4 Reaction Time and Psychometric *g*

A.R. Jensen

Nearly 120 years ago, Sir Francis Galton expressed a theoretical preconception or intuition which most people – certainly most present-day psychologists – would regard as highly *counter*-intuitive, namely, the notion that reaction time (RT) is related to intelligence. The common reactions of disbelief to this notion express the view that nothing as simple, trivial, and nonintellectual as RT could possibly reflect anything as subtle, complex, and mysterious as human intelligence, and it is remarked that the most highly intelligent persons often appear to be slow but deep thinkers. In much of popular thought, *speed* of mental action implies superficiality; *slowness,* profundity.

Although Galton and his immediate successors were unsuccessful in demonstrating the supposed relationship of RT to intelligence and it became common knowledge in psychology that Galton's notion was wrong, it now begins to appear – a century later – that Galton was right after all. That is, his hypothesis was right, or at least partially right; but the means for testing it were inadequate in the late nineteenth and early twentieth century, when the study of RT and intelligence was prematurely abandoned, not to be revived until recent years. Whether Galton was right for the right reason or for the wrong reason, theoretically, cannot be decided in any detail from his sketchy writings on this topic (Galton 1883, 1908).

Before defining any one type of RT more precisely in terms of particular experimental procedures, for RT refers to a class of phenomena, it now seems reasonably safe to conclude, from all of the available evidence, that there is some sort of relationship between RT phenomena and general intelligence as it is measured by our standard psychometric tests. Although there are now quite extensive data linking RT and intelligence, I find it virtually impossible at present to draw any firm conclusion about the true magnitude of the relationship as it would be expressed in terms of a coefficient of correlation. The reason for this uncertainty is mainly twofold: (a) little, if any, RT research has been based on large representative samples of the general population, and (b) virtually no account has been taken of the intertrial ability and day-to-day stability of RT measurements and the use of such information for correcting correlations between RT and intelligence test scores for attenuation. However, that there are statistically *significant* correlations between individual differences in general intelligence and a variety of RT measurements can now hardly be doubted. The general phenomenon presaged by Galton is certainly genuine, even if its general magnitude and theoretical meaning are still obscure.

The fact of a significant relationship between RT and psychometric intelligence has at least two immediate implications for theory and research on intelligence.

First of all, it directly contradicts a widespread conception in contemporary psychology that our current standard tests of intelligence measure nothing but a particular class of specific knowledge and acquired cognitive skills or strategies for dealing with certain types of problems generally considered intellectual. Indeed, intelligence itself is conceived of by many psychologists as consisting of *nothing but* a person's acquired knowledge and skills.

According to this conception, individual differences in intelligence are attributable to differences in opportunities afforded by the environment for acquiring the specific items of knowledge and skills that are called for by the standard tests of intelligence. The contrary view is that the specific knowledge and skills called for by IQ tests are merely a vehicle for measuring individual differences in intelligence, and that intelligence can be described neither adequately nor correctly merely in terms of acquired contents and skills. This is evident not only from our present knowledge of the substantial heritability of IQ, and from the finding of significant correlations between IQ and the latency and amplitude of averaged evoked potentials of the brain, but also from the correlation between RT and IQ. Certain types of RT, which are significantly correlated with IQ, are as completely devoid of knowledge content or cognitive skills, in any acceptable meaning of these terms, as one could imagine for any conscious behavioral act.

Secondly, if there is a correlation between individual differences in RT and intelligence, it seems that research on the much simpler information processing phenomenon, RT, would lead more readily to an adequate theoretical account of it than would attempts to theorize directly about the much more complex phenomenon of intelligence. The theoretical constructs developed to deal with the much simpler instances of information processing exemplified in several distinct RT paradigms might then provide a basis for theoretical formulations about the nature of intelligence. What I have in mind, of course, is the development of potentially falsifiable theories, which are sufficiently limited and specified as to generate emprically testable hypotheses. Attempts to develop a theory of intelligence that are based at the level of the traditional instruments used for the measurement of intelligence, viz., various psychometric tests, seem to have reached a theoretical cul-de-sac, ending with the description of factors and apparently unresolvable arguments over the most appropriate factor model. Three-quarters of a century of factor analytic research with psychometric tests has not led to any generally accepted theory of the nature of intelligence. This is not to say that factor analysis is a useless methodology. Quite the contrary. But its real usefulness is not for the purpose of theory construction itself but merely to help identify and delineate the particular categories or dimensions of individual differences that we wish to investigate with a view to theoretical formulation. It would be a wholly unreasonable and hopeless approach to try to develop a theory to explain individual differences in every single psychometric test item in existence. The fact that test items are intercorrelated to varying degrees means they involve certain common features or processes, whatever these may be, and that items can be grouped or classified according to their degrees of intercorrelation. Factor analysis is the accepted tool for this purpose. If our interest is in the most general ability, which accounts for the intercorrelations among virtually all tests of ability however diverse in external appearance, we should be interested in the best obtainable estimate of the most general factor in the abilities domain. Whether or not one wants to identify this general factor as "intelligence" is really a purely semantic issue and is not worth arguing about. It can best be given the neutral label "psychometric *g*", which I will henceforth refer to simply as *g*. But I hasten to note that *g* is probably more highly correlated with what most people, psychologists and laymen alike, mean by "intelligence" than is any other factor derivable in the abilities domain, and certainly more than any other factor or combination of factors that are orthogonal (i.e., uncorrelated) to *g*. Whether *g* is extracted as the first unrotated principal factor in a common factor analysis or as a higher order factor arising from oblique rotation of the primary factors does not seem to be as crucial an issue as some nonempirical factor analysts would seem to argue. I have yet to see an instance where factor scores based on the first principal factor and on a higher order *g*, when derived from a reasonably sized (ten or more) battery of diverse psychometric tests, were not very highly correlated, usually .90 or above. Therefore, in order to get on with the job of research on "intelligence", I advocate accepting *g*, by either method of factor extraction, as our working definition of it. Admittedly, *g* is not a perfectly determinate and invariant construct. Nor does any single test yield a perfect measure of *g*, even excluding the test's measurement error. But for practical purposes in research on the relationship of RT to *g*, with necessarily limited time for testing each subject, we must resort to one or two good *g* reference tests, that is, tests which have been found consistently to have the highest *g* loadings (after correction for attenuation) in a number of factor analyses with a variety of other tests. Raven's Progressive Matrices (Colored, Standard, or Advanced, for the appropriate level of difficulty) has been our first choice as a practical *g* reference test.

Before reviewing the results of recent studies on RT and *g*, it would be useful to view these RT paradigms in the perspective of all their main predecessors in the history of psychology.

A Chronology of Research on Reaction Time

The study of RT in relation to mental ability has a venerable though spotty history, which is outlined in the following brief chronology of landmark events in the history of mental chronometry, emphasizing particularly those aspects most germane to individual differences in intelligence.

1823: The first important recognition of individual differences in reaction time is credited to the Prussian astronomer F.W. Bessel, who coined the term "personal equation" for the consistent variations among different telescopic observers in recording the exact instant that the transit of a star crossed a hairline in the visual field of the telescope. The need to make corrections for the "personal equation" (i.e., individual differences in reaction time) led to the invention (by a German astronomer, Respold, in 1828) of the chronograph, a device for measuring reaction time (RT) in fractions of a second. A markedly improved chronograph was devised in 1850 by the United States Coast Survey. Since then there has been no real problem in measuring RT with adequate precision in terms of one-hundreths or one-thousandths of a second (milliseconds), although the preelectronic devices were mechanically complicated and cumbersome and required frequent calibration.

1850: Hermann von Helmholtz measured the speed of nerve conduction in frogs and (less accurately) in humans. This discovery was especially important for philosophic as well as scientific reasons. The greatest philosophic intellects of the era, including Immanuel Kant, had declared that mental events would forever be excluded from scientific investigation, which depends on exact measurement, because the basis of mental events is the brain and neurones, and they were postulated to act with *infinite* speed, making their functions therefore unmeasurable. This doctrine was rejected by the nineteenth century physiologists, but, prior to Helmholtz's discovery, their conjectures about the speed of the nerve impulse put it at the speed of light or faster. The leading physiologist of the time, Johannes Müller, claimed the speed of neural transmission to be *sixty times faster* than the velocity of light! Helmholtz found that the speed of neural transmission was actually less than one-third of the speed of sound. The philosophic gap between the mental and the physical was reduced.

1862: Sir Francis Galton was the first to suggest that individual differences in general mental ability could be measured by means of reaction time (RT). Galton was also the first explicitly to conceive of intelligence as a *general* mental ability, anticipating Spearman's *g*. Galton (who was Darwin's half-cousin) believed this general ability to be a product of biological evolution, reflecting Darwinian fitness in the struggle for survival. Since quickness of reaction (and keenness of other elemental sensory-motor functions) would seem to have been advantageous to prehistoric man's survival and evolutionary development, Galton thought that measurements of such functions would provide a good index of general mental ability. He invented a host of such measuring devices, including his own RT apparatus (described in his autobiography 1908, p. 248). It measured only *simple* RT to an auditory stimulus, and was rather too simple and crude to yield sufficiently reliable measurements – the subject simply hit a punching bag with his fist as quickly as possible on hearing a signal. Galton tested literally thousands of persons on this and other sensory-motor tests in his laboratory in the South Kensington Museum of Natural Science. But the results were disappointing. Fellows of the Royal Society, for example, did not perform measurably better than the average run of Londoners.

Although Galton quit his research on mental measurement, an American postdoctoral student, James McKeen Cattel, who spent 2 years working with Galton after receiving his Ph.D. (the first American Ph.D. in psychology) in Wundt's laboratory, carried Galton's ideas about mental measurement back to America, where they fully surfaced in Cattell's laboratory in Columbia University in 1901. Cattell dubbed Galton's various sensory-motor tasks "mental tests" – the first appearance of this term in psychology.

1868: F.C. Donders, a Dutch physiologist, discovered that *choice* RT (i.e., different responses to either of two or more stimuli) is longer than *simple* RT (i.e., a predetermined single response to a single expected stimulus). This observation led to Donders' invention of the *substraction method* of mental chronometry. By subtracting the subject's RT to relatively simple stimuli from the RT to more complex stimuli involving discrimination, choice, and decision, one could measure the higher mental processes involved in the more complex situations. The strictly sensory and motor components in simple RT could be subtracted from choice RT, yielding measurements of the speed of "purely mental" events. This discovery, too, helped in advancing psychology from speculative philosophy to natural science. Much of the essential methodology of recent research in mental chronometry (e.g., RJ Sternberg 1977) represents more sophisticated uses of Donders' subtraction procedure.

1873: Sigmund Exner, an Austrian physiologist, coined the term "reaction time" and discovered the importance of "preparatory set" and the preparatory interval (i.e., the interval between a "warning" or "ready" signal and the reaction stimulus). These procedural factors, he found, affect the variability of RT from trial to trial. If the preparatory interval is not controlled by using a "ready" signal, intraindividual variability in RT is increased. Following Exner, a preparatory signal became standard practice in RT studies.

1885: J Merkel, working in Wundt's laboratory in Leipzig, elaborated on Donders' choice RT experiment and discovered that RT increases quite systematically as a function of the increasing number of choice alternatives in the stimulus and response arrangement. This finding clearly anticipates Hick's law (Hick 1952). Merkel's multiple-choice RT data, as I have plotted them in Fig. 1, nicely illustrates Hick's law. Merkel, of course, did not describe his systematic findings in terms of *bits* of information, for the concepts of information theory and the *bit* as a unit of information were not invented until 1949 (Shannon and Weaver). But the psychological importance of Merkel's finding was that it showed that the time for mental activity (as reflected in RT)

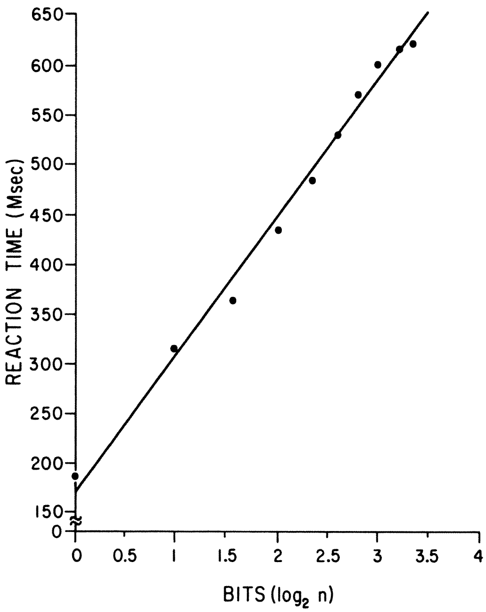

Fig. 1. Mean choice RTs to stimulus arrays conveying various amounts of information scaled in bits; *n* is the number of choice alternatives Data from Merkel (1885) as reported by Woodworth and Schlosberg (1954, p. 33)

is systematically related to the objective complexity of the task.

1894: J Allen Gilbert, at Yale University, was the first to demonstrate what Galton had tried but failed to find – a relationship between RT and "intelligence". Groups of children between ages 6 and 17 who were classified by their teachers as "bright", "average", and "dull" were tested on simple, choice, and discriminative RT. The mean RTs of the three groups were consistently in the same rank order, the "bright" children showing the fastest average RT and the "dull" the slowest. But if IQ test scores had been used and correlation coefficients obtained (neither had yet been invented), probably no statistically significant correlation would have been found. The group mean differences in RT were small (about 20 ms between "bright" and "dull") and the measures were not very reliable. The relationship of RT to intelligence could only have shown up in the differences between the group means, which of course are much less affected by individual measurement error than is a correlation coefficient based on individual scores. Gilbert was also the first to show a very regular, negatively accelerated decrease in RT with increasing age, between 6 and 17 years, and especially a decrease in the trial-totrial intraindividual variability of RT with increasing age. The mean RT of 17-year-olds was almost twice as fast as that of 6-year-olds. This suggests (but does not prove) that RT is related to mental age (a concept that was not to be invented until 1905).

1901: Clark Wissler, working under J McK Cattell at Columbia, was the first to use the coefficient of correlation (invented by Karl Pearson in 1896) to measure the degree of relationship between simple RT and "intelligence" as indexed by the course grades obtained by men students in Columbia College. The correlation was a nonsignificant −.02 – a singularly unimpressive finding. But the deck had been strongly stacked against finding a substantial correlation: each subject's RT was based on an average of only three to five measurements, which we now know would result in exceedingly low reliability; the "range of talent" was highly restricted in this highly selected group of Ivy League students, which we now know greatly attenuates correlations between any *g*-loaded measurements; and the reliability and validity of course grades as a measure of intelligence leave much to be desired. (The best present-day IQ tests show correlations of less than .50 with grades in highly selective colleges.) It was this disappointing result, coming from the then most prestigious psychological laboratory in America, that got into all the psychology textbooks and, for the next three-quarters of a century, cast a pall over the idea of using RT in the study of individual differences in intelligence.

1905: Alfred Binet and Theophile Simon invented the first practically useful intelligence test and conceived of mental age as a means of scaling general ability. This event is important in the history of RT because the Binet-Simon approach to assessing intelligence completely eclipsed the "brass instrument" laboratory techniques for measuring individual differences suggested by Galton and Cattell. For better or worse, no other event has so greatly influenced the whole course of psychometrics as well as present-day theories of intelligence.

1926: H Peak and EG Boring were the first to try to correlate RT with actual intelligence test scores. They insured sufficiently reliable measures of RT by obtaining 100 trials on each subject. Correlations between simple RT and scores on the Army Alpha and Otis intelligence tests were fabulous: −.90 and −1.00, respectively. Unfortunately, these correlations were based on a sample consisting of only five subjects. No one, apparently, was impressed. Peak and Boring (1926, p. 93), however, noted the potential significance of their finding: "...if the relation of intelligence (as the tests have tested it) to reaction time of any sort can finally be established, great consequences, both practical and scientific, would follow".

1927: Vernon Lemmon, working in Cattell's lab at Columbia under Henry Garrett, was the first to find a Pearsonian correlation between both *simple* RT and *choice* RT and scores on an intelligence test (Thorndike Intelligence Test), and he showed that *choice* RT is more highly correlated with IQ than simple RT (−.25 vs −.08) in 100 Columbia College students – a rudimentary demonstration of the relationship of *g* to task complexity. This was the last published study of RT in relation to intelligence until 1964. The low correlation between RT and test scores was an anathema to the psychometric Zeitgeist, which was much more bent on developing tests with practical predictive validity than in experimenting with laboratory techniques for investigating the nature of intelligence.

1949: CE Shannon and W Weaver invented information theory and proposed the *bit* (for *binary digit*) as a measure of information; a *bit* is the amount of information that will reduce uncertainty by one-half. The concepts of information processing theory have played an important role in the subsequent development of mental chronometry as a tool of experimental cognitive psychology.

1952: WG Hick discovered that multiple-choice RT increases as a linear function of the increase in amount of information in the stimulus array, when information is measured in *bits*, that is, the logarithm (to be base 2) of the number of choices. This relationship has become known as Hick's law. The relationship was demonstrated again the following year by Hyman (1953). Hick's law is nicely illustrated by Merkel's (1885) data (as reported by Woodworth and Schlosberg 1954, p. 33), shown in Fig. 1. The slope of this function can be interpreted as a measure of the speed or rate of information processing, expressed as the number of milliseconds per *bit* of information. The reciprocal of the slope (×1000) expresses the rate of information processing in terms of number of *bits* per second.

1964: E Roth, using multiple-choice RTs in an experimental paradigm conforming to Hick's law, found that individual differences in the *slope* of RT as a function of bits (i.e., the rate of information processing) are correlated with IQ. This was probably the first demonstration of a relationship between RT and intelligence that was predicted from the theory that an IQ test measures (among other things) information processing capacity. Individuals differ in the amounts of knowledge and skills called for by ordinary IQ tests, in part, because they differ in the rates with which they process (and hence "acquire") the information offered by the environment. Other things being equal, individuals with greater speed of information processing acquire mor cognitively integrated knowledge and skill per unit of time that they interact with the environment. Seemingly small individual differences in speed of information processing, amounting to only a few milliseconds per *bit* of information, when multiplied by months or yeras of interaction with the environment can account in part for the relatively large differences observed between individuals in vocabulary, general information, and the other developed cognitive skills assessed by IQ tests.

The Hick Paradigm

For convenience, I shall henceforth refer to the general type of procedure used by Roth (1964, see above) as the Hick paradigm, because it is based on Hick's law, that is, the linear increase in RT as a function of the number of *bits* of information conveyed by the reaction stimulus (RS). This paradigm is actually just an elaboration of the simple RT – choice RT (or SRT–CRT) paradigm. The number of choices (n) is merely extended in the Hick paradigm.

Roth's (1964) finding of a relationship between RT (or more exactly the *slope* of RT as a function of bits) and psychometric intelligence, which was first brought to my attention by Eysenck (1967), was the first interesting finding on RT and g in many years. But the encouraging results of this paradigm required replication before we could confidently proceed with it, and that is where I began. Because I now have more information on this paradigm than on any other, I will review in some detail what I and others have learned about it, and point out those aspects which seem the most promising clues for the development of a theory that can account for individual differences (IDs) both in RT and in at least a substantial part of IDs in g – that part of g which can be conceived of as "biological intelligence".

Procedural variations in RT measurement, we have found, have quite important effects on the absolute values of the obtained measurements. It is more doubtful, however, that small procedural variations interact importantly with IDs. Investigators using fairly different RT measurement procedures obtain quite similar relative differences between groups differing in age and intelligence level, and similar correlations with intelligence test scores. But knowledge would cumulate faster in this field if more attention were paid to the procedural aspects and if an attempt were made to make these as uniform as possible, not only for any given RT paradigm, but also across different paradigms. The results of different investigators would be more directly comparable and theoretically useful if there were some more generally agreed upon uniformity of such procedural variables as the modality, intensity, and duration of the preparatory stimulus (PS) and the average length of the (usually) random interval by which the PS precedes the reaction stimulus (RS). The intensity, discriminability, etc., of the RS should also be standardized, when it is not itself the object of experimental investigation. The same strictures should apply equally to the response mode – the type, distance, and strength of movement required for registering the response, the latency of which is the RT. In short, procedural variation should be minimized when it is not the subject of investigation and our chief interest is in IDs. Neither the physical nor biological sciences were able to develop very far without standardized instruments and procedures, and there is no reason to believe that psychology will be an exception. There comes a point in theory development where the absolute values of physical measurements (not just standardized normative scores) that constitute a ratio scale become of crucidal importance, as in direct comparisons (not just correlations) of the periodicity or intraindividual variability of measurements of RT, evoked brain potentials, and critical flicker frequency (CFF).

A Reaction Time-Movement Time Apparatus for the Hick Paradigm. Roth's (1964) RT apparatus and procedures were not very clearly specified. Subjects (Ss) were required to turn off a light as fast as possible after it went on by pressing a button directly adjacent to the light. The amount of information was varied by presenting a different number of light/button alternatives in the array. On each trial only one light in the array goes on. As the particular light that goes on in any given trial is determined at random, the S is kept in complete uncertainty until the instant one of the lights goes on. Only when there is but one light/button in the array is the S confronted with zero uncertainty. Roth's RT measure, that is, the interval between the light's going on and the S's turning it off, includes not only the shortest time it takes for the S to decide to react to the RS, but also the time it takes the S to move his hand through some unspecified distance to push the button which turns out the light. This can be termed movement time (MT) as distinct from RT. RT has also been referred to as "decision time", but the time for any overt act probably includes something more than sheer mental decision time, and so in this behavioral context I prefer the term "reaction time" or RT. But the "RT" in Roth's procedure can be, and should be, experimentally divided into RT and MT. I have devised the RT – MT apparatus to accomplish this and other refinements of Roth's procedure.

The S's console of the apparatus for measuring RT and MT is shown in Fig. 2. It consists of a panel, 13 × 17 in., painted flat black, and tilted at a 30° angle. At the lower center of the panel is a red pushbutton, 1/2 in. in diameter, called the "home" button. Arranged in a semicricle above the "home" button are eight red pushbuttons, all equidistant (6 in.) from the "home" button. Half an inch above each button (except the "home" button) is a $^1/_2$-in. faceted green light. Different flat black panels can be fastened over the whole array so as to expose arrays having either 1, 2, 4, 6, or 8 light/button combinations.

The subject is instructed to place the in-

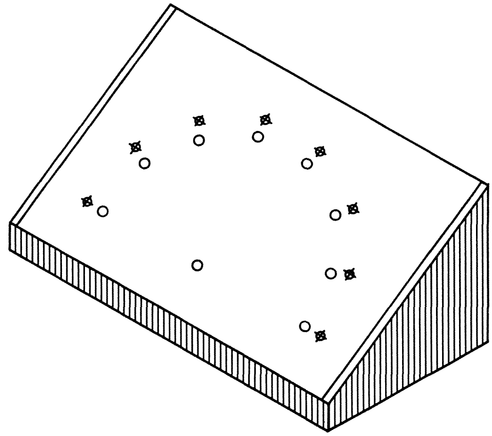

Fig. 2. Subject's console of the RT – MT apparatus. Pushbuttons indicated by circles, green jeweled lights by crossed circles. The "home" button is in the lower center, 6 in. from each response button

dex finger of his preferred hand on the "home" button; then an auditory warning signal (the preparatory stimulus or PS) is sounded (a high-pitched tone of 1-s duration), followed (after a continuous random interval [the preparatory interval or PI] of from 1 to 4 s) by one of the green lights going "on", which the subject must turn off as quickly as possible by touching the microswitch button directly below it. RT is the time the subject takes to remove his finger from the "home" button after the green light goes on. MT is the interval between removing the finger from the "home" button and touching the button which turns off the green light. RT and MT are thus experimentally independent. On each trial RT and MT are registered in milliseconds by two electronic timers.

In various studies using the RT – MT apparatus, we have given Ss either 15 or 30 trials, spaced at about 10- to 15-s intervals, on each level of information (i.e., 1, 2, 4, 8 light/button alternatives, corresponding to 0, 1, 2, 3 *bits* of information, where a *bit* is $\log_2$ of the number (n) of alternatives). (Some studies also included six alternatives [or 2.58 bits] in the array.) The levels of information in the array are always presented in their order of magnitude, so the S always begins with the simplest (one light/button) task. Several preliminary practice trials are given to insure that the S understands the task requirements. This has never posed the slightest problem, except in the case of severely retarded Ss, with IQs below 30, who often require more detailed instructions along with demonstration by the experimenter. Under these conditions, Ss with Stanford-Binet IQs as low as 14 have met the task requirements.

Basic Phenomena of the Hick Paradigm. We have now tested about 900 Ss on the RT–MT apparatus, sampled from diverse populations: university students, vocational college students, junior high school and elementary school pupils, borderline mentally retarded in sheltered workshops, and institutionalized mentally retarded. The main expected phenomena of the Hick paradigm have been examined in every set of data. These can be described in general terms for all data sets, noting the few exceptions.

1. *RT and MT as a Function of Bits of Information.* Because the distribution of RT over trials for a single S at any one level of bits is positively skewed, the best measure of the central tendency of RT for an individual is the median RT. This is also true for MT. But the distributions of median RT and median MT over individuals are so nearly normal (although they have a slight positive skew) that we represent the central tendency of groups of Ss by the mean of the individuals' median RTs (or MTs). Woodworth and Schlosberg (1954, p. 37), incidentally, present a graph of the distribution of RT (the average of 30 trials) for 1 000 men; it is as perfectly symmetrical and "normal" as one could ever find for any distribution of 1 000 physical measurements of any kind.

Figure 3 shows the mean RT and MT as a function of bits for 280 university students. The only statistically significant departure of RT from the linear function known as Hick's law that we have found was in a group of 60 severely retarded adults with a mean IQ of 39. (See group F in

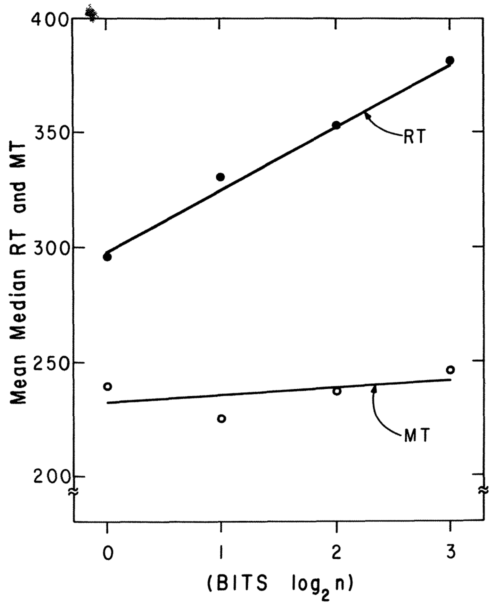

Fig. 3. Mean median RT and MT on the RT–MT apparatus for 280 university students, with 15 trials at each level of bits

Fig. 10.) For borderline retarded and nonretarded Ss, Hick's law is a very robust phenomenon. It is not merely an average statistical effect for a large group of Ss, but appears clearly, with rare exceptions, for individuals when the individual's median RT is plotted as a function of bits. The linear correlation (Pearson *r*) between median RT and bits for individual Ss averages .97, which attests to the close fit of individual RT data to Hick's law.

Hick (1952) suggested calculating bits as $\log_2(n+1)$ instead of $\log_2 n$, where n is the number of alternatives (i.e., light/buttons in the array). Hick reasoned that there are two sources of uncertainty – the uncertainty of which light will go on, which is $\log_2 n$, and the uncertainty as to the precise moment the light will go on. He conjectured that the temporal uncertainty is equivalent to the increase in uncertainty that would result from the addition of one more alternative, i.e., $(n+1)$, and hence bits $=\log_2(n+1)$. However, we have found no consistently better fit to this function in our RT data than to the simpler $\log_2 n$, and so we have used the simpler formulation. The differences in goodness of fit are usually so minute as to be negligible. For example, the data points in Fig. 3 are correlated .996 with $\log_2 n$ and .995 with $\log_2(n+1)$. Conceptually, $n+1$ makes sense, but it seems likely that the uncertainty as to when the RS will occur amounts to something less than the amount of increase in uncertainty that results from the addition of one more alternative to the array of potential reaction stimuli, at least in the present RT−MT procedure, with its short preparatory (random) interval (PI) of 1–4 s. The amount of uncertainty as to when the RS will occur is a function of the PI.

MT in all Ss but the severely retarded is much shorter than RT, a fact which virtually all Ss find very surprising, as it is contradicted by their subjective impressions. This is probably related to the fact that RT is generally faster than the speed of conscious awareness of a peripheral stimulus, which is about 500 ms, as determined by a neurophysiological method involving direct electrical stimulation of the brain (Libet 1965, Libet et al. 1971).

MT always parts company with RT in its relation to bits. MT never shows a significant increase as a function of bits, or in fact any significant or consistent correlation at all with bits. RT and MT clearly seem to involve different processes. Over single trials for an individual S, RT, and MT show zero correlation. That is, there is no correlation whatever between RT and MT (paired over trials) within individual Ss. Individual differences in median RT and median MT, however, are correlated about .40, indicating that they share some common source of variance among individuals. Median RTs for different levels of bits are much more highly intercorrelated than the correlation between median RT and median MT for the same level of bits. The same thing is true for MT. This amounts to saying that IDs in RT and MT involve both a common factor and uncorrelated specific factors, and for this reason it is inadvisable to allow the two variables to be lumped together, as is done in many RT paradigms in both the past and current literature. I suggest that any RT paradigm involving manual response selection should use a "home button" so as to permit the separate measurement of RT and MT.

2. *Reaction Time and Hick's Law Without Response Selection.* I had wondered if Hick's law, as manifested in the RT−MT paradigm, depended on the S's uncertainty of the reaction stimulus (RS) per se or on the task's requirement of response selection. Are the increments in RT with an increasing number of possible response alternatives the result of having to select from among *n* alternatives the appropriate "program" for the execution of the precise ballistic movement to press the button which turns out the light? We investigated this by having 25 college students do the RT−MT task under two conditions: first, 15 trials under a "single response" condition, then 15 trials under a "double response" requirement. The single response condition only required the S to remove his index finger from the "home button" as fast as possible when the RS (green light) occurred; no other response was called for. The double response condition, which we have routinely used in all other studies, requires the S to remove his finger from the "home button" and press the button adjacent to the light (i.e., the RS) that went on, thus requiring a "double" response – removing the finger from the "home button" and pushing the button 6 in. away, which turns out the light. The results are shown in Fig. 4. Having to make a "double" response adds about 30 ms to the RT and slightly increases the slope of the regression of RT on bits. When the S is required to make the ballistic response to turn out the light, he apparently cannot remove his finger from the "home" button (i.e., RT) until the ballistic response has been "programmed"; the RT under the double response condition thus reflects in part the programming time for the execution of the specific ballistic response required. This outcome is highly suggestive

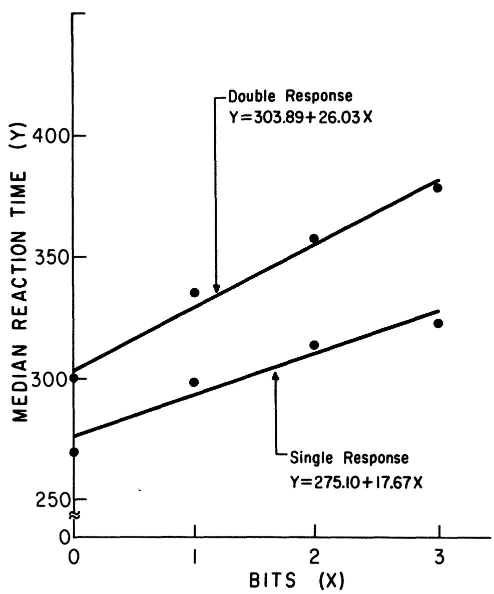

Fig. 4. RT as a function of bits when response selection (i.e., pressing a button to turn off one of the lights) is not required (single response) and when response selection is required (double response)

of Fitts' law, which essentially relates the time for beginning the execution of a movement to the required precision of the movement (Fitts 1954). The ballistic movement programming time of about 30 ms is only slightly affected by the numer of response alternatives. The slope of RT over bits is mainly a function of uncertainty about the RS. But it should not for that reason be thought of as a *sensory* phenomenon per se, for the signal to noise ratio of the RS (a jeweled half-inch diameter green light going on very brightly) is so great as to minimize any between Ss or within S variance due to the discriminability of the RS.

Individual differences in the intercept, slope, and intraindividual variability (over trials) of RT are almost as highly correlated across the "single" and "double" response conditions as the test-retest reliabilities of these variables will permit, and their correlations with psychometric *g* (Raven's matrices) are nearly the same (about −.35) for the two conditions. It seems most likely that *g* is related to the RS uncertainty aspect of RT rather than to the relatively small movement programming component.

3. *Intraindividual Variability in RT and MT.* Surprisingly little attention has been paid to intraindividual variability in the RT literature, with the exception of research on the mentally retarded, which has pointed out that the magnitude of intraindividual variability in RT is one of the most distinguishing features between retarded and normal Ss (Berkson and Baumeister 1967; Baumeister and Kellas 1968a, b, c; Liebert and Baumeister 1973, Wade et al. 1978). In our own work with college students we generally find that intraindividual variability in RT is more highly correlated with *g* measures than is any other single variable that can be derived from the RT−MT paradigm. The reason for the neglect of RT intraindividual variability in most chronometric research is probably that researchers are interested in "goodness" of performance, and the *speed* of RT is a more obvious measure of "goodness" than is the trial-to-trial *variability* of RT. *Speed* of reaction has more the appearance of an "ability" than does *variability* of reaction.

Theoretically, too, variability of RTs would seem to have priority over the average speed of RTs. Assuming an inherent periodicity in the nervous system, the average speed of RT can be seen as a consequence of variability of RT more easily than the reverse relationship.

Intraindividual variability in RT (and MT) is measured by the standard deviation of a S's RTs (or MTs) over trials for any given level of bits, and will henceforth be symbolized as $\sigma_i RT_0$ (or $\sigma_i MT_0$), with the subscript on the RT (or MT) indicating the bits of information conveyed by the RS. The mean of the standard deviations over all levels of bits is symbolized $\bar{\sigma}_i RT$ (or $\bar{\sigma}_i MT$).

Hick (1952, p. 25) claimed that, in his highly practiced Ss, the intraindividual *variance* of RT increases as a *negatively* accelerated function of bits. (This would mean that the *standard deviation* of RT would form

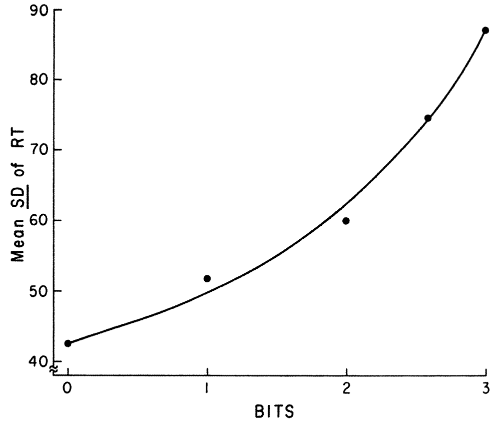

Fig. 5. Mean intraindividual variability (measured by the standard deviation of RTs in milliseconds on 30 trials) as a function of bits on the RT–MT apparatus, for 160 school children in grades four to six

an even more negatively accelerated curve.) In all of our studies, however, intraindividual variability (σ_i) in RT increase as a *positively* accelerated function of bits. Typical results, based on 162 school children in grades 4, 5, and 6, are shown in Fig. 5. A most interesting feature of this curve is that it becomes an almost perfectly linear function if the scale on the ordinate is transformed to a logarithmic scale. Without such a transformation, the function can also be made almost perfectly linear by changing the scale on the abscissa to n (number of alternatives), instead of $\log_2 n$ (=bits). That is to say, RT increases as a linear function of log n, whereas intraindividual variability (σ_i) of RT increases as a linear function of n. This finding will have to be accounted for by any theory of RT.

Intraindividual variability in MT (σ_i MT) is about 1.7 times greater than the average σ_i RT, and, like MT, is completely unrelated to the level of bits. Individual differences in σ_i RT and σ_i MT are correlated only slightly (but significantly) greater than zero, with most rs between about .10 and .20. (These correlations would be raised by about .10 by correction for attenuation.) Also, σ_i MT, very unlike σ_i RT, probably shows the least correlation with g of any of the individual variables derived from the RT–MT paradigm, such as the intercept and slope of RT, $\bar{\sigma}_i$ RT, and even median MT.

4. *The Random Nature of RT Variability.* Intraindividual variability of RT from trial to trial during a single test session displays all the characteristics of random sampling from a population of RTs having a somewhat skewed distribution with a given mean and standard deviation which are characteristic of the S during the particular test session. We know these parameters of RT performance are characteristics of the S, because they show highly reliable IDs within a single test session. However, each S's RTs appear to be generated by a strictly random process, showing a quite consistent variability about the S's mean RT over n trials.

First of all, as would be expected from a random generator, the values of RT show no consistent trend over trials in sessions of 15–30 trials. We have never found a statistically significant practice effect. Dividing trials into first half versus second half yields no greater average difference in RTs or in the σ_i of RT than dividing trials into odd versus even.

Secondly, the covariance matrix of trial-to-trial RTs was tested for homogeneity in a sample of 100 university students. A stringent test of the homogeneity of all of the trial-to-trial covariances in the matrix fails to reject the null hypothesis. (The obtained chi-squared was less than 1/70 th as large as the chi-squared required to reject the null hypothesis at the .05 level of confidence.) In other words, the covariance between any pair of trials does not differ from the covariance between any other pair of trials by more than would be expected from random variation. This is true when there is either 0 or 3 bits of information conveyed by the RS. In other words, the intertrial covariances do not vary more than one should expect if the RTs on each trial represented a sample of one RT drawn *at random* from each of 100 individual distributions having different means and σs. The fact of individual differences is shown by the average intertrial correlation of about +.40. One useful implication of the equivalence of RT from trial-to-trial, except for purely random fluctuation, is that the assumptions of the Spearman-Brown prophesy formula are perfectly satisfied by RT data obtained on a number of trails in a single session.

Although trial-to-trial intraindividual variability of RT meets the two above-described criteria of a random generator, day-to-day variability of the individual median RTs for each daily session, or any other parameter of the Hick paradigm we have examined, such as the intercept, slope, and within-session intraindividual variability, does not meet both criteria of a random generator. Ten Ss tested approximately every other day for nine sessions with 60 trials per session showed no overall average trend in mean RT over the nine sessions (spread over 3 weeks). (An analysis of variance shows nonsignificant F ratios for the main effect of days, i.e., sessions.) But there were slight, statistically significant systematic upward and downward trends for different Ss over the course of nine sessions. The average intercorrelation of RT (median of 15 trials) between days is about +.75, and does not vary as a function of bits. The corresponding MT shows much greater day-to-day stability, with an average correlation of about +.90.

The day-to-day covariance matrix for median RT is not homogeneous, but shows significant variation among the covariances, which form a pattern that approximates a simplex, that is, the largest covariances are between adjacent days or test sessions and they systematically decrease as the number of intervening sessions increases. This simplex pattern of covariances (or correlations) indicates that some form of nonrandom variation in individuals' median RTs occurs over the course of nine test sessions, even though there are no changes in the *average* RT of the group. The same kind of simplex pattern of intercorrelations is usually found for repeated measurements of many other variables that are undergoing gradual and systematic change, such as yearly measurements of children's height and weight, IQ, and trial-to-trial performance on laboratory learning tasks.

Little is known about the sources of day-to-day fluctuations in RT. An individual median RT even fluctuates significantly at different times of the day, and seems to be very sensitive to changes in physiological states associated with eating, sleep cycle, and fatigue. Body temperature fluctuates from hour to hour throughout the day, and RT parallels these temperature fluctuations, higher temperature producing faster RT. Simple RT probably varies about 9 or 10 ms per degree Fahrenheit change in body temperature in the normal range of diurnal variation in temperature. Reviewing this evidence, Woodworth and Schlosberg (1954) note that "the amount of [RT] change [with temperature] corresponds pretty well to what would be expected from the temperature coefficient of chemical processes, and suggests that the cerebral process in reaction depends closely upon chemical activity" (p. 38). It is also of considerable theoretical interest that choice RT shows much larger shifts with change in temperature than does simple RT.

5. *Relationship of RT—MT Parameters to Age of Subjects*. We have examined this in a group of 160 school children ranging in age from 9 to 14 years. Older studies had shown that simple RT has a fairly linear decrease with age between about 5 and 15 years of age, thereafter becoming very negatively decelerated and becoming asymptotic by 17 years of age (e.g. Gilbert 1894). We, too, have found quite linear regressions of RT and MT on age in the range from 9 to 14 years. Thus there is a developmental trend in RT that parallels the developmental trends in physical growth and in other indices of mental development.

Of greater interest to us is the finding that the slope of the regression of mean RT on age increases markedly as a function of the bits of information conveyed by the RS. This is true also for RT σ_i. These results

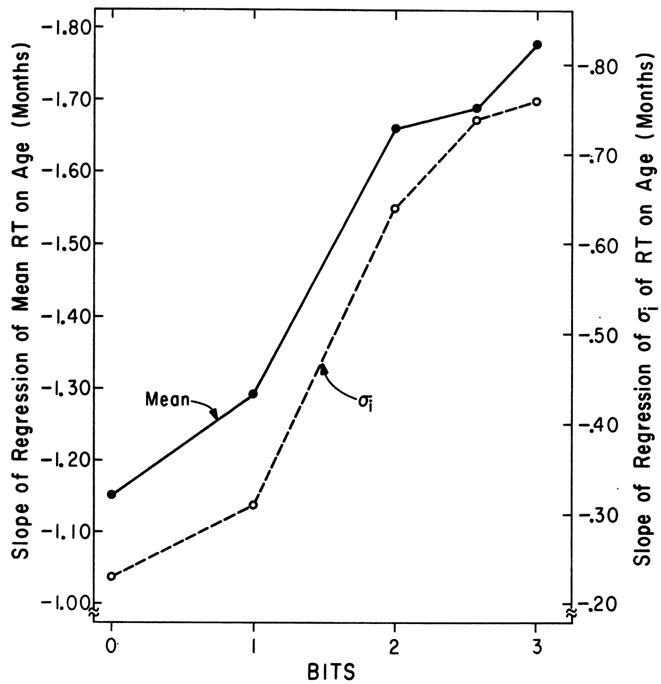

Fig. 6. Slope (i.e., RT decrement in Milliseconds per month of age) of the regression of mean RT and intraindividual variability (σ_i) of RT on age, as a function of bits of information, for 160 children of ages 9–14 years

are shown in Fig. 6. This indicates that performance on the more complex RT tasks (i.e., a greater number of bits) reflects age differences much more sharply than does performance on simpler RT tasks. Children differing 4 years in age, for example, differ about 55 ms in mean RT for simple RT (0 bit), but differ about 85 ms for eight-choice RT (3 bits).

MT shows significant but smaller change with age than RT, the slope of the regression of MT on age being only about 70% of the slope for RT. But more striking is the fact that the regression slopes of mean MT and σ_i MT on age show no relationship to task complexity. Thus, once again MT appears less "cognitive" than RT. Although MT shows a slight but significant developmental trend, it does not seem to be associated with the information processing demands of the task, whereas RT is clearly related to Ss' information processing capacity, which increases much more dramatically than motor speed and accuracy between ages 9 and 14.

RT Paradigms and Psychometric *g*

Consideration of the relationship of RT to psychometric *g* is a complex affair. For one thing, RT is merely a generic term for a great variety of procedures and paradigms for measuring reaction time, and each of these paradigms yields data from which a number of parameters can be derived, such as the intercept, slope, and intraindividual variability, as was pointed out for the Hick paradigm in the previous section. Each of these paradigms and parameters may show correlations with *g*, singly (by Pearson *r*) or in various weighted combinations (multiple *R*).

The correlation coefficient is not necessarily the best or most efficient method for initially discovering which particular paradigm and parameters are related to *g*. Comparison of the *means* of various RT variables obtained in groups that differ in *g* is an efficient exploratory method. Its efficiency, as contrasted with that of correlation analysis, is mainly due to two factors:

1. First is the fact of the day-to-day instability of IDs in RT parameters, especially those most highly related to *g*. A low stability coefficient, like low reliability in general, puts a low ceiling on the maximum correlation that can be obtained between RT variables and *g* or any other external criterion measurements. A group's mean, however, is highly stable for all RT parameters. The day-to-day rank order of sample means on RT parameters, provided they are sampled from different populations with respect to the average *g* of the population, remains highly stable, so that relatively small samples can be used to establish a connection between RT parameters and *g*. Correlations within any relatively homogeneous group, on the other hand, are highly attenuated by the inherent temporal instability of certain RT parameters and often barely reach significance in samples of less than about 40 Ss. In reviewing the entire literature on various RT correlates of *g*-loaded tests, the modal Pearson *r* appears to be somewhere near .35. This much can be said for the correlations, however: virtually never in my examination of this literature, nor in any of our own work, have I come across any RT $\times$ *g* correlations, whether statistically significant or not, that were on the "wrong" side of zero. That is, the correlations, although often unimpressive, are always in the theoretically expected direction, namely, higher *g* predicting faster overall RT, lower intercept, and less slope of RT when complexity of the RS is varied over two or more levels, and smaller intraindividual variability in RT over trials. If there have been surprises in this field, they have been due to finding significant and replicable correlations where they were not expected in terms of our earlier theoretical conceptions – for example, the quite pronounced relationship of MT to *g* in normal children and retarded adults.

2. Second is the fact that investigators are rarely in a position to obtain random or representative samples of the general population. Almost every study I have found in the literature on RT and intelligence, including all of my own studies, have used samples drawn from quite restricted populations with respect to general intelligence. Almost any "natural" group from which one may draw a sample represents some restricted range of the total distribution of IQ in the general population. Restriction of the "range-of-talent", as is well known, plays havoc with correlations. Corrections of the obtained correlations for restriction of range are questionable without highly reliable estimates of the variances of the correlated variables in the general population. Some investigators have made up "artificial" or ad hoc samples composed of individuals selected over a very wide range of IQs, from retarded to gifted. But these "artificial" groups do not represent a sample of any population, and the distribution of IQs within them is usually rectangular (i.e., nearly equal frequencies at every level of IQ), or even bimodal. Correlations between RT and IQ based on such ad hoc samples are usually very high. Their one and only important feature is their statistical significance, for the magnitude of the *r* is not generalizable to any real population, including the general population, in which the full range of *g* has an approximately Gaussian frequency distribution. Representing nearly the full range of *g* found in the general population by a sample with a rectangular distribution, of course, greatly exaggerates the true correlation in the population. Therefore, in our research we prefer to report the raw correlations found within samples of "natural" populations, however restricted in range of IQs, and to observe mean differences in RT parameters between "natural" groups that happen to differ in mean level of IQ.

Because of these complications, it is practically impossible at present to conclude just what the correlations between RT variables and psychometric measures of intelligence might be in the general population, except to say that there is undoubtedly a true correlation between the two classes of variables and the population correlations are probably larger than those found in more restricted "natural" groups. However, the more important point at this stage, from a theoretical standpoint, is that a significant relationship exists between RT phenomena and *g*. That is the primary basis for further investigation.

When I began researching the correlation between RT and *g*, and reviewed the quite sparse literature on this topic, with its significant but usually modest correlations, mostly in the .30 to .40 range, I naturally wondered if there was the risk that these few reports were merely instances of Type I error, and that failures to reject the null hypothesis with respect to RT × *g* correlations had simply not found their way into the published literature. However, I now have very little doubt that our knowledge of the RT × *g* correlation could not be merely Type I error due to the failure of investigators to report negative or insignificant results. In recent years a number of researchers have reported quite consistent results from different RT paradigms. Also, in our own research on the Hick paradigm with a wide variety of groups from different parts of the IQ distribution, we have always found a statistically significant relationship, invariably in the predicted direction, between certain RT (and MT) paramters and mental test scores.

As I have already reviewed the research relating RT paradigms and parameters to psychometric intelligence in some detail elsewhere (Jensen 1980, 1981), I will here only briefly summarize the main findings obtained with different RT paradigms, using graphs to highlight the most telling results.

Simple and Choice RT. Comparison of simple (SRT) and two-choice (CRT) reaction times is probably the simplest of the RT paradigms. CRT is invariably longer than SRT, and usually CRT is the more highly correlated with *g*. Developmental trends from childhood to adolescence are also more pronounced for CRT than for SRT. These findings are typically illustrated in Fig. 7, from a study by Keating and Bobbitt

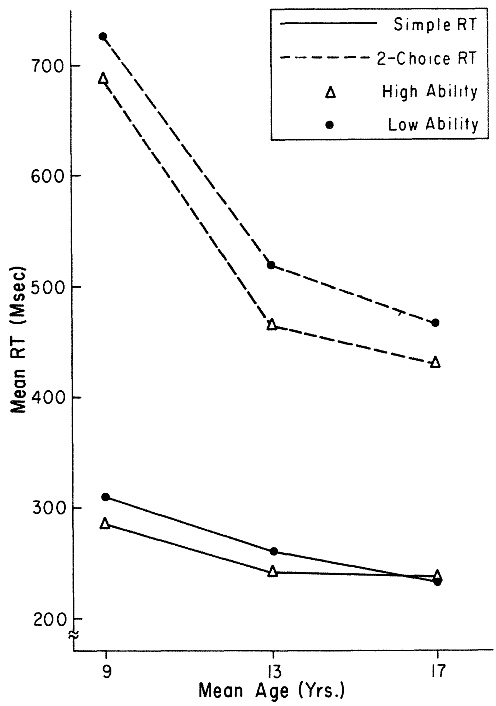

Fig. 7. Simple and choice RT as a function of age and ability level (Raven's Matrices). Keating and Bobbitt (1978)

(1978). SRT required the S to press a button when a red light went on; in CRT the S pressed either a red or a green button when either a red or a green light appeared (in the same aperture). Low and high ability groups were selected from the 40–45 and 90–95 percentiles, respectively, on Raven's Matrices. In this study there was no attempt to distinguish between RT and MT: both variables are amalgamated in the nominal RT, which, therefore, is not directly comparable in absolute magnitudes to the RT obtained in the Hick paradigm using the RT – MT apparatus. The form of the relationships of SRT and CRT to age and ability level, however, is typical.

Hick Paradigm. The typical findings for SRT and CRT extend to the more complex Hick paradigm, which further magnifies the increased relationship of RT to *g* as the complexity of the reaction stimulus is increased. This generalization, which is repeatedly supported by our own research on the Hick paradigm, using the RT – MT apparatus, is most clearly illustrated in a study by Lally and Nettelbeck (1977) reporting the correlation between choice RT and IQ (in a very heterogeneous group ranging from IQ 57 to 130) as a function of bits or $\log_2$ of the number (n) of choice alternatives, as shown in Fig. 8. The same trends are seen in much more homogeneous groups tested in our laboratory, as shown in Fig. 9. This increase in the correlation between RT and *g* as the complexity of the RS is increased is one of the key phenomena that any theory of intelligence must deal with. The theory must also explain why this generalization holds true only in the lowest range of task complexity, extending perhaps from 0 to 4 or 5 bits of information. The upper limit is not clear. But the increasing relationship between RT and IQ seems not to extend beyond the range of tasks to which RT is

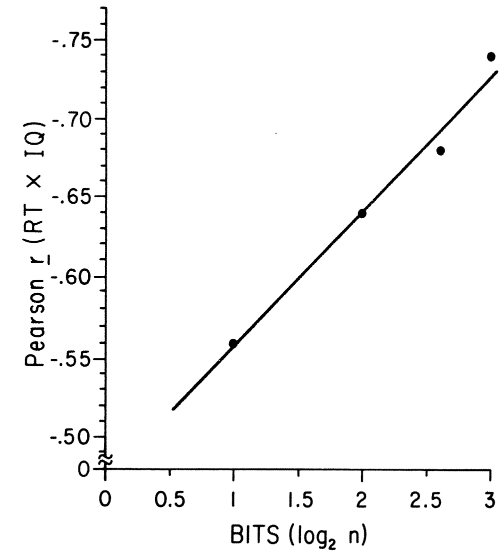

Fig. 8. The correlation (Pearson r) between choice RT and IQ as a function of number of alternatives (n), in a group of 48 Ss with Wechsler Performance IOs ranging from 57 to 130. Lally and Nettelbeck (1977)

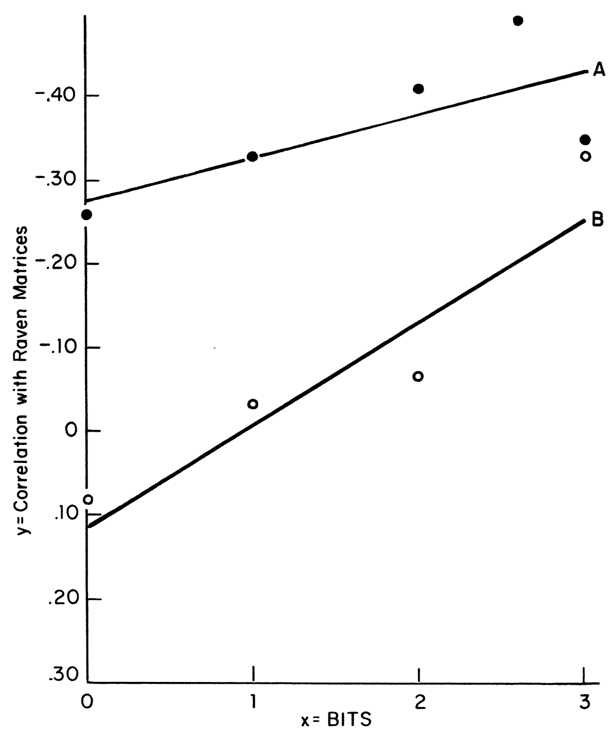

Fig. 9. Correlation (r) of Raven Matrices scores with RT as a function of complexity of the reaction stimulus scaled in bits for (A) 39 female ninth graders (age 14 years) and (B) 50 university students, who, probably because they are more highly selected and consequently more restricted in variability on g, show the smaller correlations

greater than about 1,000 ms. When the processing time is greater than that, further increases in task complexity do not result in a further increase in the RT − IQ correlation (e.g., Spiegel and Bryant 1978). When we measure response time to problems of the degree of complexity of typical intelligence test items that are difficult enough to measure individual differences in terms of number of right and wrong answers under unspeeded condition, the correlation between individual differences in response times and ability as measured by number of items gotten correct on a test usually breaks down completely. For example, the correlation between individual differences in solution times for Raven Matrices items and total score on the Raven has been found to be near zero in three studies (Jensen 1979, Snow et al. 1976, White 1973). I emphasize that the nonsignificant correlations are between (a) individual differences in response times to test items and (b) total scores (i.e., number right) on the test. When solution times for items are *averaged* over Ss, the correlation between mean item solution times and difficulties (i.e., proportion of Ss attempting the item but failing to get the right answer) approaches unity (Elliott and Murray 1977). In other words, more difficult test items (when answered correctly) have longer average response times, but the response times are barely, if at all, correlated with intelligence. I would predict that one would obtain a higher correlation between IQ and response latencies to test items in college students if the test items were from intelligence tests of a difficulty level appropriate for elementary school children than if the items were from ability tests of a difficulty level suitable for college students. I call this the *test-speed paradox*. The explanation of it involves a number of factors.

First, it should be understood that the test-speed paradox holds for test items answered correctly. It would be trivial if it only held for a mixture of right and wrong solutions, as a wrong solution can hardly be expected to reflect all the mental processes that may be necessarily involved in a correct solution. Also, the response times of bright and less bright Ss should be compared on only those items that all Ss get right, otherwise the response times of the brighter Ss would be slower simply because they have solved more difficult items. But beyond these obvious controls, there are other factors that work against a high correlation between test speed and ability, even though, paradoxically, we may find a substantial correlation between test scores and RT parameters derived from relatively simple paradigms in the 0–3 bits range of information processing demands. We know that both intra- and interindividual differences in RTs increase with increasing amounts of information in the RS. However, the *nominal* information in the RS is not linearly related to RT beyond a point. Because of the brain's limited channel capacity, increasing the informational input invokes other processes, such as holding encoded stimuli and partial solutions in short-term memory while performing other operations. So with increasing task complexity, beyond a certain point, the RT departs from linearity. Also it appears that complex tasks requiring considerable time and persistence, such as difficult matrices items, allow personality factors to enter the picture, and these are uncorrelated with ability. We have not found significant correlations between personality variables and performance on relatively simple RT tasks with RTs below 1,000 ms among university students. Yet total time on Raven's Matrices was found to be correlated −.46 with E (extraversion) scores on the Eysenck Personality Inventory, whereas the correlation between total time and Raven scores was exactly zero.

Both the *intercept* and the *slope* of the regression of RT on bits of information in the Hick paradigm are correlated with *g*. This is true when intercepts and slopes are calculated for individuals and when they are calculated for groups of different intelligence levels. In general, the slope parameter seems to be more discriminating for *g* among individuals in more intelligent

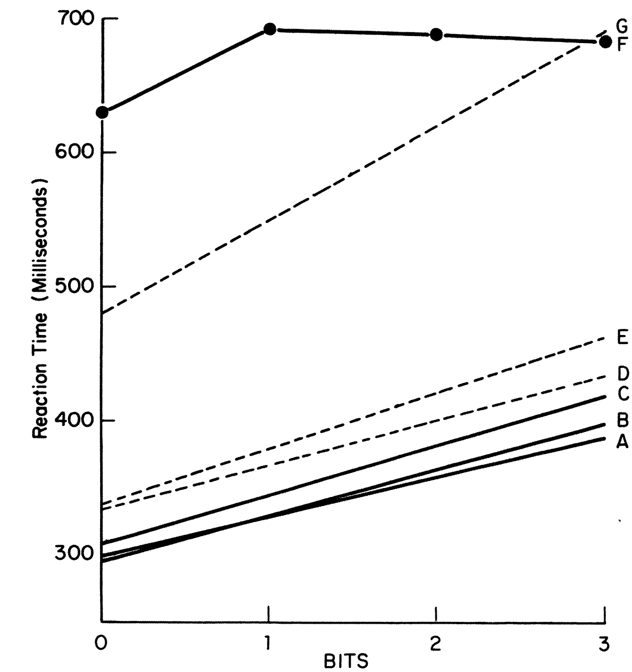

Fig. 10. Reaction time as a function of *bits* in seven different groups: *A*, university students ($N=155$); *B*, ninth grade girls ($N=39$); *C*, sixth graders in a high SES-high IQ school ($N=50$); *D*, *E*, white ($N=119$) and black ($N=99$), respectively, male vocational college freshmen; *F*, severely retarded young adults ($N=60$); *G*, mildly retarded young adults ($N=46$)

groups and the intercept becomes a relatively more important correlate of g in children and retarded adults. One problem with the slope is that it is much less stable from day to day than the intercept. Therefore group comparisons of slope are more informative than correlations between individual measures of slope and g within groups. Figure 10 shows the Hick phenomenon for several groups differing in age and general ability. For all groups except the severely retarded (group F) the data points are omitted for clarity, for in no group except the severely retarded do the data points depart significantly from a linear trend. All of the group in Fig. 10 differ significantly from one another in slope except groups A and B. The two most extreme groups, except for the severely retarded, groups A and G, are shown separately in Fig. 11 and 12. Also shown are the movement time (MT) and the average intraindividual variability (indicated by vertical lines).

When the mildly retarded group in Fig. 12 is split in two at the group's median of the distribution of Raven's scores, we found, to our suprise, that MT discriminates more than RT between the groups, as shown in Fig. 13.

MT also discriminates between IQ levels in a junior high school sample (ninth grade girls), but not as much as RT, as shown in Fig. 14, in which the distribution of Raven scores of the 39 Ss was trichotomized. Note that MT is much faster than RT and MT does not increase significantly over bits.

The only group which is markedly at variance with these general findings is the severely retarded, with IQs ranging from 14 to 60, mean = 39. They fail to manifest Hick's law and it is the one group for which MT is slower than RT, as seen in Fig. 15. In this group, median RT and MT were correlated with g only −.13 and −.18 respectively, but the $\bar{\sigma}_i$ of RT and $\bar{\sigma}_i$ of MT correlated −.44 and −.57 (both significant at the .01 level). A simple sum of standardized scores on median RT, median MT, RT$\bar{\sigma}_i$ and MT$\bar{\sigma}_i$, and a measure of "neural adaptability" derived from the average evoked potential were correlated .64 ($P<.001$) with g factor scores based on 15 psychometric tests (Jensen et al. 1981).

The reversal of the speeds of RT and MT

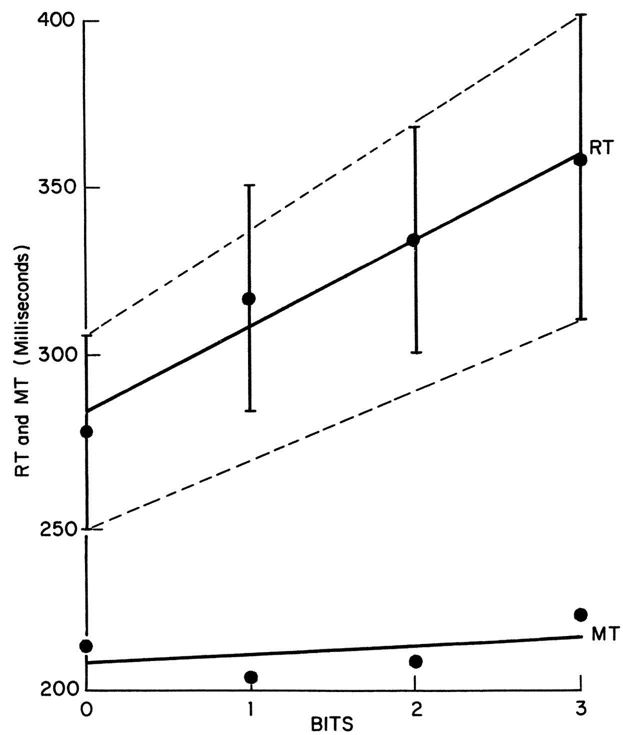

Fig. 11. Mean RT and MT, and the mean $\pm 1\ \sigma_i$ of RT over 15 trials (vertical lines) in 50 university students (group *A* in Fig. 10)

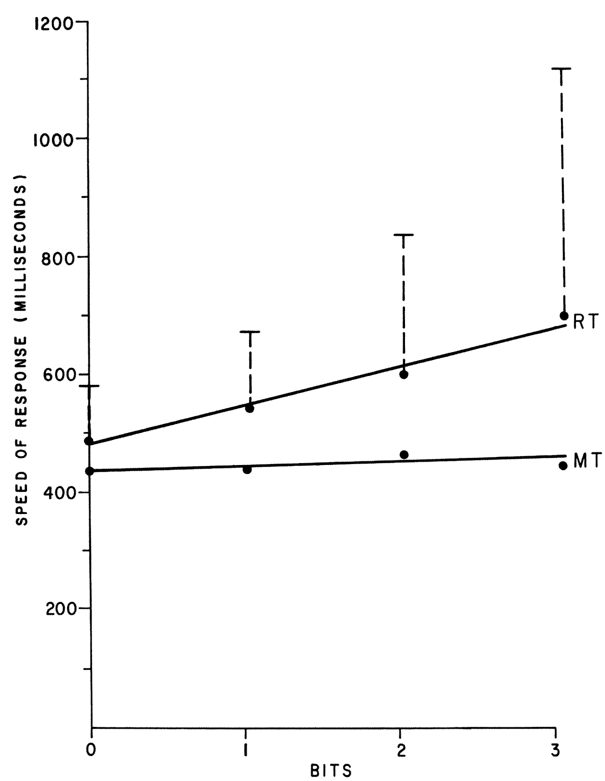

Fig. 12. Mean RT and MT and mean σ_i of RT over 15 trials (*vertical dashed lines*) in 46 borderline retarded young adults (group G in Fig. 10). Vernon (1981)

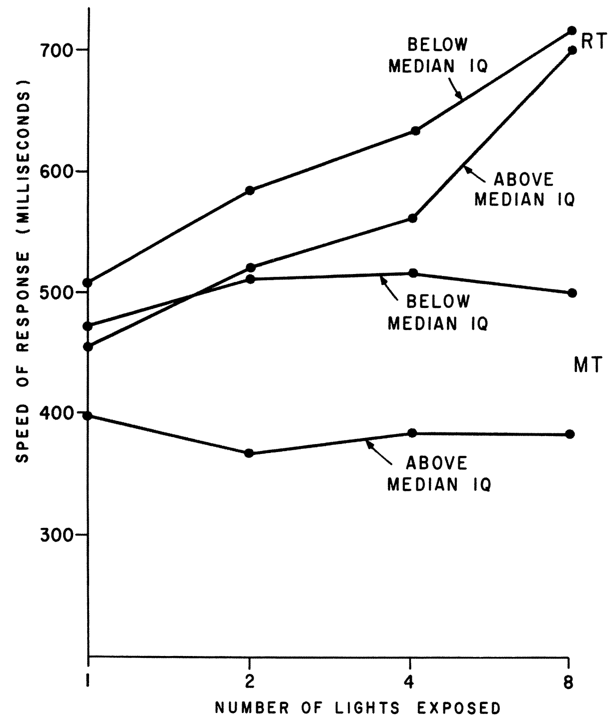

Fig. 13. RT and MT of mildly retarded young adults who are above or below the sample's median IQ (Raven). Vernon (1981)

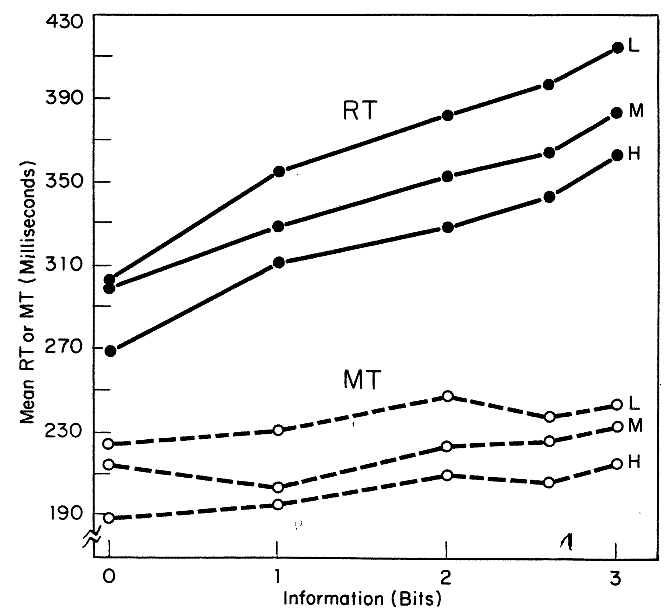

Fig. 14. Mean RT and MT as a function of bits for the high (*H*), middle (*M*), and low (*L*) thirds of the sample ($N = 39$) of ninth grade girls on Raven's Standard Progressive Matrices scores. Jensen and Munro (1979)

in this retarded group caused us to wonder if the ratio of RT/MT bore any relationship to level of intelligence. When the ratio of mean RT/mean MT is plotted for the four adult groups differing in mean IQ, the results show a rather consistent relationship, as seen in Fig. 16. I have hypothesized, in accord with similar findings by Sternberg (1977), that brighter Ss use up relatively more of their RT for "programming" the

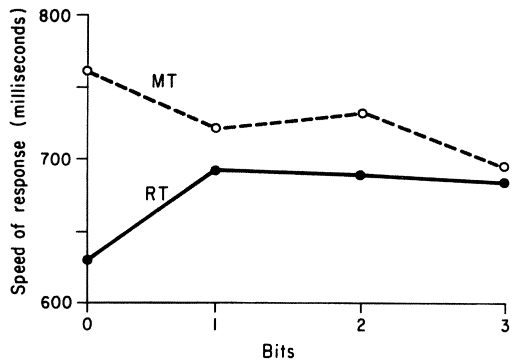

Fig. 15. Mean RT and MT as a function of bits, in 60 severely retarded adults (mean IQ = 39). Jensen et al. (1981)

precise ballistic response required to push the button which turns out the light; this lengthens RT relative to MT. Data relevant to this hypothesis are discussed in detail elsewhere (Jensen 1982).

Intraindividual variability ($\bar{\sigma}_i$) in RT, among all of the RT − MT parameters, has generally proved to be the best correlate of *g*. It is the one parameter that shows a significant, and usually the most substantial, correlation with *g* in relatively homogeneous groups at every ability level we have tested from the severely retarded to university students. The *r*s range from about −.30 to −.45 with a mean of −.35, impressive figures considering that RT$\bar{\sigma}_i$ is one of the least stable RT parameters, with a correlation of .42 between RT$\bar{\sigma}_i$ for 100 university students obtained in each of two test sessions 1 day apart. If this represents the typical stability coefficient of RT$\bar{\sigma}_i$, then the average correlation between RT$\bar{\sigma}_i$ and *g*, when corrected for attenuation, would be about −.55. On the assumption that any one group in which the correlation has been determined represents only half of the total variance of *g* in the general population, a correction of the correlation of −.55 for restriction of range on *g* would boost it to about −.70. The true-score population correlation between RT$\bar{\sigma}_i$ and *g* might even be slightly higher than that, because there is undoubtedly also some restriction of range on RT$\bar{\sigma}_i$ in our sample. Mean differences in RT$\bar{\sigma}_i$ between groups, expressed in standard score units (*z*), are almost as large as the mean IQ differences between the groups. For example a university sample and a vocational college sample differ 13 points in IQ and differ 0.68 *z* ($P < .001$) in $\bar{\sigma}_i$ of simple RT.

Individual differences in median RT and

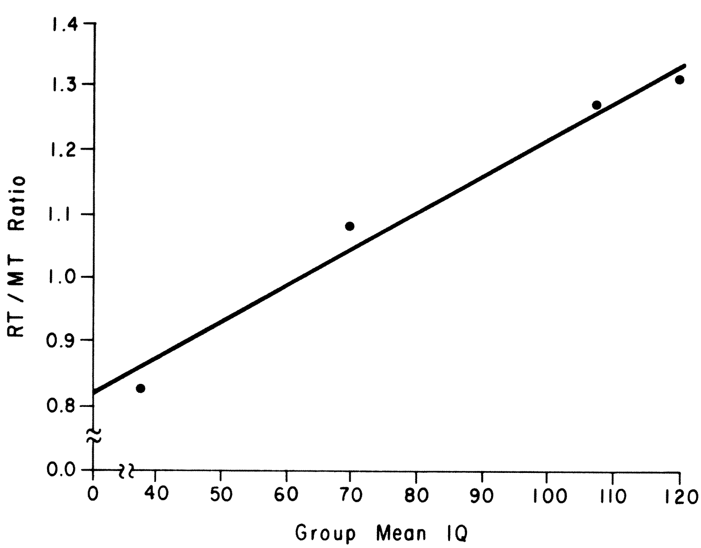

Fig. 16. Mean RT/MT ratio plotted as a function of average IQ levels of four groups: severly retarded ($N = 60$), borderline retarded ($N = 46$), vocational college students ($N = 200$), university students ($N = 50$). Mean RT and MT are based only on the one light/button task (0 bits)

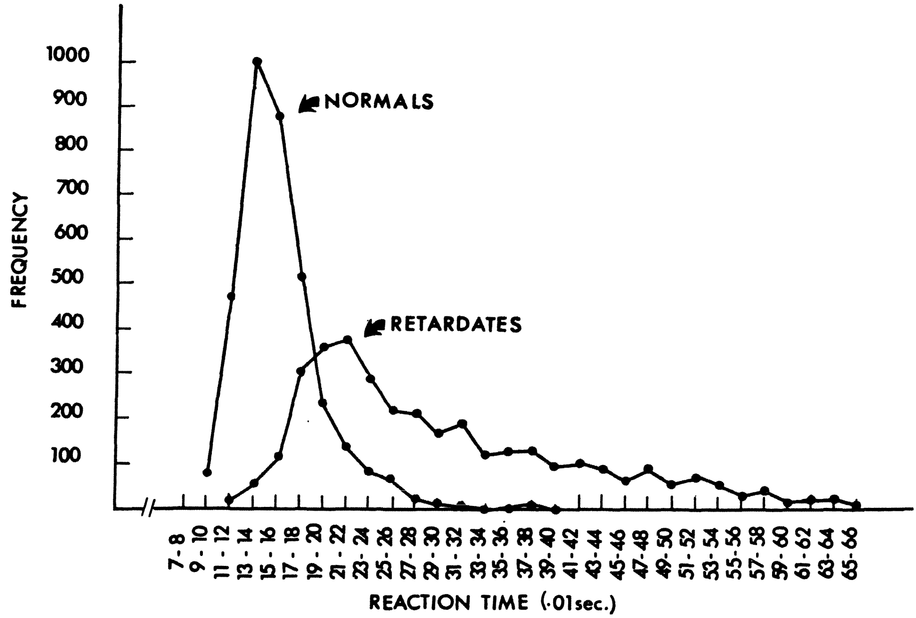

Fig. 17. Frequency distribution of 600 trials per subject of simple RT for six retarded and six normal subjects. Baumeister and Kellas (1968 b)

RT $\bar{\sigma}_i$ are positively correlated (about +.40) and the question arises as to which variable is the more fundamental aspect of IDs. It is fairly easy to imagine how IDs in RT σ_i could cause IDs in median RT, but the reverse is much harder to understand. If there were a physiological limit for the speed of RT, with negligibly small IDs in this limiting speed, and if there were considerable IDs in σ_i, then there would inevitably be considerable IDs in median RT (over *n* trails), and σ_i and median (or mean) RT would be positively correlated. IDs in *g* would be hypothesized to be related primarily to RT σ_i and the correlations of *g* with median RT, and with the intercept and slope of RT in the Hick paradigm, would all necessarily follow. One expectation from this model is that bright and dull Ss should differ not at all or only slightly in the fastest RTs of which they are capable on any trial, whereas their median RTs over *n* trails should differ considerably. A study by Baumeister and Kellas (1968 b) presents suggestive relevant data in the frequency distributions of RTs (simple RT) obtained in 600 trials for six university students and six mildly retarded (IQs 50–81, mean IQ 62), but physically normal, persons of about the same age. As shown in Fig. 17, the groups differ much less in their fastest RTs than in any measure of the central tendency of each of the two distributions. But it is also noteworthy that in a total of 3,600 trials of *simple* RT, the retarded Ss do not produce a single RT that is as fast as the 60 or 70 fastest RTs (out of 3,600) of the normal Ss. Any theory must account for this difference in the fastest possible RTs bright and retarded Ss can produce, even for simple RT. It must also account for the important fact that there is a close relationship between a S's fastest RTs and the mean or median RT over *n* trials. Liebert and Baumeister (1973) have reported correlations as high as .96 (for college students) between mean RT over 100 trials and the average of the ten fastest RTs in 100 trials. They also note that the lower limit of RT decreases with age between 6 and 18 years, as does also RT σ_i.

We have examined this phenomenon in

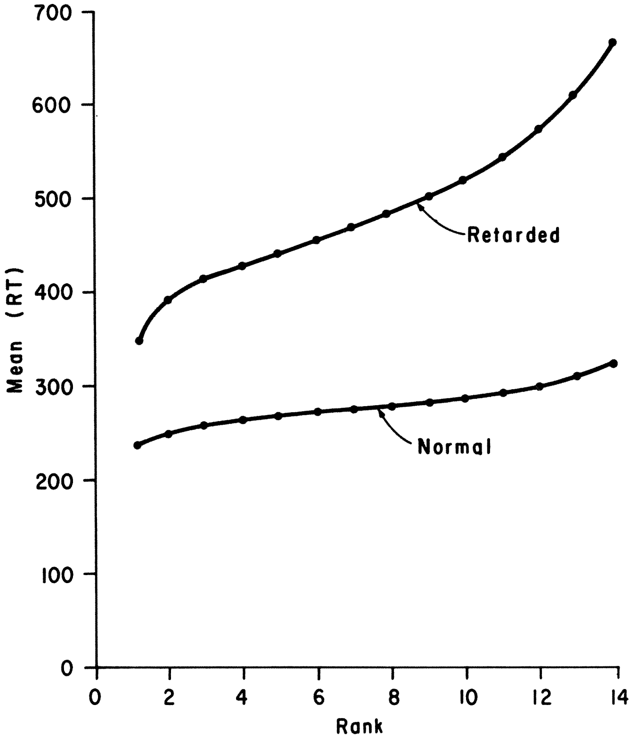

Fig. 18. Mean simple RT for 0 bits in the Hick paradigm, plotted after ranking each individual's RTs on 15 trials from the fastest to the slowest RT (omitting the 15th rank) for 46 retarded and 50 normal Ss

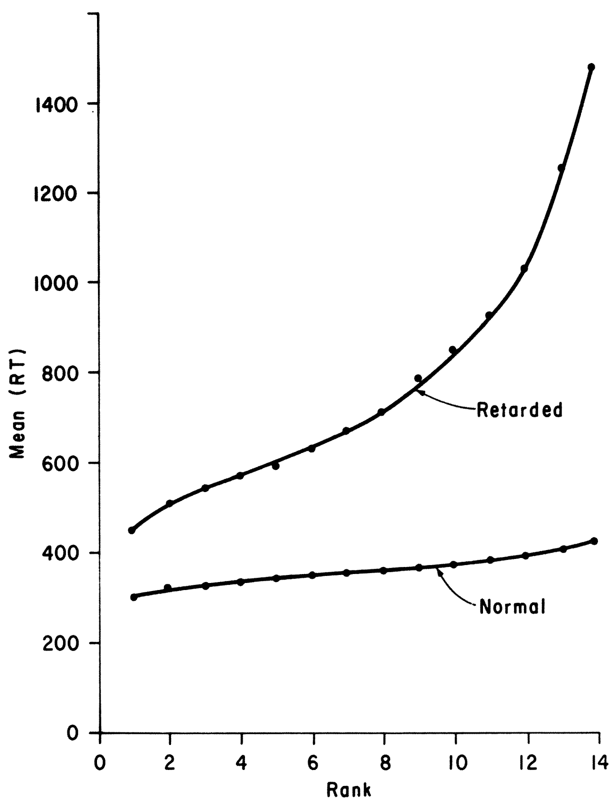

Fig. 19. Mean choice RT for 3 bits in the Hick paradigm, plotted after ranking each individual's RTs on 15 trials from the fastest to the slowest RT (omitting 15th rank) for 46 retarded and 50 normal Ss

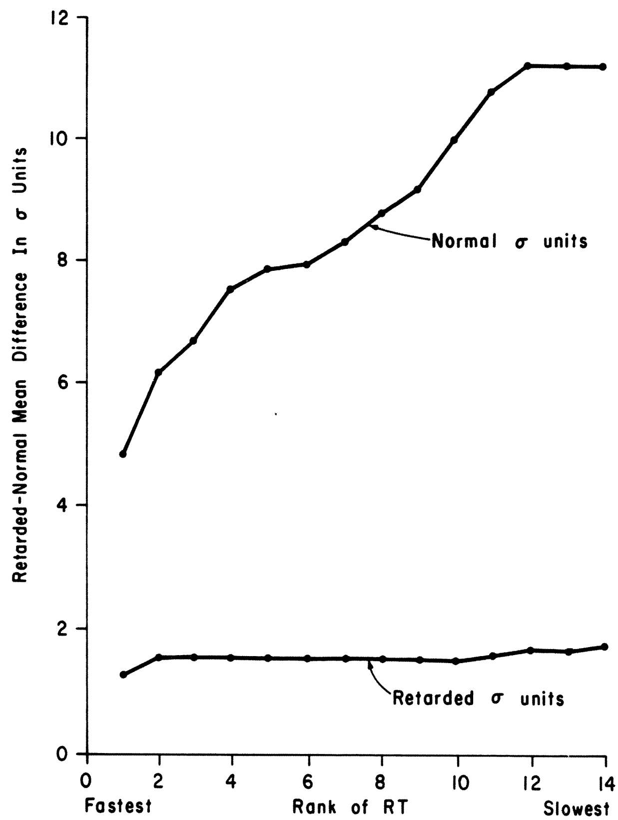

Fig. 20. The mean differences in RT between the retarded and normal groups at each rank, from fastest to slowest RTs in 15 trials, are here expressed in terms of each group's standard deviation (σ) at each rank

the Hick paradigm, using the RT – MT apparatus. Each S's RTs are rank ordered from the shortest to the longest in 15 trials. (The 15th rank is eliminated to get rid of possible outliers.) Figures 18 and 19 show the means of the ranked RTs to 0 and 3 bits, respectively, for 46 mildly retarded (mean IQ 70) and 50 bright normal young adults (mean IQ 120) given 15 trials at each level of bits. Even for simple RT, the retarded and normal groups differ by 111 ms on their fastest RT in 15 trials (rank 1); the normal group's *slowest* RT (rank 14) is 32 ms shorter than the retarded group's *fastest* RT. These differences becomes more exaggerated for choice RT involving 3 bits (i.e., eight light/button alternatives (Fig. 19), in which the fastest RTs of the retarded and normal groups differ by 142 ms.

These differences are seen to be quite substantial when viewed in terms of each group's standard deviation, i.e., in σ units, as shown for simple RT in Fig. 20. The *fastest* simple RT of the retarded and normal groups differs by 1.2 σ in terms of the retarded group's σ units and 4.8 σ in terms of the normal group's σ units.

These findings suggest that RT differences between persons who differ in *g* do not depend on complex cognitive processes, although RT differences are certainly amplified by increasing the complexity of the reaction stimulus, as can be seen in the overall difference between Fig. 18 (0 bit) and Fig. 19 (3 bits).

The S. Sternberg Short-Term Memory Scan Paradigm. This RT paradigm, invented by Saul Sternberg (1966), measures the S's speed of scanning his short-term memory for information. The S is shown a series of (usually 2–7) digits or letters (termed the "positive set") for several seconds. Then a

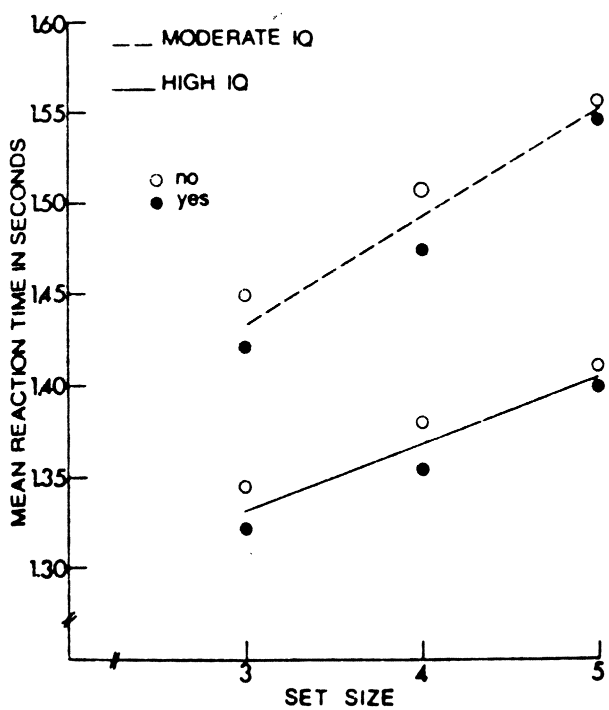

Fig. 21. Sternberg memory scan paradigm for groups of school children of moderate and high IQ, showing mean RT for determining presence ("yes") or absence ("no") of probe digit in sets of 3, 4, or 5 digits. McCauley et al. (1976)

single "probe" digit is presented. In a random half of the trials the probe digit is a member of the positive set. The S is required to respond as quickly as possible to the probe digit by pressing either a "yes" or a "no" button to indicate whether the probe was or was not a member of the positive set. RT increases linearly with size of the positive set. The fact that the ordinal position of the probe digit in the positive set has no effect on RT indicates that the scanning process is exhaustive, i.e., the S scans his memory of the entire list, regardless of where or whether the probe digit is found, although the RT is slightly longer for the absence of the probe digit than for its presence.

Several studies have shown a relationship between the intercept and slope of RT as a function of set size and mental test scores. McCauley et al. (1976), for example, applied the Sternberg paradigm to fifth and sixth grade children divided into two groups: moderate and high IQ, which yielded significantly different intercepts and slopes, as shown in Fig. 21. Keating and Bobbitt (1979) compared average and high IQ groups at ages 9, 13, and 17 years in the Sternberg paradigm, with the results shown in Fig. 22. The main effects of age,

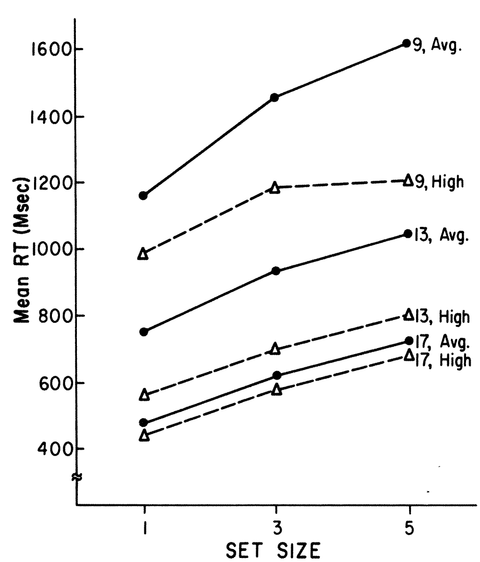

Fig. 22. Mean RT for each age/ability group as a function of number of digits in the memory set. Keating and Bobbitt (1978)

ability, and set size are all significant ($P<.001$), as is the interaction of set size and ability ($P<.05$), which accords with our generalization from the findings of simple versus choice RT and of the Hick paradigm that RT is increasingly correlated with *g* as a positive function of task complexity.

Stanford University students given the Sternberg task (Chiang and Atkinson 1976) showed much lower intercepts (about 400 ms) but showed about the same slope (i.e., a scan rate of 42 ms per digit in target set) as the high IQ children in the study by McCauley et al. (1976) (see Fig. 21) (with a scan rate of 40 ms per digit), whose IQs (with a mean of 126) are probably close to the IQs of the Stanford students. The moderate IQ group had a significantly greater slope (i.e., slower STM scanning rate) of 58 ms per digit. IQ would appear to be more crucial than mental age for short-term memory scan rate. This has interesting implications for scanning and rehearsal of information in STM to consolidate it into LTM. In terms of such a model, and in view of the observed differences in scan rates as a function of IQ, it should seem little wonder that high IQ persons in general know more about nearly everything than persons with low IQs. Snow et al. (1976) were able to "predict" the intercepts and slopes of the Sternberg memory scan paradigm for individual Stanford students, with multiple *R*'s of .88 and .70, respectively, using scores on several psychometric tests (in addition to sex). The intercept and slope parameters of the Sternberg scan, on the other hand, predicted each of four factor scores derived from a large battery of psychometric tests with *R*'s between .33 and .56. SAT-Verbal and SAT-Quantitative scores were predicted with *R*'s of .54 and .21, respectively. Remember, we are dealing here with the quite restricted range of ability in Stanford University students.

The Posner Long-Term Memory Access Paradigm. This paradigm, invented by Michael Posner (1969, Posner et al. 1969), is a measure of the time it takes a S to access a highly overlearned item of information stored in his long-term memory (LTM). The experimental procedure is based on the comparison of a S's discriminative RTs to pairs of stimuli which are the same or different either physically or semantically. For example, the letters AA are physically and semantically the same, whereas Aa are physically different but semantically the same. When Ss are instructed to respond "same" or "different" to the physical stimulus, RTs are faster than when Ss must respond to the semantic meaning. The physical discrimination is essentially the same as classical discriminative RT, but RT in the semantic discrimination involves access to semantic codes in LTM, which takes considerably more time than physical discriminative RT. The difference between semantic and physical RT thus measures access time to highly overlearned semantic codes in long-term memory.

Hunt (1976) reported the now classic experiment relating RT performance in the Posner paradigm to mental ability. Figure 23 shows these results for groups of university students who scored in the top (high) and bottom (low) quarters of the distribution of the verbal portion of the Scholastic Aptitude Test (SAT-V). AA represents the

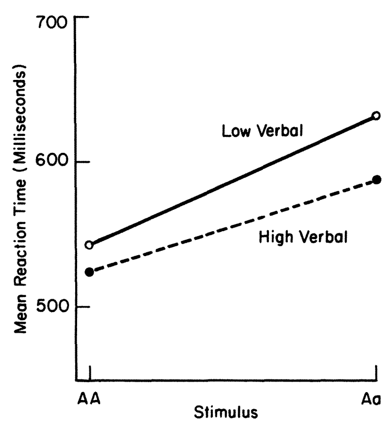

Fig. 23. Time required to recognize name identity (e.g., *Aa*) or physical identity (e.g., *AA*) of letter pairs by university students who scored in the upper (*High*) or lower (*Low*) quartile on the SAT-Verbal. Adapted from Hunt (1976, Table 1, p. 244)

physical identity choice (same-different) RT task; Aa represents the semantic identity task. University students require on the average about 75 ms more to respond to Aa than to AA types, which is the time taken by semantic encoding of the stimulus. Two features of Fig. 23 are particularly interesting in relation to findings from the Sternberg and Hick paradigms: (a) the high and low groups on SAT-V show a mean difference in RTs even on the physical, nonsemantic identity task, which is essentially just a form of classical two-choice discriminative RT; and (b) the average RT difference between AA and Aa (i.e., semantic encoding time) of 75 ms for Hunt's university students is exactly the same as the difference in RT between 0 and 3 bits of information in the Hick paradigm with university students.

Hunt's essential results with the Posner paradigm were replicated with children by Keating and Bobbitt (1978), who found significant ($P<.001$) interactions of task (physical [AA] versus semantic [Aa]) with both age and IQ level.

Unfortunately, no one has yet looked at intraindividual variability in the Sternberg and Posner paradigms or its correlation with g. Studies which will do so are presently underway in our laboratory.

The Nettelbeck Inspection Time Paradigm (see also Chap. 5). This method, first described by Nettelbeck and Lally (1976), measures the time required for a visual stimulus to be encoded in sufficient detail to permit a discriminative judgment. By means of a tachistoscope, the S is presented with a brief exposure of two vertical lines of markedly different length, followed by a backward masking stimulus. The S must then report whether the long line appeared on the right or the left, the position varying randomly from trial to trial. Inspection time (IT) is the duration of stimulus exposure for which the S's judgment is correct on at least 19 out of 20 trials. In highly heterogeneous groups of Ss ranging from the retarded to the gifted, correlations between IT and IQ are larger than $-.80$ (Nettelbeck and Lally 1976). Several studies that replicated this finding in small, intellectually heterogeneous groups have been reported by Brand (1979). In my laboratory, P.A. Vernon obtained a correlation of $-.31$ between IT and Raven's Advanced Progressive Matrices in a group of 25 university students – a highly restricted sample representing the top 10%–12% of high school graduates in scholastic apitude. When IT was combined with Hick paradigm RT$\bar{\sigma}_i$, the multiple R with Raven scores was .51, $P<.04$ (shrunken $R=.40$).

IT seems to reflect a very basic level of simple stimulus encoding similar to Spearman's (1927) first noegenetic law: the *apprehension* of experience. No *eduction* of relations or correlates is called for by the IT task. Yet it has shown remarkably high correlations with g-loaded tests in unrestricted samples. The correlation in a truly representative sample of the general population, however, remains to be determined.

Combination of Paradigms. It seems a reasonable hypothesis that these four pardigms reflect "mental speed" in each of several different systems – stimulus encoding, expectancy, scanning of short-term memory, retrieval of overlearned codes in long-term memory – and that each system contributes a unique component to IDs, in addition to a general factor in all of these variables. If this is true, and if the various cognitive systems represented by these paradigms are also operative in the much more complex information processing called for by psychometric tests, then we should expect that an optimally weighted combination of parameters derived from all four paradigms should show a much more substantial correlation with mental test scores than measurements derived from any one RT paradigm. This is exactly what Keating and Bobbitt (1978) found. Three RT-derived measures were obtained on each S: (1) choice RT minus simple RT, (2) semantic minus physical same/different RT to letter pairs (Posner paradigm), and (3) slope of RT on set size with sets of 1, 3, or 5 digits (Sternberg paradigm). The multiple *R* of these three measurements with Raven scores of 60 school children of average and superior IQ in grades 3, 7, and 11 was .59, .57, and .60 in the three grades, respectively. Higher correlations might be obtained if intraindividual variability were taken into account and if the correlations were corrected for attenuation, using the between-days test-retest stability coefficients. The average intercorrelation among the three paradigm measures was only .27, indicating that they are tapping different processes as well as sharing some variance in common.

If a substantial proportion of the true score variance in highly *g*-loaded psychometric tests can be "accounted for" by an optimally weighted combination of variables derived from these or other RT paradigms, it would warrant intensive investigation of the nature of IDs in these paradigms as the basis for developing an adequate theory of IDs in RT paradigms and their parameters. We are now pushing this attempt to the limit in our laboratory, using all of the previously described paradigms in combination to determine how much of the variance in psychometric *g* can be accounted for by means of these RT variables. The development of a theory of IDs in this realm, I venture, will be the essential first step toward developing a detailed theory of general intelligence. The inadequacy of the traditional and prevailing conceptions of intelligence is highlighted by the fact that they would not have predicted most of the phenomena and correlations with *g* found in the research with these several RT paradigms.

Toward a Theory of IDs in RT and *g*

Theoretical formulations of the RT phenomena I have described, and their relationship to psychometric *g*, will have to advance beyond the commonplace psychological explanations characterized by statements such as "the bright mind is the quick mind", and the like. Such generalizations, which usually are false as often as they are true, are of no help to understanding the details of the phenomena that our RT studies have revealed. Nor can we think in terms of a general "speed of work" factor which Ss bring to every kind of test or task in which they wish to excel. As I have already noted, there is often zero correlation between *g* and speed of test-taking when the test items are highly complex. Such general concepts cannot come to grips with the fine grain of the research findings relating RT to *g*, such as the correlation of *g* with intraindividual variability (σ_i), the increase in correlation between RT parameters and *g* as a function of the complexity or amount of information conveyed by the RS, Hick's law, and the systematic relationship between the σ_i of *simple* RT and the magnitude of the difference between the median of simple RT (0 bit) and two-choice RT (1 bit), and between two-choice RT and four-choice RT (2 bits), etc., in which the successive equal increments of RT as a function of information are approximately equal to the σ_i of simple RT. I believe that "easy" psychological "explanations" of these findings are suspect. If we invariably settle for an explanation of every new phenomenon in terms of a few simple and familiar psychological concepts, then the discovery and further investigation of new phenomena have no possibility of increasing our theoretical understanding of the nature of these phenomena, which virtually everyone agrees is inadequate. I also believe that adequate theoretical formulations will have to involve concepts at a molecular, neurophysiological level, rather than at just the conceptual level of psychological factors or cognitive processes.

A few well-established concepts and principles of cognitive psychology, however, afford a rationale for the importance of a time element in mental efficiency. The first such concept is that the conscious brain acts as a one-channel or *limited capacity* information processing system. It can deal simultaneously with only a very limited amount of information. The limited capacity also restricts the number of operations that can be performed simultaneously on the information that enters the system from external stimuli or from retrieval of information stored in short-term or long-term memory (STM or LTM). Speediness of mental operations is advantageous in that more operations per unit of time can be executed without overloading the system. Secondly, there is *rapid decay* of stimulus traces and information, so that there is an advantage to speediness of any operations that must be performed on the information while it is still available. Thirdly, to compensate for limited capacity and rapid decay of incoming information, the individual resorts to *rehearsal and storage* of the information into intermediate or long-term memory (LTM), which has relatively unlimited capacity. But the process of storing information in LTM itself takes time and therefore uses up channel capacity, so there is a "trade-off" between the storage and the processing of incoming information. The more complex the information and the operations required on it, the more time that is required, and consequently the greater the advantage of speediness in all the elemental processes involved. Loss of information due to overload interference and decay of traces that were inadequately encoded or rehearsed for storage or retrieval from LTM results in "breakdown" and failure to grasp all the essential relationships among the elements of a complex problem needed for its solution. Speediness of information processing, therefore, should be increasingly related to success in dealing with cognitive tasks to the extent that their information load strains the individual's limited channel capacity. The most discriminating test items thus would be those that "threaten" the information processing system at the threshold of "breakdown". In a series of items of graded complexity, this "breakdown" would occur at different points for various individuals. If individual differences in the speed of the elemental components of information processing could be measured in tasks that are so simple as to rule out "breakdown" failure, as in the several RT paradigms previously described, it should be possible to predict the individual differences in the point of "breakdown" for more complex tasks. I believe this is the basis for the observed correlations between RT variables and scores on complex *g*-loaded tests. But now we are in need of much more precise, fine-grained detail in our theoretical formulation of the phenomena than it seems cognitive theory presently has to offer.

Facts About RT with Theoretical Implications. I will here review some of the well-established findings about RT which seem to have the most suggestive implications for the development of a theory of IDs in RT and *g*. Most of these facts can be found in reviews of the effects of experimental variables on RT, such as the comprehensive chapter on RT by Woodworth and Schlosberg (1954).

1. IDs in RT are not specific to particular stimulus or response modalities. Correlations among a variety of RT procedures using different sense organs and response modes indicate that IDs in RT involve common central processes more than peripheral mechanisms. There is a substantial general factor of RT.

2. RT is related to the intensity of the reaction stimulus (RS) or the discriminability of a change in stimulation, a stronger RS producing faster RT. This suggests that the signal/noise ratio must rise above some threshold for response evocation and that increases in the signal/noise ratio (i.e., intensity of the RS) activates a greater number of the (neural) elements, increasing the probability, within a given interval of time, that the requisite threshold of neural activation will converge on the final common path for response evocation. The increase in the speed of RT as a function of RS intensity follows the Weber-Fechner law, i.e., the speed of RT increases as a linear function of the log of RS intensity. This implies a

model wherein each equal unit of increase in RS intensity activates a constant proportion of the remaining potential elements in the system that converge on the final common path, thereby monotonically increasing the probability, within a given interval of time, that the total amount of simultaneous activation will exceed the threshold for response. Increase in intensity of the RS thus makes for a negatively accelerated increase in speed of RT up to some maximum value which is limited by such factors as the activation times of sensory receptors, speed of neural conduction, muscular contractions, etc. These peripheral factors have been estimated to take up some 60–80 ms; processing in the central nervous system takes up a minimum of another 50 or 60 ms, thus making for an "irreducible minimum" RT of something between 100–150 ms. Variation in RT due to other conditions must be thought of as additions to this "irreducible minimum" of RT, hence the skewness of the distribution of RT for any individual. There are almost certainly reliable IDs in the "irreducible minimum" RT, but they are probably much smaller than IDs in the median RT under experimental conditions that add large increments to the irreducible minimum, such as an increase in the degree of uncertainty of the RS.

2. Intensity of the RS also decreases intraindividual variability (σ_i) in RT. This implies that as more elements are activated, the more "reliable" is response evocation within any interval of time. With more elements simultaneously converging on the final common path, the variance in time for reaching threshold will be reduced. If a critical number (n) of a pool of N activated elements, with random excitatory-refractory oscillations, must converge simultaneously to exceed a threshold for response evocation, the probability that n will occur within a given interval of time during which N oscillation elements are activated will increase as N increases. N is hypothesized to be a function of RS intensity.

The *area* and *duration* of a stimulus are also related to RT and RT σ_i, as both of these stimulus variables increases N, the number of activated neural elements. Because of rapid decay of the stimulus trace in the nervous system, duration of the physical stimulus becomes important by keeping N elements activated long enough for the critical N-element simultaneous activation to occur; its probability of occurrence in any interval of time decreases with a decrease in total activation, N, which falls off rapidly after the cessation of the RS. Thus, in effect, a RS of short duration is like a RS of weak intensity with respect to RT. Similarly, the *area* of stimulation affects the amount of neural activation.

These notions suggest a basis for IDs in (a) number of neural elements activated by a stimulus and (b) rate of oscillation of the excitatory-refractory phases of the activated elements. These two variables would most likely interact, because activation is transmitted throughout interconnected elements, each with a threshold of activation requiring simultaneous activation from some critical number (n) of other elements. The probability of their simultaneous convergence per unit of time would be directly related to the total number N of activated elements in the system and their rate of firing, i.e., their period of oscillation. I see oscillation as a basic concept here, not only because it is needed to help account for intraindividual trial-to-trial variability in RT, but because there are many other lines of evidence of oscillation or periodicity in the nervous system at different levels of neural organization, from refractory-excitatory oscillations in single neurones to brain waves in localized regions of the cerebral cortex involving millions of neurones, which implies a synchrony of action potential in large pools or networks of neurones. Oscillation is also a phenomenon at a chemical level; certain molecules and liquid crystals display regular rapidly oscillating structural changes over long periods. The hypothesis of IDs in the amount of hologramic neural "redundancy", i.e., the potential N of elements activated by an RS of a given intensity, area, and duration in a given sensory modality, and IDs in the rate of oscillation of activated elements (or in synchronized groups of elements) would seem to be a reasonable beginning point for the development of a theory of IDs in RT with implications for IDs in that proportion of *g* which may be shown to be correlated with RT parameters.

3. RT shows a number of interesting and theoretically suggestive parallels to phenomena in psychophysics. I have already mentioned that the relation of RT to RS intensity follows the Weber-Fechner law, which states that the increment in intensity of a stimulus necessary for a perceptible increment in sensation increases as the log of the level of stimulus intensity. Not only does the speed of RT increase as the log of RS intensity, but it decreases as the log of the number of alternatives among which the RS will occur, that is, Hick's law. There are fairly narrow boundary conditions for both the Weber-Fechner law and Hick's law, but the parallel within those conditions seems worth considering theoretically in terms of possible similar neural processes.

Just as we have found a positive correlation between IDs in simple RT (SRT) and the size of the increment in two-choice RT (CRT), the increment being median CRT minus median SRT, so, too, in psychophysics there is a positive correlation between the *absolute* threshold and the *difference* threshold, i.e., the smallest perceptible change in stimulus intensity.

As there is intraindividual trial-to-trial variability in RT, so, too, do sensory thresholds fluctuate from moment to moment. Some psychophysicists postulate an inherent Gaussian variability in thresholds and refractory periods of individual neural elements. Synchrony of individual units causes oscillation of larger groups, increasing the probability of simultaneous activation of some critical number of elements required for perceptible changes in sensation or for response evocation.

It is also interesting that momentary intraindividual *variability* in sensory discrimination is correlated with the increment in the physical stimulus needed to produce a j.n.d. (just noticeable difference) in sensation. In the Hick paradigm for RT, there is a close parallel between RT σ_i for simple RT(0 bit) and the *slope* of RT as a function of bits, i.e., the average increment in RT with each increment of information in the RS. Not only are these two variables correlated, but they are of about the same order of magnitude, as can be seen in Table 1. The correlations among the intercepts, the mean slope, and mean RT σ_i for these groups are shown in Table 2.

Table 1. Mean intercept, slope, and intraindividual variability (RT σ_i at bit) of RT in Hick paradigm for seven samples

Group	*N*	Intercept	Slope	RT σ_i at 0 bit
Mildly retarded adults	46	476.2	72.5	108.1
Elementary school children	162	305.9	39.2	42.6
Vocational college students	218	348.7	34.1	48.8
University students	25	306.4	28.4	32.3
University students	50	286.9	26.0	29.4
University students	105	305.2	30.7	32.0
University students	100	297.7	26.1	27.1
Mean of all univ. students	280	299.4	28.0	29.8

Table 2. Correlation[a] among group mean intercept, slope, and RT σ_i of the groups listed in Table 1

Variable	Intercept	Slope	RT σ_i at 0 bits
Intercept		.959	.988
Slope	.923		.987
σ_i at 0 bits	.965	.912	

[a] Above diagonal: all seven groups; below diagonal: five nonretarded adult groups

4. Choice RT increases as the physical similarity between the alternative RS increases, even when there is not the least subjective impression that changes in the degree of physical similarity of the two (or more) RS makes for any difference in their discriminability. For example, choice RS consisting of red versus yellow lights result in significantly longer choice RT than when the RS consists of red versus green lights, which are less similar than red and yellow in electromagnetic wavelengths. Presumably more similar stimulus energies produce greater overlap of excited neural elements converging on a final common path, which decreases the probability that the threshold of simultaneous activation needed for a correct discriminative reaction will be attained within a given interval of time. Greater redundancy and shorter refractory periods (i.e., faster oscillation) would increase the probability. This suggests an interesting and intuitively improbable theoretical prediction: a red-yellow choice RT task should discriminate more between high and low IQs than a red-green choice RT. (Of course there would have to be appropriate controls for stimulus intensity and color blindness, and it would be wise to use a variety of two-choice RS that differ in physical similarity). In this connection, we may recall that Spearman found that tests of pitch, brightness, and area discriminations are moderately *g* loaded (e.g. Spearman and Jones 1950, pp. 72–73, 119), and Binet included discrimination of weights as a part of his intelligence scale.

5. RT is an increasing function of the preparatory interval (PI), i.e., the interval between a "warning" or preparatory signal (PS) and the RS. This fact can be thought of in terms of the PI contributing directly to the uncertainty. Thus, even simple RT involves the uncertainty of precisely *when* the RS will occur, and Hick (1952) assumed that this uncertainty was equivalent to the increase in uncertainty resulting from one additional alternative in the number of RS. This assumption is, of course, a simplification, because we know that the amount of uncertainty as to the time of occurrence of the RS, as reflected in simple RT, varies as a function of the PI. But the fact that a PI of about 1–2 s is usually optimal for simple RT, and the fact that any shorter (or longer) PI results in longer RT, implies that there is some change in the S's "set" which facilitates RT and takes some time to attain optimal level following the PS. What, precisely, does this "preparatory set", as it is termed, consist of? A reasonable hypothesis is that it consists of a focusing or concentration (psychologically termed "attention", "alertness", or "expectancy") of the neural elements most relevant to the sensory-motor requirements of the task. Electromyograms reveal an increase in muscle tension during the PI. Also, there is a deceleration of heart rate during the PI, and mentally retarded persons show less deceleration than the nonretarded (Nettelbeck and Brewer 1981). The degree of expectancy as indicated by the increase in tension is reflected in the speed of the S's RT, although of course it is only one of a number of factors that affect RT. In *choice* RT, it seems reasonable to hypothesize, the expectancy is necessarily diffused over the two or more stimulus and response alternatives, which would reduce the redundancy of neural elements that are keyed on "ready" for any particular alternative. This might be compensated to some extent by an increase in the number of potentially activated elements involved in choice RT.

Schafer and Marcus (1973) have demonstrated a neurophysiological counterpart to expectancy, which they controlled by having Ss administer the stimulus, as contrasted to automatic presentation at random intervals, while the S's average evoked potential (AEP) to the stimulus was recorded. Self-stimulation, implying foreknowledge of the exact moment of arrival of the stimulus and hence a reduction in uncertainty, resulted in shorter latency and smaller amplitude of the AEP to both visual and auditory stimuli. The percentage reduction in amplitude under the self-stimulation condition as compared with a condition in which the subject has no control over the timing of the stimuli was termed the "self-stimulation effect". This measure, which indexes "neural adaptability", was found to be significantly related to level of intelligence, even showing a significant and striking difference between hospital technicians of average IQ and Ph.D. scientists. A subsequent larger study has further substantiated this general finding of a relationship between "neural adaptability" and psychometric intelligence. That is, people who gave larger than average evoked potentials to unexpected stimuli and smaller than average EPs to stimuli whose timing they knew as the result of self-stimulation tend to have higher IQs (Schafer 1979). A later study showed significant correlations between the "neural adaptability" measure, parameters of the RT − MT Hick paradigm, and *g* factor scores derived from a battery of 15 psychometric tests (Jensen et al. 1981). Schafer is now recording S's AEPs at the same time that Ss perform on our RT − MT apparatus. It appears that the latency of the AEP follows Hick's law, as does RT. There is undoubtedly a fairly close connection between the latencies of evoked potentials and RTs. Kutas et al. (1977) have reported correlations of +.48 and +.66 (under different conditions) between choice RT and the simultaneously recorded P300 component of the brain potential evoked by the RS. Interestingly, the P300 latencies were slower than the RT, except on the relatively few RT trials that Ss made an erroneous choice, in which case the P300 evoked potential was faster than the RT.

6. Although sense organs have analog characteristics, their output to the brain is apparently filtered through a series of "logic gates" and end up in digital form. Neurones are binary processors, i.e., they are capable of being either "on" or "off", "go" or "no go". Therefore it should not be surprising if the speed of information processing by the brain showed a binary ratio characteristic, as exemplified by Hick's law, i.e., $RT = \log_2 n$, where n is the number of alternatives of the RS. It should be noted that Hick's law is not merely peculiar to human Ss in RT experiments, but has also been demonstrated in pigeons (Blough 1977).

I have not found any attempt in the literature to explain the fact that the S Sternberg short-term memory scan paradigm yields RTs which are a linear function, not of $\log_2 n$, but simply of n, i.e., the number of *items* (not bits) in the memory set that the *S* must mentally scan. This, too, is not just peculiar to humans, but has been found to hold also for monkeys (Eddy 1973, as described by Riley 1976). My hypothesis is that the difference in outcomes between the Hick and Sternberg paradigms depends on the nature of the RS. In the Hick paradigm, the occurrence of any one of the RS alternatives immediately "rules out" all the other alternatives, and the search is ended as soon as the RS and its corresponding response are classified in this binary manner, a greater number of alternatives (n) merely taking longer as a linear function of $\log_2 n$. In the Sternberg paradigm, however, the search process (to find whether the probe digit is or is not in the memory set) requires the scanning of each single item in the series. RT data for comparable Ss in the Hick and Sternberg paradigms suggest that the same amount of time (about 30 ms for college students) is required for each *item* of the memory set in the Sternberg paradigm as is required for each *bit* of information in the Hick paradigm.

7. There is a negatively accelerated decrease in RT and in RT σ_i from early childhood up to the late teens. The form of the curve, which is a typical growth curve, is consistent with the hypothesis that some constant proportion of a limited number of undeveloped or dormant neural elements gradually becomes functional during each year of the developmental period. It is hypothesized that this growth consists of an increase in redundancy of functional neural elements, which hence increases the probability, in any unit of time, of there being simultaneously enough active elements to exceed the threshold for response. Decrease

in response latencies during the developmental period occurs in rats as well as in humans (Woodworth and Schosberg 1954, p. 36).

In humans, the decrease in RT and RT σ_i throughout the developmental period is paralleled by a decrease in the intraindividual variability of latency of the visual and auditory evoked potential (Callaway 1975, pp. 36–42).

The biological basis of these age effects is hypothesized to be the body of evidence from developmental neurophysiology which indicates that the maturing mammalian brain shows an increase in both functional capacity and the complexity of neurones (Conel 1939–1963). Although the human brain contains all the neurones it will ever have at the time of birth, the myelination of cortical nerve fibers, on which neural conductance depends, is far from complete at birth, and takes place gradually throughout the entire period of physical growth. The typical negatively accelerated growth curve would result from an approximately constant proportion of the unmyelinated neurones becoming myelinated each year.

A Model for RT in the Hick Paradigm

Hick (1952) discussed various possible types of "search" processes to find one that would best explain the phenomenon now known as Hick's law. His theoretical speculations seem obscure, which is perhaps inevitable at this stage. He stated, "With regard to the mechanism responsible for these results, speculation about neural networks is outside its present scope. There is no objection to trying to depict schematically the component operations, but it must be admitted that what analysis of the data has been carried out does little more than draw attention to the difficulties involved in finding any simple scheme" (p. 20). The model Hick proposed gave a good fit to some aspects of the data, such as the mean RT at each level of bits, but not to other aspects, such as the variances of RT at each level of bits.

The main feature of the Hick model is dictated by the necessity for hypothesizing a type of "search" process which can be thought of as successive dichotomization of the total number (n) of stimulus elements to be searched, a type of central "search" process which, on average, would take $\log_2 n t$ amount of time, where t is the time required for a single element. (This is equivalent to bits $\times t$.) I put "search" in quotes, because the RT situation does not seem to call for a search in the ordinary sense of the term. What the "search" in the Hick paradigm seems to consist of is the resoluton of uncertainty. The greater the uncertainty as to the RS, the greater the "search" (a central brain process) required for resolution, i.e., reduction of the uncertainty to zero. Why such "search" should fit a model of successive dichotomizations, each taking an equal amount of time, is not known. All that can be said at present is that this seems to be the way the nervous system operates.

Given this basic search model proposed by Hick, I have speculated about possible mechanisms that could account for the main *average* features of the RT data, as well as for IDs in these features, derived from the RT – MT apparatus. Explication of the hypothesis is facilitated by reference to Fig. 24, which depicts the dichotomizing or binary resolution of uncertainty, as measured in bits. The n choices or alternatives in the physical stimulus array can be thought of as being isomorphically represented in the neural network of the cerebral cortex. The dots in Fig. 24 represent focal points or nodes of excitation which will fire when a critical level of stimulation is reached. The number of aroused or primed nodes in the RT task corresponds to the number of alternatives in the array of RS. I hypothesize that the level of excitation at each node *oscillates*, so that half of the time the node is refractory. (The actual number of neurones involved in each node is unim-

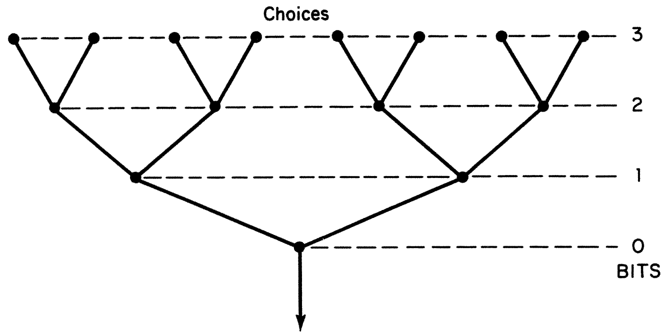

Fig. 24. Hierarchical binary tree illustrating the dichotomizing search process and the relationship of the number of choice elements to bits

portant at this point.) Above-threshold stimulation of a node at any given level (bits) is transmitted (downward in Fig. 24) through the chain of nodes to the final common path for response. For example, a RS which is one element of eight possible alternatives will excite one of the eight nodes (in top row of Fig. 24) to discharge, and the discharge will be transmitted to the final common path via three intervening nodes (at the levels of 2, 1, and 0 bits). When the RS is one of four alternatives, the excitation would be transmitted via only two intervening nodes. And so on.

The amount of time it takes to respond to the RS (over and above the irreducible minimum RT, which is attributable to peripheral sensory-motor mechanisms) hence will depend essentially on two factors: (a) the number of levels in the chain through which the excitation must be conducted, and (b) the average period of oscillation of the transmitting nodes. Excitation, of course, is not transmitted by a refractory node. Volleys of stimulation must persist until the node is excitable. The refractory phase of the oscillation at the node is the chief source of time delays in the system. IDs in the rate of oscillation would cause IDs in RT. Oscillation would also cause variability in RT from trial to trial, because the onset of the RS is random with respect to the refractory and excitatory phases of the oscillation, and we assume that the phase of oscillation of a node at any point in the chain is random with respect to the phase of any other node. Stimulation of a node at one level thus may or may not be delayed by the phase of oscillation of every other node in the chain. We have assumed for simplicity that the refractory and excitatory phases are of equal duration. The probabilities that simulation will pass through n nodes with 0, 1, 2, 3, etc. delays due to impulses arriving during refractory phases at each node conform to the binomial distribution. If p and q are the refractory and excitatory phases, respectively, and if $p=q$ and $p+q=1$, then the coefficients of the expansion of $(p+q)^n$, where n is the number of nodes in the chain, indicate the relative frequencies of there being $0, 1, 2, \ldots, n$ equal delays in a chain of n nodes. The average length of each delay will be half the time of the refractory phase of the oscillation cycle. (Speed of nerve impulses in individual neurones is so fast as to be a negligible factor in this model.) Because of the uncertainty of when the RS will occur even for simple RT, we will assume that the excitation leading to response evocation must traverse n nodes, where n is equal to bits + 1. Thus the distribution of relative frequencies of the number of delays that occur in any chain of n nodes, and the means, standard deviations, and variances of these distributions are shown Table 3. Various characteristics of these theoretical distributions can be compared with the corresponding characteristics of actual RT data obtained in the Hick paradigm using the RT−MT apparatus. It should be understood that RT is a linear function of the number of delays at the n nodes in the chain transmitting the excitation set off by the RS and leading to the response.

Table 3. Hypothetical (binomial) relative frequency distribution of time delays due to oscillation of excitatory nodes as a function of bits of information

Number of delays	Bits of information			
	0	1	2	3
0	.50	.25	.125	.0625
1	.50	.50	.375	.2500
2		.25	.375	.3750
3			.125	.2500
4				.0625
Mean	.50	1.00	1.50	2.00
σ_i	.50	.71	.87	1.00
σ_i^2	.25	.50	.75	1.00

First, note that the means in Table 3 increase as a linear function of bits, in accord with Hick's law.

Second, the σ_i of delay (=.50) at 0 bits is equal to the constant increment (=.50) in the mean delay resulting from each additional bit. (This constant increment, of course, is the slope of the Hick function.) This, too, accords with our finding that the RT σ_i at 0 bits is approximately the same absolute value as the slope of RT as a function of bits. In a samle of 280 university students, for example, the mean RT σ_i and the mean slope were 29.81 and 28.01, respectively and the correlation between IDs in these variables is almost as high as their reliabilities will permit. (Also see group comparisons in Table 1.) It is theoretically most interesting, although possibly just coincidental, that the mean critical flicker fusion (CFF) threshold in a sample of 100 of our university population is 30 Hz (i.e., 30 cycles per second), which is a light/dark cycle of 33.4 ms duration – a value remarkably close to the RT σ_i and slope of RT in this population. In terms of our bionomial oscillation model, the RT σ_i and slope of RT are equal to one-half the refractory phase of the average oscillation at a single node. It is also noteworthy that in this sample of 100 university students, there is a significant correlation ($r = +.25$, 1-tailed $P < .01$) between IDs in CFF and RT σ_i. It seems a reasonable hypothesis that the CFF threshold, that is, the rate of light/dark flicker at which subjective fusion occurs, cannot be less than about half the length of the refractory phase of the Ss rate of neural oscillation. The "neuronal filter" cannot detect a succession of stimuli as discrete if they occur at a much faster rate than the rate of neural oscillation, just as a sieve cannot screen out any mixture if the largest particles of the mixture are smaller than the sieve's finest mesh.

Third, the theoretically derived σ_i increases as a function of bits, as does intraindividual variability (RT σ_i). So far, so good. But beyond this, the simple binomial oscillation model falters. For one thing, the model's σ_i increases at a *negatively* accelerated rate as a function of bits, whereas we have found that actual RT σ_i increases in a positively accelerated fashion. A typical set of RT data, from 160 pupils in grades four to six, are plotted in Fig. 25, showing the mean RT and RT σ_i as a function of bits. The straight line and the curve are the empirically best fitting functions of the mean RT and RT σ_i, respectively.

Now, we can also fit these data to our theoretical model, which dictates that the slope of mean RTs should be equal to RT σ_i at 0 bits, and which generates RT σ_i at each level of bits. Figure 26 shows the straight line and the curve generated by the binomial oscillation model, along with the actual data points. The fit of the mean RTs to the model, of course, is very good, but the fit of RT σ_i is quite unsatisfactory – essentially the difference between a negatively (model) and positively (data) accelerated curve. In this one important specific point the binomial model fails. Could it be the case that the RT data in this particular sample ar simply anomalous with respect to RT σ_i? Before faulting the model, it would pay to look at other samples. Figures 27 and 28 show the model and data points for 218 vocational college students and 180 university students, respectively. Clearly, for both samples the discrepancy between the model-

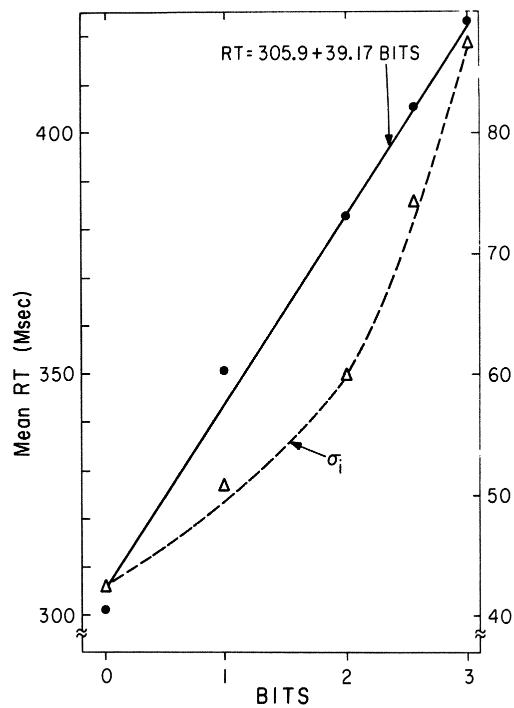

Fig. 25. Mean RT and mean σ_i of RT (i.e., mean intraindividual variability) as a function of bits in 160 pupils in grades four to six. (Note that RT and σ_i are plotted on different scales [both in milliseconds], indicated or the left and right vertical axes, respectively.)

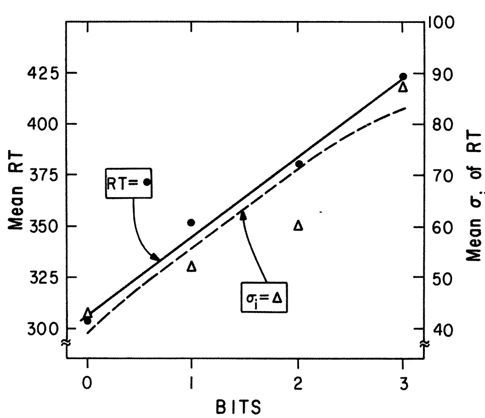

Fig. 26. The data of Fig. 25 are here fitted to the model, indicated by the straight line (predicted mean RTs) and the curve (predicted RTσ_i). Note the model's poor fit to the data points for the obtained mean RTσ_i

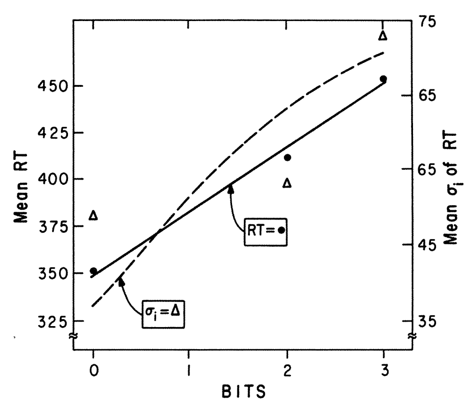

Fig. 27. RT data and predictions of mean RT and RTσ_i from binomial model (*straight line* and *curve*) for 218 vocational college students

predicted RT σ_i and the corresponding obtained values shows essentially the same difficulty as was found in the elementary school sample.

One other deficiency of this model is that it generates a symmetrical distribution of RTs at each level of bits, instead of the skewed distribution of RTs that is actually found for an individual tested on many trials. A simple but purely ad hoc improvement of the model that would produce any desired degree of skewness would be to assign unequal values to the p and q (corresponding to the relative durations of the ex-

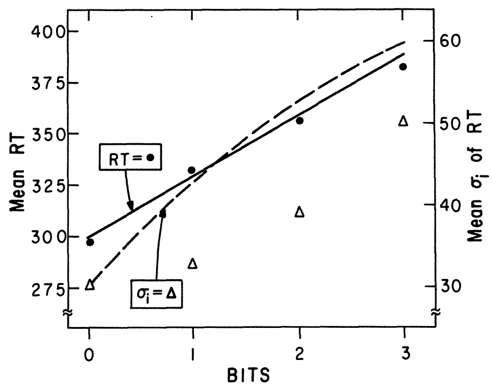

Fig. 28. RT data and predictions of mean RT and RTσ_i from the binomial model (*straight line* and *curve*) for 180 university students

citatory and refractory phases of oscillation) in the binomial equation, for example, $p=.75$ and $q=.25$. Although this ad hoc artifice will create the required skewness of the distribution of RTs, it does not cure the model's problem of negatively accelerated RT σ_i as a function of bits. Attempts so far to remedy this defect are so ad hoc as to seem unconvincing. The solution may lie in the incorporation of redundancy into the basic model, with different, and hopefully better fitting, frequency distributions being generated by *multiples* of the binary tree such as that in Fig. 24, each tree having nodes with the same frequency of oscillation, but with unsynchronized oscillations. The frequencies of refractory delays, then, would be determined by the joint action of two or more such binary trees receiving the same initial input and converging in a probabalistic fashion to exceed the excitation threshold for response. The detailed statistical implications of such a model can perhaps best be derived through computer stimulation, which we are planning to do.

Surely, the development of a mathematical-neurological model that will generate all of the specific parameters of the RT data so clearly yielded by the Hick paradigm is a priority item on the future agenda of research on the nature of IDs in RT and the mechanism of their relationship to general intelligence.

References

Baumeister AA, Kellas G (1968a) Reaction time and mental retardation. In: Ellis NR (ed) International Review of Research in Mental Retardation, vol 3. Academic Press, New York, pp 163–193

Baumeister AA, Kellas G (1968b) Distribution of reaction times of retardates and normals. Am J Ment Defic 72:715–718

Baumeister AA, Kellas G (1968c) Intrasubject response variability in relation to intelligence. J Abnorm Psychol 73:421–423

Berkson G, Baumeister AA (1967) Reaction time variability of mental defectives and normals. Am J Ment Defic 72:262–266

Blough DS (1977) Visual search in the pigeon: hunt and peck method. Science 196:1013–1914

Brand C (1981) General intelligence and mental speed: their relationship and development. In: Friedman MP, Das JP, O'Conner N (eds) Intelligence and Learning. Plenum Press, New York, pp 589–593

Callaway E (1975) Brain electrical potentials and individual psychological differences. Grune & Straton New York

Chiang A, Atkinson RC (1976) Individual differences and interrelationships among a select set of cognitive skills. Mem Cogn 4:661–672

Conel JL (ed) (1939–1963) The postnatal development of the human cerebral cortex. vol 1–4. Harvard University Press, Cambridge MA

Eddy DR (1973) Memory processes in Macaca speciosa: mental processes revealed by reaction time experiments. PhD disertation, Carnegie-Mellon University

Elliott CD, Murray DJ (1977) The measurement of speed of problem solving and its relation to children's age and ability. Br J Educ Psychol 47:50–59

Eysenck HJ (1967) Intelligence assessment: a theoretical and experimental approach. Br J Educ Psychol 37:81–98

Fitts PM (1954) The information capacity of the human motor system in controlling the amplitude of movement. J Exp Psychol 47:381–391

Galton F (1883) Inquiries into human faculty and its development. Macmillan, London

Galton F (1908) Memories of my life. Methuen, London

Gilbert JA (1894) Researchers on the mental and physical development of school-children. Stud Yale Psychol Lab 2:40–100

Hick W (1952) On the rate of gain of information. Q J Exp Psychol 4:11–26

Hunt E (1976) Varieties of cognitive power. In: Resnick LB (ed) The nature of intelligence. Erlbaum, Hillsdale NJ pp 237–259

Hyman R (1953) Stimulus information as a determinant of reaction time. J Exp Psychol 45:188–196

Jensen AR (1979) *g*: Outmoded theory or unconquered frontier? Creat Sci Tech 2:16–29

Jensen AR (1980) Chronometric analysis of mental ability. J Soc Biol Struct 3:181–224

Jensen AR (1982) The chronometry of intelligence. In: Sternberg RJ (ed) Advances in research on Intelligence, (vol 1. Erlbaum Hillsdale NJ, pp 242–267

Jensen AR, Munro E (1974) Reaction time, movement time, and intelligence. Intelligence 3:121–126

Jensen AR, Schafer EWP, Crinella FM (1981) Reaction time, evoked brain potentials and psychometric *g* in the severely retarded. Intelligence 5:179–197

Keating DP, Bobbitt B (1978) Individual and developmental differences in cognitive processing components of mental ability. Child Dev 49:155–169

Kutas M, McCarthy G, Donchin E (1977) Augmenting mental chronometry: the P300 as a measure of stimulus evaluation time. Science 197:792–795

Lally M, Nettelbeck T (1977) Intelligence, reaction time, and inspection time. Am J Ment Defic 82:273–281

Lemmon VW (1927) The relation of reaction time to measure of intelligence, memory, and learning. Arch Psychol 15:5–38

Libet B (1965) Cortical activation in conscious and unconscious experience. Perspect Biol Med 9:77–86

Libet B, Alberts WW, Wright EW Jr, Feinstein B (1971) Cortical and thalamic activation in conscious sensory experience. In: neurophysiology studied in man. Procedings of a symposium, 20–22 July, 1971. Excerpta Medica, Amsterdam, pp 157–168

Liebert AM, Baumeister AA (1973) Behavioral variability among retardates, children, and college students. J Psychol 83:57–65

McCauley C, Dugas J, Kellas G, DeVellis RF (1976) Effects of serial rehearsal training on memory search. J Educ Psychol 68:474–481

Merkel J (1885) Die zeitlichen Verhältnisse der Willensthätigkeit. Philos Stud 2:73–127

Nettelbeck T, Brewer N (1981) Studies of mental retardation and timed performance. In: Ellis NR (ed) International review of research in mental retardation, vol 10. Academic Press, New York, pp 97–125

Nettelbeck T, Lally M (1976) Inspection time and measured intelligence. Br J Psychol 67:17–22

Peak H, Boring EG (1926) The factor of speed in intelligence. J Exp Psychol 9:71–94

Posner MI (1969) Abstraction and the process of recognition. In: Bower GH, Spence JT (eds) The psychology of Learning and Motivation, vol 3. Academic Press, New York, pp 43–100

Posner MI, Boies S, Eichelman W, Taylor R (1969) Retention of visual and name codes of single letters. J Exp Psychol 81:10–15

Riley DA (1976) Comments on Simon's paper, and some observations on information processing in animals. In: M.R. Rosenzweig MR, Bennett EL (eds) Neural mechanisms in learning and memory. MIT Press, Cambridge MA, pp 224–229

Roth E (1964) Die Geschwindigkeit der Verarbeitung von Information und ihr Zusammenhang mit Intelligenz. Z Exp Angew Psychol 11:616–622

Schafer EWP (1979) Cognitive neural adaptibility: a biological basis for individual differences in intelligence. Psychophysiology 16:199

Schafer EWP, Marcus MM (1973) Self-stimulation alters human sensory brain responses. Science 181:175–177

Shannon CE, Weaver W (1949) The mathematical theory of communication. University of Illinois Press, Urbana IL

Snow RE, Marshalek B, Lohman DF (1976) Correlation of selected cognitive abilities and cognitive processing parameters: an exploratory study. Technical Report 3, aptitude research project. School of Education Stanford University, Palo Alto CA

Spearman C (1927) The abilities of man. Macmillan, New York

Spearman C, Jones LLW (1950) Human Ability. Macmillan, London

Spiegel MR, Bryant ND (1978) Is speed of processing information related to intelligence and achievement? J Educ Psychol 70:904–910

Sternberg RJ (1977) Intelligence, information processing, and anological reasoning: the componential analysis of human abilities. Erlbaum, Hillsdale NJ

Sternberg S (1966) High speed scanning in human memory. Science 153:652–654

Vernon PA (1981) Reaction time and intelligence in the mentally retarded. Intelligence 5:345–355

Wade MG, Newell KM, Wallace SA (1978) Decision time and movement time as a function of response complexity in retarded persons. Am J Ment Defic 83:135–144

White PO (1973) Individual differences in speed, accuracy, and persistence: a mathematical model for problem solving. In: Eysenck HJ (ed) The Measurement of Intelligence. Williams & Wilkins, Baltimore, pp 246–260

Wissler C (1901) The correlation of mental and physical tests. Psychol Rev Monogr 3:

Woodworth RS, Schlosberg H (1954) Experimental psychology. Holt, Rinehart and Winston, New York