be used only to refer to the processes or operating principles of the nervous system that make possible the behavioural functions that mediate an organism's adaptation to its environment —functions such as perception, attention, learning, remembering, thinking (e.g., seeing relationships), and problem-solving. In this sense, some aspects of intelligence are a property of virtually every organism in the animal kingdom, and intelligence is a broadly generic term. It would be meaningful to speak of interspecies differences in intelligence, but improper to speak of intraspecies differences, at least for all biologically normal members of a species, that is, those without exogenous or endogenous defects of the nervous system. All biologically normal members of a given species would possess the same intelligence, that is, the neural structures and processes that make intelligent behaviour possible. From an evolutionary standpoint, it is most improbable that there are intraspecies differences in intelligence as defined here.

The *g* factor, on the other hand, is an altogether different concept. Its existence depends entirely upon the existence of intraspecies *variation*, or individual differences, in the overall effectiveness of performing the various functions associated with intelligence, as described above. "Overall effectiveness" simply

means that intraspecies individual differences in the various functions are all positively correlated. The magnitude of the *g* loading for any specific performance indicates the degree to which that performance reflects a source of variance (i.e., individual differences in effectiveness of performance) that is common to a great many other specific performances.

The explanation of intelligence calls for a description of the operating principles of the nervous system that make the functions of intelligence possible in all normal members of the same species. The explanation of *g* calls for a description of those features of the nervous system associated with individual differences in the effectiveness of the organism's abilities and particularly with whatever feature(s) of the nervous system causes positive covariance (or correlation) among individual differences in virtually all adaptive abilities.

As a heuristic for research on the neurophysiological basis of *g*, therefore, we can propose the following working hypothesis: Individual differences in behavioural capacities do not result from differences in the brain's structural operating mechanisms per se, but result entirely from other aspects of cerebral physiology that modify the sensitivity, efficiency, and effectiveness of the basic information processes that mediate the individual's responses to certain aspects of the environment. Thus research on the neurophysiology of mental ability has two aspects, the first dealing with the brain structures and neural processes that make possible intelligent behaviour, the second dealing with the physical conditions that cause individual differences in intelligent behaviour. The first problem will probably be more difficult to solve than the second problem, but investigation of the second need not depend upon a prior solution of the first problem. Investigation can be directed at discovering the relationship between *g* and neural conditions that affect a number of functions or abilities which, though served by different brain modules, are nevertheless correlated across individuals.

The key question, then, is which features of brain physiology show reliable individual differences and have common effects across many different modules or other specialised neural functions? Most probably *g* is not a localised property of the brain. However, certain simple behavioural reflections of *g*, such as inspection time (IT) or reaction times (RT) in various elementary cognitive tasks are probably localised in the specific regions of the brain that subserve task performance. A fundamental question is whether these different brain processes share something in common that affects their efficiency, thereby causing correlated individual differences. If different simple types of performance subserved by different neural modules (or different regions of the brain) are not correlated with one another, but each one is correlated with *g*, it would mean that *g* is not the result of some property that the different modules (or regions) have in common, but arises from the fact that each of two or more of the independent modules is involved in the more complex forms of *g*-loaded performance. In other words, *g* could arise from *correlated* individual differences in the speed and efficiency of performance among a number of distinct neural processes located in

different regions of the brain, or from the *averaged* individual differences in efficiency of a number of distinct and *uncorrelated* neural processes.

Most of the evidence we have so far would seem to favour the first possibility, that is, some property (or properties) common to many kinds of modules serving various forms of information processing. Consider the correlation between *g* and total brain volume (about +.40 for IQ, which is an attenuated measure of *g*). There is no doubt about this correlation, which has now been demonstrated *in vivo* in several studies by different investigators using magnetic resonance imaging (Deary & Caryl, 1997). Hence brain size probably accounts for about one-fifth of the total variance in *g*. (By zeroing in on the brain mass of just those regions that serve cognitive functions, the correlation with *g* could be considerably greater). Moreover, the correlation of IQ with head-size (a proxy for brain size) exists within families (i.e., among full siblings; Jensen & Sinha, 1993), which indicates that the correlation represents a pleiotropic or *functional* relationship between IQ and brain size rather than just a simple genetic correlation between them, such as would result from the common assortment (via cross-assortative mating in the population) of distinct polygenes for both traits, as is the case for the (non-functional) correlation between IQ and stature.

Hence a prime question for neuroscientists is: Which general properties of the brain that are represented by its volume could account for its correlation with *g*? There are four classes of likely candidates that contribute to the brain's mass and that have functional significance: (1) the total number of neurones (or neurone density), (2) the number of synaptic connections and the amount of dendritic arborization, (3) the average size or diameter of neurones (both cell bodies and axons), and (4) the amount of extraneural structures (i.e., the myelin sheath and the glia involved in the formation of myelin and the regulation of chemical neurotransmitters). Other empirically demonstrated physical correlates of *g*, such as nerve conduction velocity (NCV), brain glucose metabolic rate, and the average evoked potential (Deary & Caryl, 1997) could be secondary products of one or more of the four primary variables listed above. For example, both axon diameter and especially the amount of myelin are related to NCV. And cerebral glucose metabolic rate and event related potential measures are related to the number of neurones that are engaged during a brief time period in response to the evoking stimulus.

One speculation especially worthy of attention along these lines is the hypothesis that the degree of myelination of neurones is at least one of the physiological sources of individual differences in the level of *g* (Miller, 1994). A larger part of the brain's volume consists of myelin and its supporting glial cells than consists of neurones. There is probably a great amount of neural redundancy throughout the brain so that, within limits, the sheer number of neurones may not be crucial for normal function. Myelination of neurones increases rapidly over the developmental period from infancy to maturity, and then there is a gradual demyelination in later maturity, with an accelerating rate in old age (Miller,

1994). The same trajectory occurs for psychometric measures of fluid ability, or *g*, and both the speed and the trial-to-trial intraindividual consistency of reaction times show the same trajectory. Also, the lipids and fatty acids (measured by blood cholesterol levels) of which myelin is composed are found to be positively correlated with *g* (Miller, 1994). The effects of myelination (and demyelination) on NCV could play a part in the relation between speed of information processing and *g*. And the fact that the myelin sheath insulates nerve impulses from neural "noise," "cross-talk," or other interference arising from contact with adjacent neurones (Miller, 1994) would suggest that myelination should be inversely related to intraindividual variability in RT (over a number of trials), which is generally more highly correlated with *g* than is the median RT itself.

These are examples of the kinds of hypotheses that the present technology of neuroscience should enable us to test; using these, the concerted efforts of researchers should be able empirically to establish the physical basis of *g* .

REDUCTIONIST APPROACHES TO INTELLIGENCE

This section examines the problems of understanding correlations between "basic" measures and intelligence. The reductionist investigator of intelligence must be a polymath, because the research draws from brain anatomy and neuroradiology, neurophysiology, psychophysiology, experimental psychology, and psychophysics, as can be illustrated by considering one example in detail.

Inspection time—which we shall take as our representative "basic" information processing measure—is a technique derived from psychophysics. Inspection time (IT) is operationally defined as the time needed by an observer in order to make a simple discrimination (Vickers, Nettelbeck, & Willson, 1972). This is the duration of the stimulus exposure that is required by the observer, not the response time. Typically, the stimulus involves the exposure of two parallel, vertical lines of markedly different lengths. The observer must indicate whether the longer of the lines was on the right or left. As the exposures become briefer the probability of a correct response becomes less, until it falls to 50% (chance) at very short durations. People who score higher on tests of psychometric intelligence can make discriminations at a given level of accuracy at briefer stimulus durations than people who score less well. The correlation between scores on tests of psychometric intelligence and ability on the inspection time test is about .4 to .5 for tests of performance/fluid IQ and about .2 for tests of verbal IQ (Deary & Stough, 1996; Kranzler & Jensen, 1989; Nettelbeck, 1987).

Establishing this correlation took a lot of the effort of the first 10 years of IT-IQ research, and the next 10 years consolidated this result. This period also saw a variety of attempts at understanding the association. Early papers on inspection time and intelligence tended to make the assumption that, with the correlation, came also an indication of the direction of causation and a mechanism for the

association (Deary, 1995): Neither is, in fact, the case. Later, the association between IT and cognitive ability became the focus of hypothesis formation and testing. In an effort to understand the meaning of the IT-IQ association—why an apparently simple psychophysical measure should account for between 16% and 25% of the variance in fluid cognitive ability test scores—a variety of approaches were adopted.

Psychophysical

Comprehensive criticisms of the original theoretical model of IT have appeared (Levy, 1992; White, 1993, 1996). As a result, there has been a retrenchment of the claims that IT assesses a single parameter and that the parameter in question is a basic, benchmark measure of speed of the brain's processing. Work in this area is discussed in more detail below.

Psychoacoustic

Following the argument that the limitations on visual processing captured in the IT measure/construct might reflect general mental speed, some have extended the procedure to the auditory modality by devising tasks which are intended to assess the same types of processing speed limitation (Deary, 1994, 1995; Raz, Willerman, & Yama, 1987). Although low-level auditory processing tasks using simple stimuli and discriminations have been found to correlate at similar levels with IQ test scores there is currently a lively debate about the basic constructs that cause the correlations.

Psychopharmacological

One way to understand the aspects of brain function responsible for IT and psychometric intelligence differences is to administer a drug that can impair or improve the functioning of a specific neurotransmitter-receptor system. Nicotine has been found to improve IT and also scores on Raven's progressive matrices (Stough et al., 1995), though there are contradictory results (Petrie & Deary, 1989). IT is slowed in Alzheimer's but not in Korsakoff's syndrome, which might suggest the involvement of cholinergic neurones in IT performance (Deary, Hunter, Langan, & Goodwin, 1991). This type of research is labour intensive and few studies have been completed to date. It is known that low levels of brain glucose impair IT as well as more general cognitive performance (McCrimmon, Deary, Huntly, MacLeod, & Frier, 1996).

Psychophysiological

A promising avenue of research—one that combines different reductionistic approaches to intelligence—has been to explore the evoked potential correlates of inspection time. As discussed elsewhere in the chapter, there seems to be an epoch between 140 to 200 msec following a stimulus onset within which

individual differences in the brain's response are associated with inspection time and intelligence differences (Caryl, 1994).

Experimental

This approach includes, for instance, the efforts to discover whether high IQ people do well on inspection time because they use high level cognitive strategies rather than because of more efficient low-level processing (Egan, 1994; Simpson & Deary, 1997). Also, the suggestions that motivation and personality differences partly cause the IT-IQ correlation have been explored and found to have no substance (Larson, Saccuzzo, & Brown, 1994; Stough et al., 1996).

Developmental

If inspection time is basic to intelligence differences then there is an important question about whether it changes from birth to intellectual maturity and then declines in old age. At present there are opposing views on this, with some suggesting that development—improvement in the efficiency of processing—does occur up to adolescence (Deary, 1995) and others viewing it as a constant (M. Anderson, 1992). Little research has been done directly in terms of longitudinal studies, but there is some evidence for (and against) improvement in auditory and visual processing over time (Deary, 1995; Massaro & Burke, 1991).

To master even the research that is specific to inspection time, just one of the potential information processing approaches to intelligence, will require almost as wide a range of expertise as does the entire enterprise. All of the above lines of investigation are necessary to explore the meaning and mechanisms of the association between mental ability and inspection time, and any one of these approaches—individually—might be seen as a huge endeavour.

ELEMENTARY COGNITIVE TASKS AND INTELLIGENCE

Inspection time, visual information processing, and intelligence

Inspection time arose from the field of psychophysics. Vickers—the originator of the test and its theory—brought together two ideas in order to create a task that assessed a single parameter related to visual functioning (Vickers et al., 1972; Vickers and Smith, 1986). One notion was that of the perceptual moment, the idea that visual perception and processing take place in time quanta rather than continuously. Second, Vickers included a particular theory of decision making. He assumed that, in a two alternative forced choice experiment, a stimulus offered information as to the response alternatives and that stimulus information went into one of two "counters" and was added to neural noise. When one of the counters passed some criterion then a preference for one of the alternatives could be given. The original IT task was designed to assess just one parameter, a

person's inspection time. When Nettelbeck and Lally (1976) studied IT and intelligence in a small group of individuals, highly heterogeneous with respect to mental ability, and found a strong association, it seemed as if a benchmark test of brain function had shown a correlation with human intelligence, and as if a single parameter—IT—effectively measured a threshold that constrained the level of intellectual achievement. Much has changed over the subsequent 20 years.

First, the theoretical bases for inspection time have been critically reassessed. IT theory combined a model of visual perception and a theory of decision making. With reference to the former, White (1993, 1996) has set out various possibilities with respect to the level of processing which is tapped by IT, ranging from low-level sensory to high level cognitive processes. With reference to the latter, the critical comment of Levy (1992, p. 994) that "the original basis for IT measurement ... is mathematically intractable in some respects" appears unjustified. Exact expressions for response probabilities, response times and confidence ratings from an accumulator model (together with numerical methods for evaluating them) were presented by Smith and Vickers (1988).

Second, researchers have realised that IT studies usually obtain insufficient psychophysical data. The task has been used in two types of study. Often the aim was to correlate IT with cognitive test scores. To maximise the reliability of the correlations, such studies maximised the number of participants and administered relatively few IT trials to each; participants were often unpractised and psychophysically naive. In contrast, models of the task and its parameters must be explored using psychophysical procedures which maximise the amount of data collected on any one observer, but there have been few such psychophysical studies of IT. As a single-parameter model of performance, IT theory proposed that only an observer's inspection time parameter would be involved in task performance and that no extra parameters were required to describe the changes in IT over time. Since then, it has been shown not only that there are temporal dynamics in the task, but that these are idiosyncratic (Deary, Caryl, & Gibson, 1993): One observer showed very long term practice effects on the task, whereas another showed contrasting improvements and decrements in performance over time at durations that were as little as 1 msec apart.

Inspection time and visual information processing

Such limitations in the underlying psychophysical theory or the procedures for data collection strike at the heart of the whole edifice linking IT—as a simple, well-defined, sensory or perceptual task—to psychometric intelligence. For example, when M. Anderson (1992) built IT into the heart of his cognitive theory of intelligence differences—the construct whose variance provided the individual differences in the Basic Processing Mechanism—he stated that,

> *"... IT is very much a psychophysical task. That is, it is a task that has well-defined psychophysical functions and whose main parameters are influ-*

> *enced by sensory/perceptual variables, rather than by cognitive ones."* (M. Anderson, 1992, p. 49)

If our understanding of what it means to be intelligent is to be advanced by studying IT, we have to ask again, and more seriously, what IT measures.

There has been a parochialism about the psychophysical aspects of the research, probably because most of the people investigating the IT-cognitive ability association came from the field of intelligence research. White (1993, 1996) emphasised that IT was merely one of a number of techniques that could be used to investigate the early stages of visual processing. Once it had become clear that the conventional IT task was supported by an inadequate theory and insufficient psychophysical data, it became essential for researchers to consider other procedures for exploring early visual processing.

Traditional backward masking paradigms

Rather than use IT-type stimuli, McGeorge, Crawford, and Kelly (1997) employed word stimuli in a more conventional (Sperling-type) backward masking set-up. They found very similar associations with WAIS-R IQ to those found by Deary (1993) who had analysed a similar data set using IT stimuli. The procedure used by McGeorge et al. demonstrates a move toward more traditional backward masking paradigms, but one can move further in integrating inspection time with other psychophysical techniques investigating early visual processing.

Latent trait approaches

Deary, McCrimmon, and Bradshaw (1997) employed a technique first described by Phillips and Singer (1974; and see Royer & Gilmore, 1985) which assessed the efficiency of the process of visual change detection. The task is as follows. Participants observe a monitor screen. After a warning cue an array of 49 small, non-contiguous rectangles appears. These comprise 49 randomly selected stimulus elements from a potential 10 x 10 matrix. After a delay, which is variable and controlled by the experimenter, one more rectangle is added to the array, the target. The participant must identify this additional, target rectangle. There is no speeded response. Performance is described by the curve which plots the probability of a correct response versus the delay between the appearance of the first 49 rectangles and the target. Deary et al. (1997) argued that this visual change detection (VCD) task can aid the understanding of the association between IT and cognitive ability for the following reasons. First, the task has important differences from IT. VCD involves a large array of stimuli, not a single stimulus. Thus, it emphasises a wide field of attention and parallel processing, whereas the IT task involves attention in a very narrow area. Second, VCD involves no backward masking: When the VCD target stimulus is added to its 49 identical predecessors the 50 rectangles remain until the participant makes a response. Many of the difficulties in interpretation of IT data stem from stimulus-mask interactions (Simpson & Deary, 1997).

The principal feature that is shared by IT and VCD is the limited time available for stimulus processing. Thus Deary et al. hypothesised that, if processing efficiency was the aspect of IT that correlated with cognitive ability test scores, then a latent trait which captured that variance which was shared by VCD and IT should correlate with mental ability, and not any variance specific to the psychophysical tests. They also used a task called visual movement detection. The best fit model (tested by structural equation modelling using EQS) may be seen in Figure 1. It was confirmed that the variance shared by the three visual processing tasks was the only significant correlate of psychometric intelligence. Also, as found in other IT studies (Deary, 1993; McGeorge et al., 1997), there was a significant association with general ability—the variance shared by all three mental tests—and further shared variance with non-verbal ability.

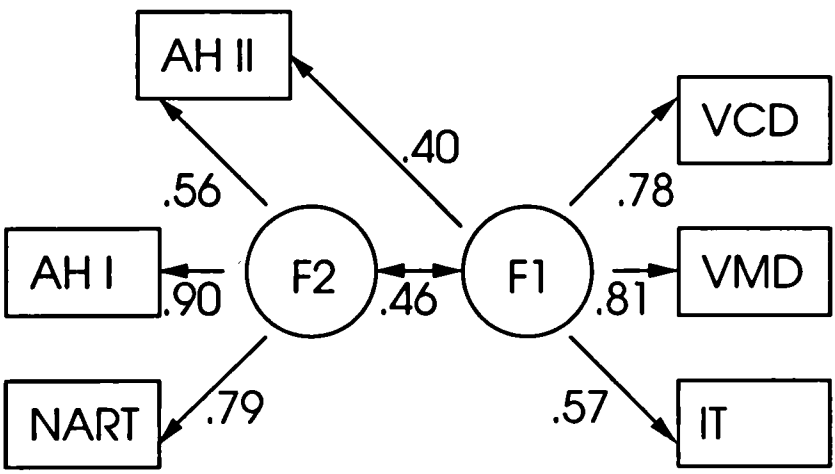

Figure 1. Structural equation model of the associations among three visual processing measures—visual change detection (VCD), visual movement detection (VMD) and inspection time (IT)—and three cognitive ability tests—Alice Heim Verbal (AH I), Alice Heim Non-verbal (AH II) and National Adult Reading Test (NART). Note that the latent visual processing trait (F1) has a correlation of .46 with the general factor from the three psychometric tests (F2). In addition there is a correlation of .4 between visual processing and non-verbal ability (AH II) (Deary et al., 1997).

A latent trait approach combining disparate-seeming visual information processing tasks brings several advantages to information processing research in intelligence (Deary et al., 1997). It circumvents the vague and seemingly endless debate about the possible idiosyncratic features of IT that might lead to its correlation with cognitive ability. In a single experiment it focuses on what is common to the tests rather than what is specific. Further, by linking IT, VCD and

VMD to cognitive ability it offers several possible routes for further reductionistic exploration of cognitive ability.

Additional routes to the understanding of IT, via brain evoked potentials and psychopharmacology, have been discussed above. For VCD there are established functional associations in the contemporaneous neuronal responses in the lateral geniculate nucleus (Singer & Phillips, 1974). This approach might be extended by the inclusion of other tasks that seem to tap the same visual processing limitations, for example of the (distinct) "inspection time" measure of Bergen and Julesz (1983). Vickers—the originator of the IT task—has devised a new task to assess the basic speed of intake of sensory information, the Frequency Accrual Speed Task (Vickers, 1995, and this chapter). Vickers and McDowell (1996) reported significant correlations in children between performance on the FAST and psychometric intelligence, but since recent work suggests the FAST is likely to tap differences in working memory rather than in information processing speed, the relationship between FAST and IT is contentious (Deary & Caryl, 1997b; Pietsch & Vickers, 1997; Vickers, Pietsch, & Hemingway, 1995).

Reaction time tasks and mental speed

The tasks most commonly used to investigate relationships between mental speed and human intelligence include IT, simple and choice RT following the rationale of Hick (1952), and the two tasks which form the topic of this section—Saul Sternberg's short term memory scanning task (Sternberg, 1966, 1969) and the Posner letter matching task (Posner & Mitchell, 1967).

Sternberg's memory scanning is a task designed to measure the speed of short-term memory retrieval. The participant is sequentially presented with a random sequence of digits (usually varying in length between 1 and 5 or 6 digits), which have to be kept in short term memory (STM). Subsequently a target item (digit) is displayed and the participant has to indicate as quickly as possible if the digit was in the previously shown memory set. The typical finding is a linear increase of RT with the number of elements in STM. From the regression of RTs on the number of items in STM, a slope measure can be calculated, which should indicate the time needed for the retrieval and comparison of a single element. The intercept of the regression gives the time for the duration of encoding and motoric response processes.

Neubauer (1995, 1997) has reviewed all studies reporting correlations between the Sternberg task and psychometric intelligence. Averaged across 10 studies with a total *N* of 972 subjects the following *N*-weighted correlations of Sternberg parameters with intelligence were obtained: r = -.27 for mean RT, -.35 for *SD* of RT, -.30 for the intercept and -.11 for the slope. Mean RTs, *SDs* of RT and the intercept correlated moderately with psychometric intelligence. Contrary to expectations, however, was the low mean correlation of the slope measure with

IQ, which probably reflects the low reliability of this parameter (cf. Roznowski & Smith, 1993).

Posner's letter matching task serves to assess the speed of long-term memory (LTM) retrieval. In this task the participant is simultaneously shown two letters on each trial, which are either physically the same (e.g. "AA"), physically different but semantically the same ("Aa") or physically and semantically different ("Ab"). First, the participants have to judge as quickly as possible the Physical Identity (PI-test) and in a second test the semantic or Name Identity (NI-test). While the PI-test only demands a visual discrimination the NI-test additionally requires an access to highly overlearned material stored in long term memory (i.e. the letters of the alphabet). The difference between the mean RTs in the NI- and PI-tests (NI - PI) should indicate the time needed for LTM retrieval.

Neubauer (1995, 1997) surveyed all studies correlating the Posner task with psychometric intelligence. Based on 1064 subjects in 11 studies he obtained the following *N*-weighted mean correlations: The mean *r* was lowest for the mean RT in the PI-test (-.23), a less complex condition compared to the NI-test, which showed a higher mean correlation (-.33). As expected, the NI-PI difference measure also correlated negatively with intelligence (-.27).

Summarising the findings from all four main ECTs (IT, Hick paradigm, memory scanning and letter matching) it can be concluded that there is a negative relationship of about -.35 maximally (uncorrected) between psychometric intelligence and performance indices of several ECTs. However, this figure probably underestimates the true relationship, because the majority of the studies used relatively homogeneous samples of an above average intellectual level. Using more representative samples ECT-intelligence correlations up to .60 have been reported (e.g., Neubauer & Bucik, 1996).

Assessing mental speed with pencil and paper tests

After years of criticism and empirical refutations of this criticism (reviewed by Deary, 1996; Neubauer, 1995, 1997) the role of mental speed or speed of information processing is now widely accepted as one of the fundamental constituents of individual differences in psychometric intelligence. One of the next goals should be to shift mental speed research out of the confines of the chronometric laboratory into the broader fields of basic and applied psychology. Such a step could be facilitated by psychometrically sound pencil-and-paper (PP) tests measuring the same constructs as in the chronometric tradition, e.g., general constructs such as mental speed or speed of information processing, or more specific constructs like speed of STM access or speed of LTM retrieval. This section describes an attempt to develop PP variants of the Sternberg memory scanning and Posner letter matching tasks (cf. also Neubauer & Knorr, in press).

In the PP variant of the memory scanning test the participants are presented with positive memory sets of 1, 3 or 5 digits by means of a slide projector. This presentation lasts 1, 3 or 5 seconds depending on the size of the positive memory set. The participants look at the screen to read the memory set; a computer gives a warning tone, which signals the participants to direct their attention to a sheet of paper in front of them and start working on a row of a pseudo-random series of digits (Figure 2a). The participant's task is to mark for each item if it was a member of the previously shown memory set (marking "yes" or "no" on the answer sheet). Instructions stressed speed and accuracy. Two rows of 30 digits are presented for each set size and the dependent variable is the number of correctly answered items in each row within the allowed time limit of 10 s per row. Subsequently the time limit is divided by the number of correctly solved items giving a mean RT for each set size.

	3	4	7	5	8	2	3	9	7	3	... ...	3	1	8	6	3	7	9	8	5
yes																				
no																				

	BB	Ab	Bb	BB	Aa	... ...	AB	aa	AA	bb	aA
yes											
no											

Figure 2. Top: (a) PP memory scanning test (1 row of 30 cells), Set Size 3
Bottom: (b) PP letter matching test (1 row of 16 cells), PI

For the PP variant of the letter matching task the participant is presented with rows of letter pairs that are either physically the same, physically different but semantically the same, or semantically different (Figure 2b). First, the participant has to judge the Physical Identity, and in a second condition the Name Identity has to be judged. For each condition two pages of 4 rows with 16 letter pairs (i.e. a total of 128 items) are presented with a time limit of 25 s per page. The task is to mark each item with respect to physical or name identity (with the possible answers "yes" or "no"). Again the time limit is divided by the number of correctly solved items within this time limit which gives mean RTs for the physical and name identity conditions.

In the two studies presented here, these PP tests were administered to fairly representative samples that were recruited via advertisements in local newspapers. The participants were offered the opportunity to receive information about their IQ and their specific intellectual abilities. In the first study 120

participants (56 females) were tested also with two psychometric intelligence tests: Raven's Advanced Progressive Matrices (Raven, 1958) and a test for the Berlin model of Intelligence Structure (BIS; Jäger, 1984; Jäger, Süß, & Beauducel, 1997). In the second study 88 participants (17 females) were tested not only with the PP versions of the memory scanning and the letter matching task but also with a computerised version. For the assessment of psychometric intelligence a well-known German intelligence test called Leistungs-Prüf-System (LPS) by Horn (1962) was used.

Table 2. Correlations of the Memory Scanning Test with intelligence

	STUDY I		STUDY II	
Mode of Presentation	PP	PP	PP	Computer
Test of Intelligence	APM	BIS	LPS	LPS
MEAN RT at Set-Size 1	-.37**	-.45**	-.46**	-.51**
Set-Size 3	-.25**	-.43**	-.52**	-.51**
Set-Size 5	-.29**	-.46**	-.58**	-.49**
Intercept	-.22**	-.24**	-.27**	-.50**
Slope	-.16*	-.32**	-.41**	-.09

Note. $^{*}p < .05$, $^{**}p < .01$ (one-tailed)

Table 2 shows correlations for the PP version of the memory scanning test with psychometric intelligence. As expected the mean RTs for set sizes 1, 3 and 5, as well as the intercept and the slope, correlated negatively with psychometric intelligence. Especially for the BIS (Study I) and for the LPS (Study II) the correlations were of a magnitude rarely found in RT-intelligence research (up to -.58). Are these unusually high correlations between speed of information processing and psychometric intelligence due to the heterogeneity of the sample or to the use of a PP variant and not a computerised test? In Study II the computerised memory scanning test (final column, Table 2) also displayed comparable correlations with intelligence; therefore the explanation seems to lie in the more heterogeneous sample tested here.

A second remarkable result in Table 2 is the fact that the slope measure correlated significantly (and substantially) with psychometric intelligence, but this relationship held only for the PP test. A possible explanation might be found in the different procedures of the PP and computer variants of the Sternberg task. While the PP test uses a fixed-set procedure (i.e., one memory set is presented and then has to be applied to a series of target stimuli) the computerised version employs the so-called varied-set procedure (i.e., on each trial a new memory set is presented). It is interesting to note that in the sample used in Study II the PP test with the fixed-set procedure gave not only a higher mean slope than the computer form with the varied-set procedure (M = 104 ms vs. 61 ms,

respectively) but also a much larger dispersion of the slope measure in the sample (*SD* = 69 vs. 22 ms, respectively). It can be hypothesised that the fixed-set procedure allows individual differences in the slope measure to emerge more clearly, and—as a result—this measure displays higher correlations with intelligence.

Similar findings have been obtained for the letter matching test (see Table 3). Again the correlations were higher for the BIS and for the LPS than for APM; in Study II the computer version gave similar correlations with psychometric intelligence. In neither study did the NI-PI difference measure show a significant correlation with intelligence in the PP or for the computerised test; a possible explanation can be found in Neubauer, Riemann, Mayer, and Angleitner (1997).

Table 3. Correlations of the Letter Matching Test with intelligence

	STUDY I		STUDY II	
Mode of Presentation	PP	PP	PP	Computer
Test of Intelligence	APM	BIS	LPS	LPS
MEAN RT for PI	-.30**	-.46**	-.57**	-.56**
NI	-.32**	-.51**	-.52**	-.56**
NI – PI	-.01	-.06	-.07	-.07

Note. $^{*}p < .05$, $^{**}p < .01$ (one-tailed)

Generally, PP and computer versions of these tasks gave similar correlations with intelligence. Do the PP and computerised tasks allow an equally good prediction of psychometric intelligence? Using stepwise multiple regressions we determined how psychometric intelligence (as measured by the LPS in Study II) could be predicted solely on the basis of computerised tasks vs. PP tests. For the computerised ECTs two variables entered the equation (mean RT from set size 5 in the memory scanning test, b = -.27; mean RT from the NI-test in the letter matching task, b = -.43) and yielded a multiple R of .61 (shrunken R^2 = .36). When using the PP tests to predict LPS scores again two variables were entered into the regression equation (again mean RT for set size 5, b = -.38, and the mean RT from the PI-test in the letter matching task with b = -.37). The resulting multiple R was slightly higher than for the computerised tests (R = .66, shrunken R^2 = .42). To determine also an overall RT-intelligence relationship a third stepwise regression was computed with variables from both PP and computer tests allowed to enter the regression. Here three variables contributed significantly to the prediction of psychometric intelligence (mean RT from set size 5 in the PP test, b = -.32; mean RT PI from the PP version, b = -.25; and mean RT PI from the computer version, b = -.31) providing an R of .71 (shrunken R^2 = .48).

With reservation as to further empirical tests, it can be concluded that these new PP tests provide an effective way of assessing the speed of elementary cognitive

processes like STM and LTM retrieval, which constitute fundamental sources of individual differences in psychometric intelligence.

Intelligence and chaos in the FAST task

Correlations averaging between .50 and .74 have been reported between psychometric measures of intelligence and accuracy in the Frequency Accrual Speed Task (FAST), involving judgement of the relative frequency with which one or the other of two lamps lit up in a fixed length sequence of regularly presented single flashes (Pietsch & Vickers, 1997; Vickers, 1995; Vickers & McDowell, 1996; Vickers et al., 1995). In these studies the trains of flashes were of a predetermined length that remained constant over trials, but a more familiar design is one in which participants are free to inspect stimuli for as long as they wish before responding. Typical of such a design are reaction time studies, and in these the usual finding is that psychometric measures of intelligence are negatively correlated with the number of errors made, as well as with both the mean and standard deviation of response times (Brody, 1992). Explanations for the above relationships include individual differences in signal-to-noise ratio (Miller, 1994) and differences in the precision of response threshold regulation.

Variation in the precision of response threshold regulation is suggested by a self regulating model of performance in reaction time tasks (Vickers, 1979, pp. 210-214) in which participants make adjustments to response thresholds to fine-tune their performance[1]. A possible reason for the poorer performance of the less intelligent participants might be that their decisions are regulated in a coarser and/or more intermittent manner. The nonlinear dynamical properties of this model are discussed in more detail by Vickers and Lee (1998). When presented with a series of trials of similar difficulty, the model predicts that threshold

[1] On a particular trial, this model assumes that the observer registers each flash, classifies it as *l* (left) or *r* (right), and keeps two separate tallies of the numbers of *l* and *r* flashes experienced. As soon as the tally of *l* flashes reaches a threshold value, k_l, or the tally of *r* flashes reaches a (possibly different) threshold, k_r, an overt response of the form "Left more frequent" or "Right more frequent", respectively, is initiated. When a given overt response is made, the difference between the two tallies at that time serves as a measure of confidence in that response, and is compared with an internal reference level, *C*. For each response, the positive and negative discrepancies from *C* are identified and summed separately over successive trials. When the accumulated positive or negative discrepancy for a response reaches a threshold level, *K*, then an appropriate adjustment is made to the corresponding primary response threshold, k_l, or k_r. The extent of this adjustment is equal to the difference between the accumulated discrepancies, multiplied by a coefficient, *a*. For the simulation of the model reported later in this section, the parameter values adopted were: C = 3, K = 5, and $a = 0.5$. Variation in the precision of control was achieved by the addition of varying amounts of noise, in the form of a uniform distribution of random increments or decrements to the threshold adjustments. These had a range of ±2 (Low noise), ±5 (Medium noise), or ±8 units (High noise).

values and response times should fluctuate around their respective average values. However, predicted response times cannot be regarded as a sequence of momentary values of a continuous function. Neither does the response time series lend itself to decomposition into a small number of periodicities. Instead, the sequence of predicted response times resembles that produced by an aperiodic, chaotic system of a kind which has become generally familiar since the publication of Gleick's popular (1987) book, *Chaos*. Like an irregularly dripping tap, the times (or intervals between drips) are not purely random, but successive values are not linked by any simple sequential relationship or set of regular periodicities.

The possibility of intelligence-related differences in precision of response threshold regulation was investigated using the following task (described in detail by Vickers, 1995). On each trial, the participant was presented with a sequence of single light flashes on *either* the left *or* the right hand of two lamps. The two events, *l* (left flash) and *r* (right flash), were sampled with replacement from a population of *l* and *r* events with probabilities *p* and *q* (=1-*p*), and with $p = .63$. The task was to judge on each trial whether flashes occurred more frequently on the left or the right hand lamp. Participants were instructed to respond as soon as they reached a decision, while, at the same time, trying to be accurate. Thus the participant determined the sequence length on each trial.

There were two types of trial. On L trials, flashes occurred more often on the left hand lamp and less often on the right hand lamp. On R trials, the situation was reversed. In each session, an equal number of L and R trials were presented in a randomised order. The duration of each flash (and of the interval between flashes) was a constant 50 msec. The participant indicated which lamp (*l* or *r*) seemed to flash more often by pressing the corresponding left or right hand of two response keys. A session consisted of 12 practice trials, followed by two blocks of 80 trials each, separated by a 2 to 3 minute rest pause. Each block of 80 trials consisted of 20 different trial sequences, randomly distributed so that each sequence occurred four times somewhere in the block.

Participants were 15 males and 16 females, selected opportunistically from the student and the general population. Due to a minor programming error, there were effectively two groups of participants. For group 1 (with 12 participants), the sequences of *l* and *r* flashes generated for each trial were different for each participant. For group 2 (with 19 participants), the sequences were the same for all participants (although, as in group 1, different participants chose to view varying amounts of each sequence). Ages ranged from 16 to 62 years, with an overall mean of 37.4 years ($SD = 12.9$). Group 1 had a mean age of 38.8 years ($SD = 14.2$). Group 2 had a mean age of 36.5 years ($SD = 12.3$). Participants were tested in a separate session on Raven's Advanced Progressive Matrices (APM: Raven, Court, & Raven, 1988).

APM score, accuracy and response time

Mean APM scores of 22.0 and 22.3, for groups 1 and 2 (with *SD*s of 5.3 and 5.1, respectively) were not significantly different. The mean APM score for the combined groups was 22.2 (*SD* = 5.1). This compares closely with the published norms of 22.5 (*SD* = 5.5) for Australian students (Raven et al., 1988).

The mean numbers of correct responses in each session of 160 trials were 149.9 and 144.1 for groups 1 and 2, with *SD*s of 7.5 and 7.4, respectively. The mean response times (numbers of flashes inspected) were 29.5 and 26.4 for groups 1 and 2, with *SD*s of 16.6 and 16.9, respectively. Neither the mean accuracy scores nor the mean response times differed significantly between the two groups.

Correlations between APM scores for the combined group of 31 participants and three primary overall descriptors of performance are shown at the top of Table 4. There is no sign of the usual relationships between intelligence and either accuracy, mean response time, or the variability in response times. The fourth, combined measure represents an attempt to capture the efficiency with which participants make use of the sampled information: Even for this single measure of "processing efficiency", there is no significant relationship with intelligence.

Table 4. Correlations between APM score and performance measures, with associated probabilities (in brackets)

	Group 1 (N = 12)		Group 2 (N = 19)		Combined (N = 31)	
Accuracy	-.35	(.27)	-.15	(.54)	-.22	(.24)
Mean no. of flashes	-.20	(.53)	-.22	(.36)	-.22	(.24)
SD	-.12	(.72)	-.10	(.69)	-.11	(.56)
Accuracy mean	.40	(.19)	.02	(.95)	.16	(.40)
Correlation dimension ν	-.60	(.04)	-.63	(.00)	-.61	(.00)

Correlation dimension

The self regulating decision mechanism mentioned above (Vickers & Lee, 1998), can be characterised as a nonlinear dynamical system. One way of exploring this is by treating the set of response times for each participant as a time series, and calculating the *correlation dimension* for each series (Kaplan & Glass, 1995). The correlation dimension quantifies the complexity of the trajectory of the time series, embedded in n dimensional space. Here, we are less concerned with arriving at precise and highly reliable estimates for each participant than with applying the estimation algorithm consistently to all 31 data sets.

Sprott and Rowlands' (1992) Chaos Data Analyzer program, version 1, was used to calculate estimates of correlation dimension, ν. In view of the small number of data points in each series, an embedding dimension of 5 was conservatively chosen for the analysis of all data. For data produced by white noise, estimates of ν should be similar to the embedding dimension. However, when the trajectory of the series is constrained, then values of ν should be less than this. If the system is periodic, ν should take some integer value; if the system is an aperiodic, chaotic one, then values of ν should be fractional.

Empirical values of ν were generally less than 5, and showed a significant negative correlation with APM scores for both groups combined (r = -.61, N = 31, $p < .001$; 2 tails) and for groups 1 and 2 considered separately (Table 4). For the combined groups, values of ν also correlated with age (r = .47, p = .008), while age correlated with APM (r = -.45, p = .005). However, a multiple regression showed that the independent contribution of correlation dimension to the prediction of APM scores was still significant (t = -2.985, p = .006).

Values of the most positive Lyapunov exponent, λ, were also calculated for each set of data. The Lyapunov exponent characterises the rate at which nearby trajectories diverge (Kaplan & Glass, 1995; Sprott & Rowlands, 1995). For periodic data, all values of λ should be negative or zero. For uncorrelated, random data, values of λ should be positive, and may become infinitely large. For aperiodic, chaotic data, the value of λ should be positive and finite. Values of λ for the present data ranged between .216 and .426.

Analyses of surrogate data

As a check on the significance of the relationship between ν and APM scores, the analyses were repeated on surrogate data in which the original response times had been randomised for each participant. The first surrogate dataset randomised the order of the data, preserving the probability distribution of the original series, but not its power spectrum and correlation function; the second preserved the power spectrum and correlation function but not its probability distribution. Estimates of correlation dimension obtained from these surrogate datasets were symptomatic of random data series (i.e., estimates of ν and its error were of the same order as the embedding dimension and the values of the Lyapunov exponent ranged between .203 and .461). Neither set of surrogate data yielded a significant correlation between estimates of ν and corresponding APM scores.

Intelligence, performance measures, and correlation dimension

The absence here of the usual relationships between intelligence and accuracy, or the mean or *SD* of response times, is not entirely surprising. Small numbers of high-ability participants were studied, and the task used differs from a standard reaction time task. Here, the rate at which the sensory input is sampled is at least partly determined by the experimental program, rather than solely by the

participant; each judgement is more drawn out in time; finally, the task is more difficult than the usual choice reaction experiment. As a result, this task might well be more sensitive to individual variations in cognitive control of the compromise between speed and accuracy. Whatever the reason, there was no evidence to support the idea that participants with a lower APM score are operating on sensory input that has a reduced signal to noise ratio (Miller, 1994).

In contrast, the results did support the idea that participants differing in intelligence differed in the precision of regulation achieved by a nonlinear dynamical control system. Estimates of the correlation dimension ranged between 2.72 and 5.03. This suggests that the output of this control system forms an aperiodic, chaotic data series, rather than either a periodic or a random process. This conclusion is supported by the contrasting results from the analyses of surrogate data, which show higher values of ν, consistent with an essentially unstructured data series, and uncorrelated with APM scores. It is also supported by the values of the Lyapunov exponents, which are all positive fractions.

No comparable, published studies are known that have attempted to relate estimates of correlation dimension for reaction times to individual differences in cognitive ability. However, in a number of papers, EEG records have been analysed as the output of a nonlinear, dynamical system (see Basar, 1990 for a review). For example Gregson, Britton, Campbell, & Gates (1990) have conjectured that measures of the correlation dimension of EEG records should *increase* as a function of the amount of information processed by the participant. There is probably too large a gap between such studies and the present analysis of cognitive performance for specific conclusions to be mapped unequivocally from one to the other. However, the present results suggest that, in the type of judgement task investigated here, a higher level of cognitive performance appears to be associated with a *lower* value of the correlation dimension (i.e., with more constraint and less randomness in responding).

Modelling the effects of intelligence on judgement tasks

Most stochastic reaction time models assume that the observer continues to sample the sensory input until a threshold amount of evidence has been accumulated in favour of one response or the other (Luce, 1986; Smith & Vickers, 1988, 1989; Vickers, 1979). Bias in responding and the observed tradeoffs between speed and accuracy are then explained by supposing that these thresholds can be varied, either relative to each other, or by a concerted increase or decrease. On this view, the simplest explanation for the correlations between intelligence and the various performance measures is that the sensory information available to the less intelligent participant has a lower ratio of signal to noise. This might be due to a higher level of noise in the sensory input for the less intelligent (Miller, 1994) or to a greater disruption of memorised information by the arrival of new input (Vickers et al., 1995).

An alternative is the proposal examined in this section that differences in intelligence modify the precision of response threshold regulation. Given the results of the present analysis, the obvious question is whether they can be interpreted in terms of the particular self regulating decision mechanism referred to previously (Footnote 1). At this stage, it is premature to attempt to estimate best fitting parameter values from these data (because the model assumes unrealistically that information is perfectly remembered). The adaptive version was simulated with what were judged to be representative parameter values; variations in the precision of control were achieved by the addition of varying amounts of noise at three levels (see Footnote 1). Values of the correlation dimension for the simulated process, operating on the stimulus series generated for group 2, increased from 3.79 to 4.18 as the level of noise increased[2]. These simulations do not claim to represent an adequate match with the data, but only to capture the qualitative features of performance on this type of task. Nevertheless, the increase in correlation dimension, as a function of the level of added noise, is consistent with the empirical data. The self regulating decision mechanism thus provides at least a preliminary, specific model, which *might* explain the observed relationship between intelligence and correlation dimension. According to this interpretation, poorer performance of the less intelligent participants is not simply due to their performance being less accurate, slower, and more variable, as would be expected if the stimulus input for these participants had a lower signal to noise ratio. Rather, their poorer performance seems to be due to a less precise regulatory control, exercised by a nonlinear, dynamical system, over the response thresholds of the primary decision process.

If the relationship between intelligence and correlation dimension turns out to be reliable, then it should be of considerable interest. The correlation dimension provides a succinct characterisation of the complex structure of an entire data set. It also suggests the general nature of the underlying system, and the analysis should facilitate comparisons with specific theoretical models. Finally, it seems less likely that performance in each different judgement task would be regulated by a separate dynamical system than that a single system would determine performance in a range of tasks. If so, then analyses of the kind presented here may turn out to provide an economical, theoretically informative, and general characterisation of individual differences in elementary cognitive performance.

Prospects for information processing analyses of mental speed

Several metaphors come to mind for the exploration of human intelligence in terms of basic information processing. Many skills and domains of knowledge are required, and the process of evaluating models in this area can be liked to changing the level of magnification on a microscope, or zooming in on the finer detail of Mandelbrot set (Gleick, 1987). As one increases the magnification, the

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[2] For Low, Medium, and High noise levels, values of ν were 3.79 (±0.65), 3.94 (±0.02), and 4.18 (±0.66), with Lyapunov exponents of .15, .24, and .21, respectively.

detail turns out to be just as rich—and there are just as many difficulties to overcome in mapping it—at every level. For instance, as we focus down from information processing to inspection time to the psychophysics of inspection time or other visual processing tasks, the challenges ahead seem just as difficult and the questions are just as numerous. Yet the endeavour is worthwhile, e.g., the work reviewed in this chapter has both increased our understanding of the IT task and confirmed a substantial correlation between the latent trait underlying several visual processing tasks, and specific and general factors of intelligence test performance.

Reductionist analyses involving RT have often faced criticism that—in spite of remarkably consistent results demonstrating a negative correlation between RT and intelligence—the absolute size of the relationship remained disappointingly low. Hunt (1980) referred to the ".3 barrier", the idea that no single elementary cognitive task can explain more than about 10 percent of variance in intelligence tests. However, these relatively low correlations may have been due to the homogeneity of the samples tested: When samples are more representative with respect to the distribution of intellectual ability, stronger RT-intelligence relationships may emerge. The computerised RT and PP studies reported in this chapter suggest that greater amounts of intelligence-test variance can be explained by speed of processing variables, and so the recent dismissal of the concept of intelligence as mental speed (Stankov & Roberts, 1997) seems premature.

One well-known drawback of RT procedures is the need to trade speed for accuracy, and the possibility that position on the trade-off curve may vary over time or between participants. The introduction of a new form of analysis based on chaos theory offers the prospect of an economical, informative and general characterisation of individual differences in control processes of this sort. The early results reported in this chapter suggest that there is a substantial correlation between parameters of these chaos-theory models, and psychometric intelligence. But here, hindsight should dictate caution: Present results from chaos theory studies of intelligence have a status comparable to the early dramatic results of studies using inspection time. Inspection time's correlation with psychometric intelligence seemed initially to offer the ideal bridge from the simplicity of psychophysical processes—IT purportedly providing a benchmark of sensory/perceptual system function—to the more important but less well understood mental processes underlying intelligent behaviour. The bridge may still be standing, but on the IT side the ground has turned out to be wild and unexplored, in contrast to the well-tended countryside it seemed to be from a distance.

EVENT RELATED POTENTIALS AND INTELLIGENCE

Efforts to link individual differences in brain event related potentials (ERPs) to human intelligence began in the mid-1960s (Chalke & Ertl, 1965) and several

factors, including individual differences in the speed or reliability of the CNS or in control of attention, have been claimed to underlie and explain ERP-IQ relationships. Recent surveys (Barrett & Eysenck, 1992; Deary & Caryl, 1993, 1997) demonstrate clearly that differences in intelligence can be reflected in differences in brain electrical response, even to trivially simple stimuli such as flashes of light, and provide overviews of this rapidly growing literature.

The structure of ERPs

ERPs are complex waveforms, time-locked to repetitively-presented stimuli, that reflect the average timecourse of electrical brain activity triggered by presentations of a particular stimulus. For example, Lubar, Gross, Shively, and Mann (1990) obtained ERPs from children (with IQs ranging from 69 to 145) in an *oddball task* in which participants had to identify and respond to rare presentations of a high-pitched tone embedded in a train of lower tones. This produced typical ERPs showing a series of peaks and troughs whose pattern depended on stimulus, electrode site, and on intelligence, and the results of this study illustrate the following general points:

1. ERP waveforms depend on the stimulus and task chosen. In the oddball task, the *P3 component* of the ERP—a substantial positive peak around 300 ms after stimulus onset—is elicited by the rare tone but not the common tone.
2. ERP waveforms vary with electrode site. The P3 component is maximal parietally, and Lubar's results showed major changes in waveform from frontal to parietal sites.
3. ERP waveform may reflect intelligence. In Lubar's study the P3 peak was low in learning-disabled children, intermediate in the normal group and high in gifted children, and there were other less easily-characterised differences in waveform between the groups.
4. There is no single correct or best measure to characterise the ERP. An ERP waveform offers several dimensions which can be measured, but variation in different parts of the ERP may be correlated rather than independent. Lubar et al. (1990) used Principal Components Analysis to separate independent variables for statistical analysis.
5. Some ERP measures may be linked to IQ while other measures from the same ERP waveforms are not. However, analysis of a range of measures can lead to enormous and uninterpretable correlation matrices—270 correlations with IQ in a study by Widaman, Carlson, Saetermoe, and Galbraith, (1993) and 570 in a study by Barrett and Eysenck (1994)—and, since many of these correlations are not independent, it is difficult to adjust the level of significance for multiple testing[3].

ERP correlates of intelligence

[3] Crawford pointed out that use of canonical correlation would solve this problem (Crawford, 1974; Duffy, McAnulty, Jones, Als, & Albert, 1993).

Several groups of ERP measures have shown important links with IQ (Deary & Caryl, 1993, 1997). They include:

1. *Latency of ERP components.* Longer latencies are believed to reflect slower operation of the CNS and expected, with longer RT, to be linked to lower IQ.
2. *ERP wave-shape.* IQ-related differences in specific timezones after stimulus onset can provide evidence for the influence of intelligence on particular mechanisms involved in stimulus analysis.
3. *Complexity and variability of the ERP.* The range of measures in this group includes the Hendrickson string length and variance measures (Hendrickson, 1982), noise-power, and measures based on Fourier analysis of the ERP. Greater complexity of the ERP and lower variance is believed to be linked to greater reliability of operation of the CNS.
4. *Neural Adaptability measures.* These offer indices of the change in overall magnitude of the waveform with changes in task demands, in the level of engagement in the task, or in the predictability of stimuli (Schafer, 1985). Bright participants allocate less processing power to predictable and unimportant stimuli.

Measures from all four categories were first used in the pioneering days of research on ERPs and IQ, and all are still important in current research. But over 30 years the emphasis of research on ERPs and IQ has shifted substantially. At first, intelligence was only one of many possible explanatory variables considered by research workers whose primary aim was to understand ERPs (e.g. Perry & Childers, 1969). By the 1980s, the main question dominating the area was "How strong is the IQ-ERP correlation—essentially zero, .3, .5, or .7?" The answer "zero" can be excluded—some authors still view IQ-ERP links as artefacts (e.g., Howe, 1988) but there is no longer any doubt as to their reality—but it is misleading to imply, as this question does, that research will ultimately provide a single value to characterise the strength of the relationship. All three non-zero options are plausible: The value depends on the choice of ERP measure and experimental paradigm and perhaps on the subject group (as is illustrated below for ERP latency measures). In the 1990s, interest has shifted to potentially more productive questions about *what mechanisms* might underlie and explain the IQ-ERP relationship, and what tasks should be used to investigate them.

Choice of ERP task may determine the strength of ERP-IQ relationship that is observed, and it is critically important in determining whether this relationship can be interpreted. It is true that differences in intelligence can be seen in some tasks which make trivial demands, such as passive viewing of light flashes (Ertl & Schafer, 1969; Duffy et al., 1993). However, ERP-IQ relationships are often better studied in more demanding tasks. When stimuli need little attention it is likely that all participants will engage in spare-time mental activity in parallel with processing the stimuli; any IQ-related differences in ERPs could be a side effect of differences in activity unrelated to the task. Schafer (1985) has demonstrated that, compared with dull participants, bright participants allocate less processing power to predictable but unimportant stimuli; so when stimuli

make trivial demands, bright participants will have extra processing power available for spare-time mental activity. Since bright and dull participants may also differ in the *kind* of mental activity engaged in, any IQ-linked differences in ERPs are difficult to interpret. In contrast, even bright participants can be stretched by demanding elementary cognitive tasks such as Sternberg's memory-scanning task or IT. In such tasks, IQ-linked variation in ERPs can be tied with greater confidence to differences in the *task-specific* mental activity that must dominate mental processes during task performance.

Work on ERP latencies has a long history and can be used to illustrate the contribution made by this approach. The pioneering studies of Ertl (e.g., Ertl & Schafer, 1969) were technically flawed, but his conclusions have not been overturned. Later work has confirmed that, generally, ERP latencies correlate negatively with IQ (Deary & Caryl, 1997). Short latencies in high-IQ participants have an obvious interpretation in terms of greater speed of mental processing. Unfortunately, there is substantial variation in the strength of relationship observed, e.g.:

1. The strength of the correlation may depend on the measure of intelligence in question (e.g., FSIQ, PIQ or VIQ) and on the precise requirements of the task (Deary & Caryl, 1997).
2. Highest correlations with IQ may be obtained using different tasks in different subject groups. Thus, O'Donnell et al., (1990) found that patients with Alzheimer's-type dementiA showed the highest P3 latency-IQ correlations in a passive version of the oddball task, whereas non-demented individuals showed highest correlations in the active form of the task.
3. Even technically faultless studies may show weak or inconsistent latency-IQ correlations, particularly where the early components of the ERP are involved (Duffy et al., 1993; Widaman et al., 1993).

These results certainly show that "smarter brains work faster" under some conditions and confirm that the difference in speed can be indexed by ERP latencies, but similar conclusions could be drawn from RT data (Neubauer, 1995, 1997; and this chapter). And while the IQ-RT correlation is notoriously low (Hunt, 1980; but see Neubauer's comments earlier in this chapter) and is dependent on the spread of RTs (Larson & Alderton, 1990), ERP techniques by themselves do not guarantee that stronger and more reliable speed-IQ relationships will be observed. What extra value could potentially come from the use of ERPs rather than RTs to index differences in speed of processing?

What added value is offered by ERPs?

This section of the chapter takes up the challenge implied by Crawford's comment on Ertl and Schafer's (1969) early work:

> *"In order for any new technique for measuring intelligence to replace traditional intelligence tests, it must do what current tests do plus something else"* (Crawford. 1974, p. 331).

It attempts to answer the implied question about the added value that is contributed by the use of ERPs, rather than non-physiological techniques, in terms of the greater information about neural mechanisms that ERPs can yield. Results from ERP wave-shape and latency measures will be reviewed to illustrate the way in which these measures potentially yield information not offered by the conventional techniques of experimental psychology.

Psychophysiologists identify regions of the ERP which reflect operation of the brain mechanisms involved in attention, memory access, etc., by comparing tasks which differ in one specific requirement. Waveform differences can mark the timing of processes that are spread out along the time axis, even if the processes overlap rather than being strictly sequential. Working in the other direction, researchers have used differences in waveform to identify—from their timing—intelligence-linked brain processes. Can we identify what mechanism(s) control speed and accuracy of performance on tasks which make *specific* processing demands? Can we identify which of these mechanisms show changes in level of activity as we move through the normal range of human intelligence? For two important elementary cognitive tasks, IT and the Sternberg memory scanning task, the answer is that we can.

IT-task performance, ERP wave-shape and intelligence

Three research groups have now shown that ERP waveform differences around 150 ms are linked to individual differences in performance in several similar tasks requiring rapid stimulus intake (detection of backward-masked visual IT stimuli or letters). Participants who are good at such tasks show a steeper N1-P2 wavefront, not only in visual ERPs to the backward-masked stimuli which require rapid intake (Caryl, 1994; Morris & Alcorn, 1995; Zhang, Caryl & Deary, 1989) but to unmasked stimuli not requiring rapid intake, such as a visual trial-onset cue (Caryl, 1994) and even to an *auditory* oddball stimulus (Colet, Peira, & Pueyo, 1993). Participants do differ in their accuracy at a given stimulus duration (and so require stimuli of different duration to attain a given accuracy) but the ERP differences are not side-effects of the duration-accuracy trade-off (Caryl & Harper, 1996; Zhang et al., 1989). This relationship between ERP waveform and performance may be stronger frontally or fronto-laterally than at the vertex (Colet et al., 1993; Morris & Alcorn, 1995). Similar differences in the N1-P2 wavefront, linked to IQ, occur in IT-type tasks; there are indications that ERP-IQ relationships are stronger for stimuli which do not demand rapid processing (Caryl, 1994; Zhang et al., 1989).

Although the contrasts in ERP waveform between subgroups differing in IQ are similar to those for IT, they are not identical (Caryl, 1994; Morris & Alcorn, 1995; Zhang et al., 1989), but the similar timing suggests a common mechanism. There are parallels in individual differences previously reported by Rhodes, Dustman, and Beck (1969), and Haier, Robinson, Braden, and Williams (1983) in the N1-P2 region of ERP waveforms to simple flashes, and in differences

observed between 100 and 200 ms in a string length measure of auditory ERPs (Stough, Nettelbeck, & Cooper, 1990). Brain-maps from an IT task show stronger string length-IQ relationships in cue- than in IT-stimulus ERPs (Bates & Eysenck, 1993), providing a parallel between string length and N1-P2 slope.

Sternberg-task performance, ERP wave-shape and intelligence

In Sternberg's memory scanning task, participants hold in memory a set of 1 to 6 letters or digits, and must decide whether a subsequent probe letter or digit was in the memory set. Sternberg (1966) concluded that they do this by exhaustive scanning at a rate of about 38 ms per item. Superficially, this task seems very different to the IT task. However, recent work (e.g., Pelosi & Blumhardt, 1992; Pelosi et al., 1992) indicates that the ERPs from this task show IQ-linked differences in waveform that begin around 165 ms, as do the IT-linked differences of the IT task. In the Sternberg task the difference peaks from 250 to 400 ms, and from 165 to at least 400 ms higher-IQ participants show an overall negative shift in the ERP.

While this difference is in the opposite direction to that identified in the IT task, the similar onset-time of the IQ-dependent section of both waveforms suggests that—in both contexts—intelligence influences the level of activation of the processes (brain mechanisms) operating around this point in early stimulus analysis. Goodin, Squires, Henderson, and Starr (1978) and Lindholm and Koriath (1985) found evidence that processes beginning around 165 ms were responsible for stimulus analysis and classification.

ERP latencies and intelligence

Why use ERPs rather than RTs as a measure of the speed of mental processes? In some contexts, ERPs have allowed investigators watch the gradual build-up of evidence for a particular decision before the response occurs (Gratton, Coles, Sirevaag, Eriksen, & Donchin, 1988) and thus to "peek inside the black box" of the S-R process. In studies of decision making, the P3 component of the ERP forms a useful marker of a boundary separating early (stimulus-processing) from later (response-processing) segments of the overall reaction time. Processes before and after the P3 boundary are sensitive to different factors, they may be separable pharmacologically (Naylor, Callaway, & Halliday, 1993), and the distinction between stimulus- and response-processing segments has been important in studies of response slowing with age.

Cerella (1985) has contrasted the changes in RT produced by individual differences in processing speed on the assumption of an *additive* or *multiplicative* model of processing. A multiplicative model of IQ-linked differences would predict small RT or ERP latency differences in tasks requiring only one or two cycles of processing, but increasingly larger differences in more complex tasks (requiring multiple cycles of processing and decision making) where the slight

differences in speed between bright and dull participants would be multiplied many times. McGarry-Roberts, Stelmack, and Campbell (1992) compared relationships between P3 latency and IQ in tasks ranging from simple RT to complex discriminations, and found the relationship grew stronger as task-complexity increased. In studies of ageing, the increase in RT with age has been interpreted as implying a general multiplicative slowing (Cerella, 1985) of CNS functions in stimulus analysis and decision making. However, subsequent analyses of age-changes in latency of the P3 component of the ERP showed that the slowing of stimulus analysis reflected a simple additive process (Bashore, Osman, & Heffley, 1989). The apparently multiplicative change with age in final RT reflected delays in response selection and confounding factors such as a change in trade-off between speed and accuracy (Strayer, Wickens, & Braune, 1987). It might therefore be worthwhile to carry out a similar analysis of IQ-linked variation in the time taken for successive stages of stimulus analysis and decision making, and in the trade-off between speed and accuracy.

ERPs might also throw light on individual differences in variability of RTs. Mean and variance of RT correlate with intelligence (e.g., Jensen, 1993) and greater variability of RTs is commonly observed in low-IQ participants. Greater variability in RT may indicate lower reliability in the neural networks that generate responses (B. Anderson, 1994). ERP measures such as string length are claimed to index reliability in the CNS (Burns, Nettelbeck, & Cooper, 1996; Hendrickson, 1982) with low reliability occurring in low-IQ participants, but "reliability-indices" such as string length have never been tied directly to the reliability of any objectively measurable brain process. However, the neurophysiological basis of the IQ-linked variation in RT might be investigated in studies of ERP latency that parallel those of age-changes in RT (e.g., Strayer et al., 1987).

ERPs and intelligence: progress and prospects

The changes in approach over three decades of IQ-ERP research can be characterised by contrasting two studies. Chalke and Ertl (1965, p. 1319) reckoned that

> *"A biologically efficient organism should process information more rapidly than a less efficient organism" [and that] "delay of components of the evoked potential is a measure of the efficiency of this process",*

hence they tried to relate ERP latencies to measures of intelligence. Robaey, Cansino, Dugas, and Renault (1995) asked more specific questions and obtained correspondingly more precise answers:

1. Do different intelligence types yield different subsets of ERP correlates? (They do: For example, amplitude measures of the ERP differentiated Verbal, Performance and Piagetian intelligence whereas latency measures of the ERP did not, and appeared to reflect general intelligence).
2. Do these ERP correlates differ, if scores are age corrected? (They do).

3. Do intelligence measures have different ERP correlates in [different] clinical groups? (There were differences between normal children and those with Attention Deficit Hyperactivity Disorder).

ERPs certainly do not provide the simple, direct route to the biology of information processing and intelligence that Ertl apparently envisaged (e.g., Chalke & Ertl, 1965). Studies of IQ and ERP latency still promise information that could not come from studies of IQ and RT, but the substantial amount of research on ERP latencies has not yet delivered the extra value potentially offered by ERP techniques. In contrast, analyses of ERP wave-shape, which indicate the time at which IQ-linked mechanisms operate, have provided valuable hints about the way in which intelligence might enhance performance in elementary tasks. Although the P2 component of the ERP has not received the intensive study that P3 has received, recent work from several laboratories has provided information about the processes occurring around the time of the N1-P2 wavefront and evidence that intelligence can modulate the activation of (some of) the brain mechanisms involved; evidence from these studies is consistent with the mechanisms we would expect in the IT task.

In time, other measures of the ERP may also provide useful evidence, but at present they are difficult to interpret in terms of the direction of causation or the nature of the underlying mechanism. String length has yielded astonishingly high correlations with IQ, and these have stimulated considerable research, but results have been difficult to replicate and conclusions are at present controversial (Burns et al., 1996); there is no clear evidence to support the belief that string length indexes "reliability of operation" of the CNS. In contrast, Schafer's demonstrations of very high correlations between neural adaptability and intelligence (e.g., Schafer, 1985) have stimulated surprisingly little research. Perhaps this is because in studies of neural adaptability, high intelligence apparently just damps down responses to unimportant or predictable stimuli. Causality appears to be acting "downwards", with intelligence orchestrating timing and investment of processing power across various mechanisms to give optimum task performance: This does not appeal to those looking for reductionist explanations for intelligence. There is an obvious contrast with work on ERP latency, in which even modest correlations have stimulated a substantial amount of research. Presumably this is because latency differences can be interpreted in terms of what may be described as the Eysenckian view of intelligence: that better biological machinery leads to greater processing speed (indexed by ERP latencies or RTs), to more rapid acquisition of knowledge, and ultimately to higher IQ-type test scores.

In summary, ERP techniques hold promise, but the route to the understanding of intelligence that they offer is just as poorly explored as that offered by information processing analyses. In particular, research workers are still some way from establishing the physical and physiological bases of *g*.

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