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Reaction Time and Intelligence: A Replicated Study

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Two samples of adult subjects of reasonably average intelligence were given IQ tests and a series of RT tests using 0, 1, 2, and 3 bits of information in a Hick paradigm. Both series showed negative correlation between IQ on the one hand, and RT and σRT, on the other, confirming earlier work. On the other hand, there was no evidence of correlation between the Hick slope and IQ, and the correlation between IQ and RT or σRT did not increase from 1 to 3 bits of information. It was found that the Hick paradigm did not apply to some 20% of the samples, and that the exclusion of these nonconformists increased the correlation between IQ and RT/σRT.

The suggestion of Galton (1883) and Cattell (1890) that RT measures might provide a good index of mental ability was apparently disproved by Wissler (1901) in a study whose methodological inadequacies were not realized at the time (Jensen, 1982a). Interest in the theory was revived when Roth (1964), using Hick's Law (Hick, 1952; Hyman, 1953) found a significant negative correlation between psychometric intelligence (*g*) and the slope resulting from the logarithmic increase in RT with increase in the number of choices in the choice RT paradigm. This finding gave rise to the extensive investigation and theorizing of the Erlangen School described by Eysenck (1985) and exemplified in the writings of Franck (1971), Lehrl (1983), and Oswald (1971). In the U.S.A., Jensen (1980, 1982b) inaugurated a similar but independent set of investigations and theories (Jensen & Munro, 1979; Jensen, Schafer, & Crinella, 1981; Vernon, 1981, 1983) which has since been extended by many other workers (e.g., Carlson & Jensen, 1982; Carlson, Jensen, & Widaman, 1983; Jenkinson, 1983; Smith & Stanley, 1983).

In addition to simple and choice RT, investigation has centered on inspection time (IT), a technique pioneered by Burt (1909) with considerable success, but used more lately by Lally and Nettlebeck (1980), Nettlebeck (1982), Nettlebeck & Kirby (1983), Nettlebeck & Lally (1976) and reviewed, together with original

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works, by Brand and Deary (1982). Other developments of RT works, linking it with short-term (Sternberg, 1966) and long-term (Posner, Boies, Eichelman, & Taylor, 1969) memory, are described by Jensen (1982a, 1982b) and more recent experiments reported by Todman and Gibb (1985), Paul (1984) and Anada (1985).

Jensen's work in particular has aroused much criticism (Carroll, in press; Longstreth, 1984), as has work on IT (Irwin, 1984); the work of the Erlangen School has escaped criticism in part because it has not come to the notice of English-speaking psychologists. Such criticisms are partly aimed at experimental paradigms, partly at choice or unrepresentative subject groups (students, retarded persons), and partly at statistical manipulations and interpretations.

On the theoretical side, both Jensen and the Erlangen School stress the function of the cortex as a *limited-capacity* channel of information processing. This limited capacity restricts the amount of incoming information (from external stimuli); it limits the number of operations that can be performed simultaneously on this information; and it restricts the amount of information that can be retrieved from short-term or long-term memory. Thus the model places great emphasis on the *speed* of mental operations, slowness leading to accumulating cognitive handicap (Eysenck, 1967, 1985; Jensen, 1982a; Lehrl, 1983). Such a theory predicts and requires negative RT-g correlations of reasonable magnitude, and as RT duration is logically linked with RT variability (intraindividual *SD*), it requires a negative RT variability-g correlation. The interest of the work so far reported lies in the support it would seem to give such a theory which relates directly to the concept of biological intelligence (Intelligence A in Hebb's, 1949, and Vernon's 1979, terminology). IQ measures, on the other hand, would seem to be related more to social intelligence (Intelligence B). Eysenck and Barrett (1985) and Eysenck (1979, 1982, 1985) have discussed these differences in some detail.

The published evidence suggests that IQ correlates with (1) Simple RT, (2) Choice RT, (3) Movement time (MT), (4) Hick slope, (5) Variability of RT, (6) IT, (7) Sternberg STM RT, and (8) Posner LTM RT (Jensen, 1982a, 1982b; Eysenck, 1985). Not all experiments, however, have given positive results. Thus Bieger (1968) found only an insignificant correlation between Hick slope and the Amthauer (1955) Intelligenz-Struktur-Test (IST); Schmidtke (1961) and Amelang (1985) failed to discover increases in correlation between RT and IQ with increase in *bits* of information; Irwin (1984) failed to find correlations between IT and IQ; and even as far as positive results are concerned, Carroll (in press) and Longstreth (1984) have severely criticized important aspects of the methodology and statistical analysis employed. Of particular concern is the unrepresentative nature of many of the samples tested; the variances of the IQ measures used were usually either much *lower* or much *higher* than those of standardization groups, and corrections for range were usually made to correct observed correlations only upwards, not downwards. Finally, experimental details have been criticized, especially by Longstreth, but as Eysenck (in press) has pointed out, the purposes of experimentalists and psychometrists are not necessarily identical, and this will determine the methods used.

The present study was carried out to test some of the suggested relationships on two separate samples of adult subjects with WAIS IQ scores whose distributions (*SD*s) were close to normal, and where no retarded persons were included in the sample. Our main concern was with the relation of IQ with simple RT, choice RT, σRT, Hick slope, and the suggested increase in correlation with increase in bits of information. Also of interest was the applicability of Hick's Law to individual subjects, published studies usually deal with its applicability to groups. Two separate samples of over 40 subjects each were used to test for replicability of observed correlations. It was hoped in this way to obtain some reliable estimate of the true correlation between IQ and the various RT measures; for this, clearly, a properly selected sample with approximately the same mean and *SD* as the general population is required.

Also of interest was the relationship between RT and personality, and the possibility of using personality variables as suppressor variables. There is a good deal of evidence that IQ and personality may not be unrelated, although usually in an inverted-U manner (e.g., Brebner & Cooper, 1974; Chatterji & Mukerjee, 1983; Eysenck, 1943; Eysenck & White, 1964; Gray & McLean, 1973; Gupta, 1977; Lynn & Gordan, 1961; Mohan & Kumar, 1973, 1974, 1976, 1979; Turner & Horn, 1977). There is little literature on the relation between personality and RT (e.g., Cromwell, Rosenthal, Shakav, & Zahn, 1961; Hummel & Lester, 1977; Nuechterlein, 1977; Thomson, 1985), but this relationship is of interest also, in view of the correlation between impulsivity and the three major divisions of personality (Eysenck, 1981; Eysenck & Eysenck, 1985). The possibility cannot be ruled out that certain aspects of RT may be related to personality functions.

For the interpretation of data, the results from Carlson et al. (1983) pertaining to the test–retest reliability of the RT measures are most relevant. If the observed correlation between RT and IQ is .50 (which is a reasonable estimate of published data, corrected for excessive or deficient range of IQ), and the retest reliability of RT around .6, then the "true" correlation is in the neighborhood of .70. Obviously corrected values of this kind are of no practical use, but they do assume considerable importance in theoretical discussions of the weight to be attributed to simple speed of reaction in producing differences in IQ.

THE STUDY

Subjects

Two groups of subjects provided reaction time and psychometric test data. The testing of the first group of subjects finished 2 months before testing was begun on the second group.

The first group, SAMPLE 1, consisting of 26 male and 14 female subjects, were volunteers from the local government unemployment bureau and from within the Institute of Psychiatry. The age range for the males was from 19 to 36 years, with a mean age of 23.92 and *SD* of 4.15 years. The age range for the females was from 18 to 39 years, with a mean age of 26.29 and *SD* of 8.30 years. Each subject also took part in an EEG experiment, followed by the Jensen paradigm, the completion of the Eysenck Personality Questionnaire (Eysenck & Eysenck, 1975) and I_7 (Impulsivity, Venturesomeness, Empathy—Eysenck, Pearson, Easting, & Allsopp, 1985) questionnaire, and finally was administered the total WAIS intelligence test.

The second group, SAMPLE 2, consisting of 22 male and 24 female subjects, was recruited via an advertisement placed in a leisure magazine circulated within the London area. The age range for the males was from 19 to 39 years, with a mean of 27.52 and *SD* of 6.77 years. The age range for the females was from 21 to 44 years, with a mean of 28.21 and *SD* of 7.16 years. SAMPLE 2 subjects carried out only the reaction time task, in addition to providing responses on the EPQ and I_7 questionnaires. A short version of the WAIS test was administered to these subjects in order to reduce the overall testing time for the entire measurement session. The particular short version used was that provided by Silverstein (1982), using the four subtests of Vocabulary, Arithmetic, Picture Arrangement, and Block Design. The estimated Full Wais IQ was shown to correlate .95 with Full Wais IQ computed on the WAIS-R 1970 standardization sample (Wechsler, 1981).

Apparatus

All experimental control, stimulus presentation, and data acquisition were controlled by an ACT SIRIUS 1 microcomputer. Signal priming, detection, and timing in ms were implemented via a BIODATA MICROLINK unit encompassing modules RR8 (8 channel reed relays), CC8 (8 channel digital inputs), and TIM (timing/clock module providing ms units). The EPQ and I_7 were administered using the SIRIUS computer. The Jensen arrangement of lights and buttons was copied exactly from the measurements and descriptions given in Eysenck (1982).

Procedure

Following the exact details of the Jensen paradigm, RTs were assessed over 4 conditions of 0, 1, 2, and 3 bits of decision information. This corresponds to 1, 2, 4, and 8 lights on show, respectively. The order of the conditions was fixed in order to increasing task complexity. Twenty trials were given on each condition with a short (1-min) rest between conditions. Covers were placed over lights not required on any one condition. The subject was tested in the same room in which the investigator and equipment were housed. The subject was seated in front of the response box, using his/her preferred hand for button pressing. He/she could not see the computer monitor at all. Since all light switching, stimulus presentation, and clock control were electronic, no auditory or visual cues were given to the subject prior to any stimulus or trial. The subject was given as many practice trials as requested until confidence in the task was expressed. The subject began the experiment with his/her finger placed on the "home" button—keeping it depressed. The following sequence describes the acquisition process:

1. A warning tone of 1000 Hz frequency and 54 ms duration was presented at approximately 70 dB SPL by the SIRIUS computer. The delay between the immediately preceding response and the next warning tone and stimulus presentation was random within the interval of 1 to 4 s. Each subject had a different randomized sequence of intervals for each condition.

2. Following the warning tone and appropriate delay, a light was illuminated in one of the possible positions depending upon the operative condition. Simultaneous with light onset was clock onset. The subject made a response by pressing the appropriate button underneath the light and turning it off. The act of releasing the "home" button in order to press another button stopped the clock, thus giving RT exclusive of MT (movement time). The particular button pressed to switch the stimulus light off was also recorded for error analysis.

3. The subject, having made a response, returned his/her finger to the "home" button and the sequence was repeated. Throughout this sequence, the investigator monitored the acquired RTs on the computer. All RT testing was carried out between 9:30 a.m. and 4:30 p.m. for each subject. The EPQ and I_7 were computer administered, with forced YES/NO responses. The order of the items was as on the respective questionnaires.

Statistical Analysis

RTs acquired throughout the 4 conditions were processed using a variety of statistics:

1. Using simple linear regression on the number of uncovered lights within each condition (x) and the RTs recorded (y). In addition, the median y response for each condition was regressed onto x lights.
2. Using simple linear regression on the number of bits of information within each condition ($\log_2 x$) and the RTs recorded (y). In addition, the median y response was regressed onto $\log_2 x$.
3. Using simple linear regression on $\log_2 x$ and $\log_e y$ RTs. In addition, the median $\log_e y$ response was regressed onto $\log_2 x$.
4. Using simple linear regression on $\log_2 x$ and arcsin y. In addition, the median arcsin y response was regressed onto $\log_2 x$.
5. Mean intraindividual variability (σRT), defined as the mean of the standard deviations of RTs computed over each condition.
6. Using simple linear regression within each condition, regressing the RT on each trial over trial sequence number. This was computed in order to

examine how subjects performed within each condition: whether previous trials tended to have an effect on later trials by either increasing or decreasing the RTs. Assuming linearity, such differences in performance would be encoded by the slope parameter of the regression function.

All regressions provided slope and intercept parameters, in addition to the percentage variance (%fit) explained by the regression function. The form of the least squares regression equation was:

$$y' = a + bx$$
and
$$y' = a + b\log_2 x$$

where x = the *n* of lights. Percentage variance explained by the regression function was simply the squared value of the correlation coefficient (the coefficient of determination).

The reason for the $\log_e$ and arcsin transformations of the RTs was simply to provide a check on the untransformed RT data. If, as both Brownlee (1975) and Winer (1971) indicate, the distribution of RTs is likely to be positively skewed, then using these two transformations would provide some help in determining the likely amount of error introduced into statistical calculations using untransformed RTs. For example, should the %fit of a regression model using a transformed RT data set be much better than that using the untransformed RTs, then it would be reasonable to adopt the transformed RT data sets for all subsequent statistical analyses. The data validity was checked by the analysis program such that if an RT was less than 140 ms or greater than 999 ms, the RT was replaced with the mean RT for the appropriate condition. (The mean RT was calculated exclusive of such outliers.)

Two sets of the above statistics were computed: one set based upon data as collected and passed through the validity check only (the uncorrected set); the other based upon data where, for each condition, the largest RT was replaced with the mean RT for the appropriate condition (exclusive of previously defined outliers and the largest value). This second set will be called the corrected set. This was an objective method for correcting excessively long RTs that sometimes occurred within a subject's data, the long RT assumed to be due to a lapse in concentration during a particular trial.

Finally, the information provided by the analysis program also included the Mean, Median, Variance, Standard Deviation, maximum and minimum RTs, and the number of incorrect button presses per condition. This information was provided for both the corrected and uncorrected data. Since the Jensen paradigm has not yet been replicated in a thorough and exhaustive manner, more measures than those actually used by Jensen were taken. The purpose of these extra data was to enable us to examine the measures used by Jensen in the wider context of alternative or theoretically better measures. The complete set of measures used may be obtained from the authors upon request. Only those that carry some theoretical import or are of sufficient empirical significance will be analyzed and discussed here.

All correlations reported here were *not* corrected for IQ variable range restriction nor were they corrected for RT or IQ test unreliability.

RESULTS

With regard to the use of the corrected versus uncorrected data (see the preceding Statistical Analysis section), examination of means, medians, and correlations between RT speed parameters and IQ, and between the corrected versus uncorrected data sets revealed negligible differences in parameter values and cross-relationships. For example, the uncorrected median RTs for the four conditions correlated greater than .99 with their respective corrected values in both samples of data. However, the uncorrected measures of RT variability were less similar to their corrected data versions, correlations ranging from .75 to .99. The corrected and uncorrected data in SAMPLE 2 were more similar to each other than were those in SAMPLE 1. Nevertheless, to maintain direct comparability with the Jensen data, only the uncorrected data are used for the results presented here.

Jensen (1982, p. 101) has indicated that the median RT per condition is the most appropriate measure of speed of a subject's performance within the paradigm. As a simple check on whether the arithmetic mean or median RTs might be equally appropriate, we compared the two values across the first 10 subjects, the first 20 subjects, and on the total 86 subjects from both samples. Figure 1 presents the results for this analysis.

As can be seen, the mean and median RTs become more similar in slope as the number of subjects increases. However, the difference between the mean and median RT in our data remains around 25 ms on the first and fourth conditions, while on the second and third conditions, it remains less than 12 ms. The %fit of the regression of *mean* RT on the number of bits of information for these 3 sets of data was 78.2%, 88.6%, and 94.7%, respectively. The %fit of a linear regression of *median* RT on the number of bits of information for the 3 sets of data was 96.4%, 97.8%, and 99.2%, respectively. Given the importance assigned to Hick's Law by Jensen, the median parameter does appear to be the optimal choice with regard to the discussion of the lawful properties of choice RTs (at least within our own data). Hence, all RTs used in all the analyses reported below are median responses within each of the task conditions. The reaction times are thus directly comparable to Jensen's reaction times.

From examination of the %fit values of each of the regressions using the two transformations of the RT variable, the simplest model that explained an optimum level of variance was that computed using $\log_2 x$ and untransformed median RTs. The difference in %fit between the untransformed versus trans-

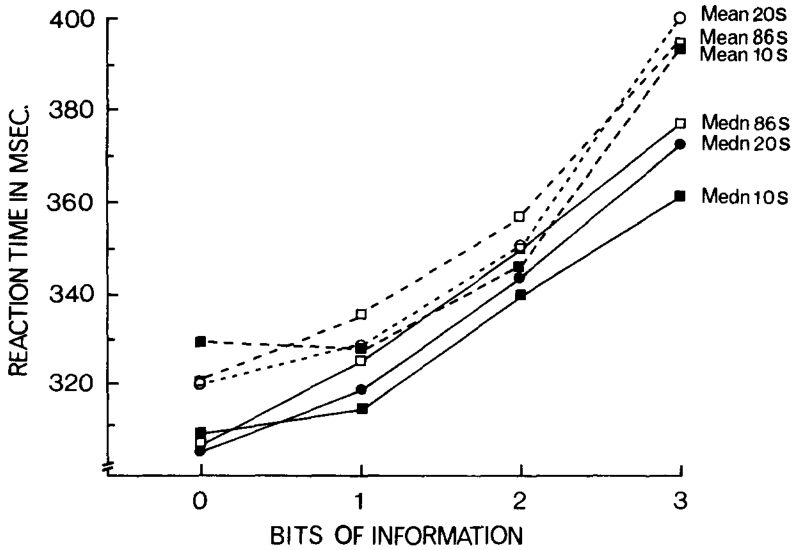

FIG. 1. Comparison of the Arithmetic mean RT with the median RT

formed RT regressions was never more than about 0.1% to 0.5% in favor of the $\log_e$ RT transform. (Computing the mean %fit for all subjects in SAMPLE 2 data yielded a mean %fit value of 72.47% using nontransformed RTs, while the value for the $\log_e$ transformed RT data was 72.59%.) Thus, the RT data presented here use the same measurement scale as Jensen's RT data.

With regard to the correlational results presented here, all significance tests involving the relationship between IQ and RT variables will be directional at the one-tailed level. All such correlations are expected to be negative.

For reference purposes, Table 1 presents the mean, standard deviation and minimum and maximum values for the relevant RT data and WAIS subtests for both samples of data.

Section 1. RT Performance–Speed

Correlating median RTs for each condition of 0, 1, 2, and 3 bits of information with the 5 possible WAIS scores yielded several significant correlations, mainly confined to SAMPLE 1. Table 2 presents these results. It is important to note that where correlations from either sample of data are significant, the alternative sample coefficient at least tends to share the sign of that value. The lower values for SAMPLE 2 may be due to the lower *SD* of the IQ scores for that sample.

For SAMPLE 1 data with 1 and 38 degrees freedom (*t* distribution), a correlation equal to or larger than ±.27 and ±.37 would be significant $p < .05$ and $p < .01$, one-tailed, respectively. SAMPLE 2 data with 1 and 44 degrees of freedom, a correlation equal to or larger than ±.25 and ±.35 would be signifi-

TABLE 1
Means and *SD*s of the Uncorrected Total Sample Data

Variable	Mean	*SD*	Minimum	Maximum
SAMPLE 1 (*N*=40)				
AGE	24.75	6.13	18.00	49.00
0 BITS RT	298.19	36.16	225.00	420.50
1 BIT RT	317.40	29.80	268.50	370.50
2 BITS RT	346.84	36.02	276.50	423.00
3 BITS RT	379.96	41.33	301.50	501.50
SLOPE	27.48	12.90	−6.15	56.05
INTERCEPT	294.38	33.51	237.65	397.85
%FIT	84.18	19.44	9.77	99.92
0 BITS *SD*	47.50	26.06	15.28	133.01
1 BIT *SD*	42.51	17.89	17.70	95.37
2 BITS *SD*	41.64	14.81	20.60	99.01
3 BITS *SD*	84.77	39.69	18.47	159.98
σRT	54.10	15.80	26.13	95.05
FULLWAIS	105.23	18.99	61.00	134.00
VERBAL	104.43	18.22	61.00	142.00
PERFORMANCE	104.35	18.50	62.00	144.00
VOCABULARY	10.25	3.17	2.00	15.00
COMPREHENSION	10.60	3.37	3.00	16.00
INFORMATION	10.73	3.75	2.00	18.00
DIGIT SPAN	10.28	2.98	2.00	17.00
SIMILARITIES	10.20	3.11	1.00	15.00
ARITHMETIC	10.58	3.09	4.00	17.00
PICTURE COMPL.	10.03	2.66	3.00	14.00
PICTURE ARRNG.	9.90	2.79	5.00	17.00
OBJECT ASSY.	10.83	3.41	2.00	18.00
BLOCK DESIGN	11.70	3.11	4.00	19.00
DIGIT SYMBOL	10.10	3.04	4.00	16.00
SAMPLE 2 (*N*=46)				
AGE	27.72	6.90	19.00	44.00
0 BITS RT	315.80	41.78	251.50	420.00
1 BIT RT	331.85	36.87	258.00	420.50
2 BITS RT	352.86	43.00	275.00	485.00
3 BITS RT	375.48	44.49	279.00	515.50
SLOPE	20.00	12.73	−16.95	42.00
INTERCEPT	313.99	39.85	259.60	415.25
%FIT	72.47	25.84	0.00	99.86
0 BITS *SD*	53.63	25.50	23.12	131.13
1 BIT *SD*	46.57	22.35	22.46	143.75
2 BITS *SD*	45.87	13.46	23.79	96.69
3 BITS *SD*	71.32	35.93	24.69	148.09
σRT	54.35	15.61	32.48	98.23
FULLWAIS	106.57	13.18	76.00	142.00
VOCABULARY	11.24	2.46	6.00	17.00
ARITHMETIC	10.61	2.92	6.00	17.00
PICTURE ARRNG.	9.63	3.21	5.00	17.00
BLOCK DESIGN	11.76	3.13	5.00	19.00

cant $p < .05$ and $p < .01$, one-tailed, respectively (given all coefficients reported have been rounded to 2 decimal places, the significance "values" have been conservatively rounded to reflect this slight error). Overall, the data in Table 2 clearly indicate a *negative* correlation between RT and IQ as expected, but with consistently higher and more significant coefficients for SAMPLE 1 as compared with SAMPLE 2. There is no increase in correlations as we go from 1 to 2 and 3 bits of information, contrary to Jensen's (1982a) findings. In comparison with the figure presented by Lally and Nettlebeck (1977), plotting RT ×

TABLE 2
Median RT × WAIS Correlations Using the Total Sample Data

VARIABLE	FULLWAIS	VOCAB	ARITHM	PICTARRNG	BLOKDESN
0 BITS RT	−.32*	−.19	−.06	−.38**	−.35*
	−.14	.01	−.23	−.02	−.20
1 BIT RT	−.41**	−.28*	−.10	−.44**	−.48**
	−.21	−.07	−.37**	.02	−.19
2 BITS RT	−.45**	−.36*	−.21	−.42**	−.48**
	−.19	−.13	−.36**	.04	−.16
3 BITS RT	−.40**	−.25	−.12	−.32*	−.43**
	−.15	−.03	−.32*	.03	−.11

VARIABLE	VERBAL TOTAL	PERFORMANCE TOTAL	INFORMATION	DIGIT SPAN
0 BITS RT	−.27*	−.32*	−.23	−.22
	–	–	–	–
1 BIT RT	−.35*	−.42**	−.35*	−.28*
	–	–	–	–
2 BITS RT	−.39**	−.47**	−.31*	−.29*
	–	–	–	–
3 BITS RT	−.29*	−.46**	−.26	−.23
	–	–	–	–

VARIABLE	COMPREHENSION	SIMILARITIES	PICTURE COMPLETN	OBJECT ASSY.	DIGIT SYMBOL
0 BITS RT	−.29*	−.23	−.21	−.27*	−.23
	–	–	–	–	–
1 BIT RT	−.41**	−.25	−.20	−.33*	−.36*
	–	–	–	–	–
2 BITS RT	−.44**	−.30*	−.28*	−.36*	−.47**
	–	–	–	–	–
3 BITS RT	−.34*	−.11	−.31*	−.38**	−.42**
	–	–	–	–	–

Note. The upper values are for SAMPLE 1, the lower values for SAMPLE 2.
* = Significant $p < .05$ one-tailed
** = Significant $p < .01$ one-tailed

IQ correlation against the number of bits of information, our results above are in obvious disagreement with their significant correlations of −.56, −.64, and −.74 for 1, 2, and 3 bits of information, respectively.

Jensen (1982b) reported a significant ($p < .01$) correlation of −.41 between Ravens Advanced Progressive Matrices and RT slope (from the regression of median RTs on the number of bits of information). This has not been replicated here. The highest correlation in our data between RT slope and the 5 WAIS scores was −.15. Correlating median RTs for each condition of 0, 1, 2, and 3 bits of information with the scores on the personality scales yielded no statistically significant correlations at all.

The slope computed from regressing the RT on each trial-against-trial sequence number for each condition was correlated with both the 5 WAIS scores and the median RTs for each condition. This slope parameter was used as an indicator of whether a subject's performance within a particular condition was affected by the preceding trials. If learning was taking place, we would expect this parameter to be negative. There was only one statistically significant correlation at the $p < .05$ two-tailed level. However, it was of marginal value and was not even closely replicated in the alternative sample. Therefore, the effect (linearly increasing or decreasing tendency) of prior RTs on preceding RTs within each condition does not appear to be related significantly to intelligence as assessed by the 5 WAIS scores. The range of the slope parameter within both samples of data was from positive to negative values. A positive slope value for a subject indicating longer duration RTs being produced toward the end of a condition.

Finally, the correlation of age with the median RTs and the WAIS scores yielded only three marginally signifcant correlations at the $p < .05$ two-tailed level. For SAMPLE 1, age correlated .35 and .32 with the 0-bit median RT and 1-bit median RT, respectively (the alternative sample values were −.03 and −.04, respectively). For SAMPLE 2, age correlated with the Block Design subtest −.38, with the corresponding SAMPLE 1 value of −.15.

Section 2. RT Performance–Variability

The results within Section 2 examine the relationships between performance variability and IQ, age, and personality. Variability in the RTs within each condition was assessed by using the standard deviation (*SD*) of the 20 trials as a descriptive parameter. In addition, the σRT (mean of the four *SD*s) was computed. This parameter is defined by Jensen as the mean intraindividual variability. The values for the significance levels of the correlations are the same as those used in the examination of the speed parameters. Correlations between the 5 WAIS test scores and the four *SD*s for each condition, the σRT parameter, and the %fit parameter are presented in Table 3.

The correlations are nearly all in the negative direction, as expected, but this time, unlike in Table 2, the trend is for higher coefficients for SAMPLE 2 in

TABLE 3
RT Variability × WAIS Correlations Using the Total Sample Data

VARIABLE	FULLWAIS	VOCAB	ARITHM	PICTARRNG	BLOKDESN
0 BITS *SD*	−.23	−.23	−.23	−.19	−.15
	−.40**	−.24	−.33*	−.15	−.36**
1 BIT *SD*	−.07	−.03	−.00	−.31*	−.18
	−.17	−.15	−.27*	−.05	−.12
2 BITS *SD*	−.33*	−.22	−.28*	−.39**	−.49**
	−.28*	−.20	−.42**	.05	−.22
3 BITS *SD*	−.16	.05	−.07	−.18	−.20
	−.20	−.00	−.19	−.27*	−.03
σRT	−.29*	−.12	−.21	−.37**	−.35*
	−.40**	−.19	−.43**	−.23	−.25*

VARIABLE	VERBAL TOTAL	PERFORMANCE TOTAL	INFORMATION	DIGIT SPAN
0 BITS *SD*	−.25	−.19	−.14	−.17
	–	–	–	–
1 BIT *SD*	−.01	−.14	−.14	.14
	–	–	–	–
2 BITS *SD*	−.26	−.37**	−.29*	−.13
	–	–	–	–
3 BITS *SD*	−.10	−.15	−.07	−.15
	–	–	–	–
σRT	−.23	−.30*	−.20	−.16
	–	–	–	–

VARIABLE	COMPREHENSION	SIMILARITIES	PICTURE COMPLETN	OBJECT ASSY.	DIGIT SYMBOL
0 BITS *SD*	−.21	−.24	−.21	−.19	−.07
	–	–	–	–	–
1 BIT *SD*	.01	−.00	−.11	−.05	−.01
	–	–	–	–	–
2 BITS *SD*	−.29*	−.23	−.28*	−.42**	−.15
	–	–	–	–	–
3 BITS *SD*	−.11	.12	−.14	−.21	.04
	–	–	–	–	–
σRT	−.22	−.08	−.27*	−.32*	−.04
	–	–	–	–	–

Note. The upper values are for SAMPLE 1, the lower values are for SAMPLE 2
* = Significant $p < .05$ one-tailed
** = Significant $p < .01$ one-tailed

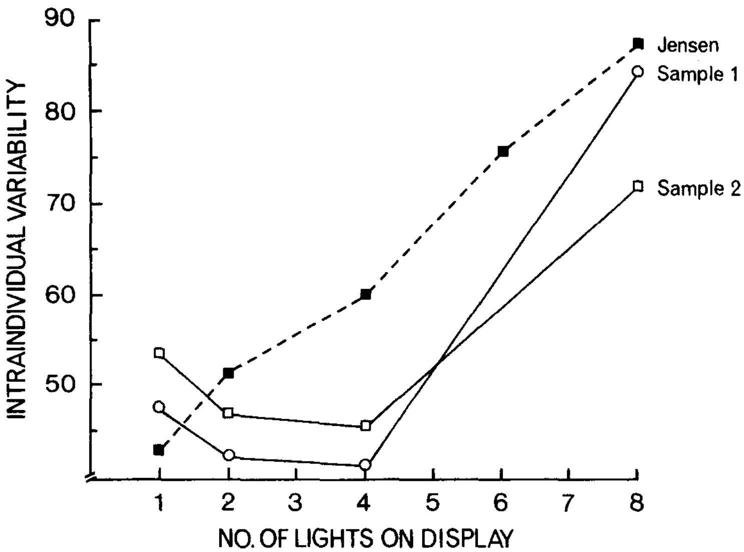

FIG. 2. Intraindividual variability as a function of lights on show

comparison with SAMPLE 1. Jensen (1982a) has indicated that plotting the *SD* of RTs against the number of lights on show for each condition results in an almost perfectly linear function. Inspection of Figure 2 below indicates that our data do not replicate the Jensen results. The Jensen data plotted in Figure 2 are drawn from 160 fourth- to sixth-grade schoolchildren using 30 trials per condition.

Correlating the *SD* of RTs for each condition of 0, 1, 2, and 3 bits of information, σRT, and %fit, with the scores on the personality scales yielded only 6 significant correlations out of the 84 computed (using a two-tailed, significance test at the $P < .05$ level). While none of these six values were replicated statistically significantly in the respective alternative-sample data, the correlation of Venturesomeness with the 3-bit *SD* and σRT parameters was fairly suggestive of a possible relationship. For SAMPLE 1, these correlations were $-.23$ and $-.39$, respectively; for SAMPLE 2, these values were $-.31$ and $-.21$, respectively. Finally, the correlation of age with the *SD*s of RTs, σRT, and %fit yielded no statistically significant correlations at all.

Overall, few of the relationships expected from Jensen's work were replicated here. While some of the results were suggestive of the negative relationship of RT, RT variability, and IQ, the slope of the regression of RTs on bits was found not to be correlated at all with the WAIS scores. Although SAMPLE 1 data provided more statistically significant and generally higher valued correlations, SAMPLE 2 data tended toward lower, if same-sign, values. Superficially, it would appear that the two samples of data have not produced consistently high valued correlations where expected. However, Section 3 provides possible reasons for this apparent disparity and demonstrates that the RT paradigm is capable of eliciting enduring, replicable, and psychologically meaningful, measures.

Section 3. The Psychometry of the Jensen Paradigm

(a) Correcting Outlier RTs. In the first paragraph of "Results," we discussed the use of corrected versus uncorrected data values. In order to maintain strict comparability with the Jensen results, we used uncorrected data throughout. However, this is not particularly sensible. As inferred earlier, the main effect of removing the highest RT within a condition and replacing it with the mean RT for that condition, for each subject, is to reduce the overall variability of the data. This is borne out by observing the mean of the *SD*s of corrected and uncorrected RT data within each condition and σRT parameters. Within the two samples of data, the *general* effect of this correction is increased-size correlations between the variability parameters and IQ, albeit few of the increased values become statistically significant. Obviously, the main reason for making such corrections is to remove outliers from each subject's range of RTs from each condition. With some subjects, the identification of an outlier is simple. Where all but one RT within a condition range from 270–480 ms, say, an observed value of 980 ms is quite clearly unexpected. If we observe the same RT range, but find our highest RT at 500 ms, this value would be unlikely to be defined as an outlier. Given that the cost of including "outliers" is enlarged variance parameters computed across the specific condition RTs; and given the apparent generalized increase in conceptually significant correlations (those between variability and the WAIS IQ scores) using the corrected data variability parameters, it makes a great deal of sense to remove the "unexpected" values. As with all data where outliers are removed, controversy exists as to the validity of altering observed data values. To assert that any change must be wrong because we are tampering with the data precludes any recognition of identifiable response errors. If the subject simply fails to attend to a trial, and responds up to four times as slowly as any other of his RTs within one condition, the researcher can make one of two choices: (a) This response includes error time due to inattention to the task and (b) this response is representative of the subject's overall performance, regardless of how unexpected it might seem within the total observed range; as such, it is a valid measure. We have opted for the first choice on the basis of the benefits of increased correlations. This suggests that these extraordinary RTs can be viewed as "true value" RTs corrupted by excessive "error," as in classical test theory. Section 4 provides inferential evidence and a more fundamental framework wherein performance variability is viewed as a crucial parameter in the Jensen choice-reaction-time paradigm.

Before going straight into Section 4, it is as well to examine the specific assumptions of the correction algorithm adopted for our two samples of data. We simply removed all highest value RTs in each condition and replaced them with the mean of the RTs (the calculation of the mean excluded the highest value). While this is a simple but efficient algorithm, it is probably not the most accurate method of removing objectively defined outliers. The definition of an outlier depends upon mainly arbitrary criteria, in addition to the number of trials within any one condition. However, given the use of our algorithm, the cost of removing all highest value RTs meant that some probable valid values would have been removed and replaced with the lower mean value. While the cost of this effect is trivial with regard to the median or mean RTs, the effect does significantly alter the variability measures. Conceivably, to increase the correlation between the variability measures and IQ, it could be hypothesized that this correction was having a systematic directional effect on the data. If IQ was correlated with the size of variance disparity between uncorrected and corrected parameter values, then it could be inferred that high- and low-IQ subjects were performing differentially with regard to the size of the highest RT values. Specifically, subjects scoring higher on the WAIS scales would be producing greater value outliers than those scoring lower. Assuming an underlying negative relationship between response variability and IQ (as inferred from our data as well as Jensen's), the effect of a large reduction in variance in higher score subjects and a small reduction in lower score subjects would be to increase negativity in the observed correlations. Alternatively, if the variability parameters are inflated by error independent of the IQ of the subjects, then the hypothesized relationship between RT-performance variability and IQ should be marginally increased in the negative direction (as reported earlier). That is, we are assuming that our algorithm is not inadvertently inducing or creating a systematic bias within our data.

We subsequently examined our data for evidence of algorithm-induced artifact. Using the five main measures of performance variability, the *SD*s of RTs within each condition and the σRT parameter, the corrected parameter values were subtracted from the uncorrected values, and these difference values correlated with the 5 WAIS scores. Using the appropriate significance values given above, with both samples of data, there were no statistically significant replicated correlations. That is, there was no relationship found between size of correction and IQ. In order to ascertain the size of correction within a higher FULLWAIS scoring subgroup compared to a lower scoring subgroup, the data from the two samples were combined, giving a total sample size of 86. These data were split into two groups: one of 31 subjects where everybody scored 99 or under and the other of 55 subjects scoring 100-plus on the FULLWAIS range. Means and *SD*s for the 5 difference values were computed for these two groups; all differences were nonsignificant $p < .05$ two-tailed using a simple t test with 84 degrees of freedom. The splitting of the groups was not perhaps the optimum separation into high- versus low-IQ subgroups, but, given the low number of subjects with FULLWAIS scores less than 90 or so, even the marginal generalizability of the above result would have been forgone. *For all the following analyses, the corrected data are used throughout.*

(b) Hick's Law–the Empirical Bases. Within our data, it was apparent that not all subjects could be said to fit Hick's Law, that is, the linear increase in RT as a function of the number of bits of information. In two samples of data, Jensen (private communication) quoted mean %fit parameters as 88% (*SD* of 16%) for a sample of 224 young adults, and 94% for a sample of 160 schoolchildren. For our data, SAMPLE 1 had a mean %fit of 85% with *SD* of 19% while SAMPLE 2 had a mean %fit of 74% with *SD* of 25%. From inspection of these comparative figures, it is obvious that our data are not comparable in "lawfulness" to those of Jensen.

If we assume that Hick's Law is an enduring psychophysical law, with certain expected properties observable within the Jensen paradigm, then the only data that could be expected to test these properties are those that fit it. As with the many psychophysical law assessments, some individual variation is expected, but overall, fit to a particular numerical function with "fixed" parameter values is generally obtained. In those cases where fit is not observed to occur, either the subjects are found to have a specific defect in the particular sensory mode under examination or they usually indicate their inattention to the task. *It is proposed here that failure to fit Hick's Law is a consequence of inattention to the task.* Primarily, this failure is assumed to be evident in excessive variability of RTs in any one or more conditions. If this hypothesis is correct, then we would expect that:

Hypothesis 1. Fit to Hick's Law is independent of IQ.

Hypothesis 2. Subjects who do not fit Hick's Law have significantly larger measures of variability than those who fit the model (*SD*s of RTs within each condition).

Hypothesis 3. The appropriately edited data from both our samples (excluding non-fitting subjects) should demonstrate replicability of IQ × RT and *SD* relationships in addition to near-equal intercept and slope median RT versus bits of information regression values.

Hypothesis 4. Our edited data should be comparable to Jensen's published data.

Before launching into the specific analyses required by these four tests, the problem of deciding a criterion for fit to Hick's Law has to be tackled. Given that we are discussing fit to a model, defined in terms of a linear function, the obvious criterion is our %fit parameter, that is, the % variance accounted for in the regression of median RT on the number of bits of information. However, as to the lowest acceptable value, choice of a parameter value is somewhat arbitrary. In order to gain some insight as to the likely effects of restricting the %fit parameter to a value above a minimum bound, three functions were plotted for each of 5 subsamples of data extracted from a combined SAMPLE 1 + SAMPLE 2 dataset ($N = 86$ subjects). The reason for combining the samples here was due to the low number of subjects encountered in the high %fit subgroups—we required at least 30 subjects in any one group to ensure some stability of correlational values. The 5 subgroups were composed using lower-bound fit constraints of 50%, 60%, 70%, 80%, and 90%. The three functions plotted were: first, the three correlations between FULLWAIS, ARITHMETIC, BLOCK DESIGN, and σRT (these three correlations were consistently the maximum RT × IQ correlations within all 5 subgroups); second, the *SD*s of the RTs within each condition versus the number of lights on display in each condition; and third, the median RTs on each condition versus bits of information. The choice of these three functions was, of course, completely heuristic although quite relevant to the problem at hand; that is, to determine the %fit parameter that encompassed a maximum number of subjects while sequentially minimizing parameter discrepancy.

The results from the analysis indicated that the *SD*s of RT and the median RTs changed very little within the 5 subgroups. The 50% group was marginally different on both these function plots. However, the first plot of the three correla-

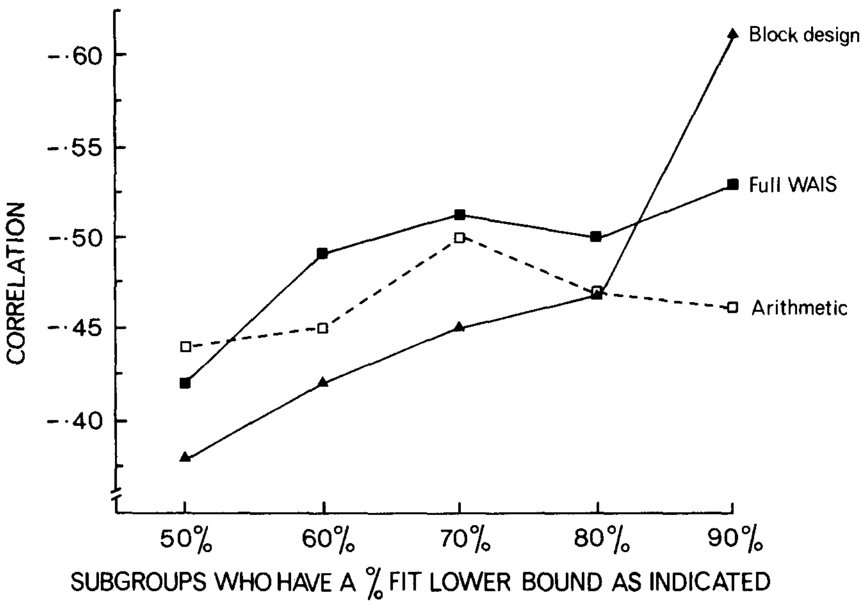

FIG. 3. Correlations between three WAIS scores and mean SD

tion values indicated that an optimum %fit lower bound was between 60% to 70%. Figure 3 provides this visual information.

As can be seen from Figure 3, correlation-value divergence is apparent after a lower bound of 70% fit. In addition, the sample sizes are shrinking rapidly. The mean %fit of the subjects' data within the 60% subgroup was 88% with *SD* of 11%. The mean %fit for the 70% subgroup was 91% with an *SD* of 8%. These values are much closer to Jensen's values previously quoted.

Accordingly, SAMPLE 1 and SAMPLE 2 data were edited using both the 60% and 70% lower-bound constraints. It was found that the 60% lower-bound SAMPLE 1 subgroup had a mean %fit of 90% with an *SD* of 10%. The SAMPLE 2 subgroup had a mean %fit of 86% with an *SD* of 11%. In order to perform cross-sample parameter comparisons with two groups of data that at least fitted Hick's Law to an equal extent, the SAMPLE 2 subgroup who fitted the linear function 70% or greater were used. This subgroup had a mean %fit value of 89% with *SD* of 8%. The SAMPLE 1 subgroup consisted of 35 subjects, rejecting 5; the SAMPLE 2 subgroup consisted of 30 subjects, rejecting 16.

Section 4. The Results Using Corrected, Edited Data. Table 4 provides the means and *SD*s for the corrected and edited data for SAMPLE 1 and SAMPLE 2. Contrasting this table of information with Table 1, it is apparent that the parameters most affected by the use of corrected data and restricted fit are those assessing variability (0, 1, 2, 3 bits *SD* and σRT).

In addition, while SAMPLE 1 and SAMPLE 2 are similar with regard to the mean FULLWAIS score (105.46 and 105.57, respectively), the *SD*s are very different (17.93 and 11.78, respectively). As can be seen from Table 1, this difference in *SD* for the FULLWAIS scores is maintained even in the total sample data. It is, therefore, not a function of the editing procedure.

With regard to the four specific hypotheses in Section 3 of "Results," the correlation between %fit and FULLWAIS was computed (computed on the total sample data both prior to, and after, the editing procedure). This was a test of the initial hypothesis of independence between IQ and fit. In addition, the means and *SD*s of the rejected subjects on the FULLWAIS score were noted. For the total sample data, this correlation was −.02 and .01 for SAMPLES 1 and 2, respectively. For the edited data, this correlation was −.17 and −.08 for SAMPLES 1 and 2, respectively. Given the nonsignificance of all the four values, it can be stated that the FULLWAIS score and fit to Hick's law (%fit) are not related within these two samples of data. In confirmation of this result, the means and *SD*s of the FULLWAIS score for the 5 rejected subjects for SAMPLE 1 and the 16 rejected subjects from SAMPLE 2 are 103.60, 27.88 and 108.44, 15.73, respectively. These values are indicative of the lack of association.

With regard to the second hypothesis, that is, subjects who do not fit Hick's Law demonstrate an elevated level of variability of response, the variability parameters from both the edited and rejected subsamples were compared accordingly. Table 4 provides the means for the 0, 1, 2, and 3 bits *SD*s for the 35-

TABLE 4
Means and *SD*s of the Corrected and Edited Sample Data

Variable	Mean	*SD*	Minimum	Maximum
SAMPLE 1 (*N*=35, FIT 60% or above)				
AGE	24.51	6.08	18.00	49.00
0 BITS RT	292.34	32.00	225.00	363.50
1 BIT RT	315.79	28.17	267.00	366.50
2 BITS RT	347.33	37.22	276.50	423.00
3 BITS RT	382.67	41.09	301.50	498.50
SLOPE	30.25	10.71	7.70	55.60
INTERCEPT	289.15	30.38	236.55	356.45
%FIT	90.34	10.19	62.52	99.80
0 BITS *SD*	29.87	12.75	12.34	67.78
1 BIT *SD*	30.31	9.76	15.02	54.11
2 BITS *SD*	32.61	11.08	17.25	74.86
3 BITS *SD*	54.24	25.76	15.42	117.31
σRT	36.76	10.49	22.28	66.04
FULLWAIS	105.46	17.93	72.00	134.00
VERBAL	104.86	17.20	69.00	142.00
PERFORMANCE	104.37	17.67	75.00	144.00
VOCABULARY	10.31	2.92	3.00	15.00
COMPREHENSION	10.71	3.28	3.00	16.00
INFORMATION	10.71	3.75	2.00	18.00
DIGIT SPAN	10.43	2.55	4.00	14.00
SIMILARITIES	10.34	2.87	3.00	15.00
ARITHMETIC	10.51	2.83	5.00	17.00
PICTURE COMPL.	10.03	2.47	5.00	14.00
PICTURE ARRNG.	10.00	2.86	5.00	17.00
OBJECT ASSY.	10.91	3.22	5.00	18.00
BLOCK DESIGN	11.80	2.91	6.00	19.00
DIGIT SYMBOL	9.91	2.90	4.00	15.00
SAMPLE 2 (*N*=30, FIT 70% or above)				
AGE	28.23	6.75	20.00	44.00
0 BITS RT	305.30	38.75	251.50	415.50
1 BIT RT	330.72	35.10	273.00	418.00
2 BITS RT	357.03	41.34	297.00	482.50
3 BITS RT	382.07	45.02	310.50	515.50
SLOPE	25.66	11.28	−17.35	41.10
INTERCEPT	305.29	36.50	256.35	408.65
%FIT	89.29	8.33	71.25	99.81
0 BITS *SD*	37.78	17.66	16.81	96.37
1 BIT *SD*	37.73	16.53	18.21	103.80
2 BITS *SD*	38.55	11.42	21.72	76.81
3 BITS *SD*	50.68	20.37	24.42	103.28
σRT	41.19	11.21	26.32	71.44
FULLWAIS	105.57	11.78	76.00	130.00
VOCABULARY	11.37	2.68	6.00	17.00
ARITHMETIC	10.40	2.81	6.00	17.00
PICTURE ARRNG.	9.43	3.09	5.00	15.00
BLOCK DESIGN	11.60	2.63	5.00	17.00

subject SAMPLE 1 subsample; the mean for these parameters for the 5 rejected subjects was 70.57, 38.04, 33.87, and 64.16, respectively. From inspection of these values, it is clear that the 0-bit condition is most affected by exclusion of the "bad fitting" subjects. The median RT for this condition in the edited data set is 292.34 with an *SD* of 32.00 ms; for the 5 rejected subjects it is 332.10 with an *SD* of 50.18. For this sample of data at least, the evidence of elevated variability is unequivocal. For SAMPLE 2 data, Table 4 presents the appropriate means for the 4 variability parameters. The values for the 16 rejected subjects are 37.85, 32.87, 35.65, and 44.65, respectively. These values are virtually the same as those in the edited data set, in fact with a slight decrease in parameter size for the 1-, 2-, and 3-bit conditions. Thus SAMPLE 2 data does not provide any evidence to support the hypothesis that "bad fitting" subjects have elevated variability of response. However, the 16 rejected subjects have a 0-bit median RT mean of 332.53 with an *SD* of 40.46; this is extremely similar to the 5 rejected subjects' values given above. More importantly, it is the value of the median RT for this particular condition which is causing the bad fit. For SAMPLE 1 rejected subject data, computing the regression of the mean median RT versus the number of bits of information yields a %fit value of 48.99%. Leaving out the RT value for the 0-bit condition yields a %fit value of 98.33%. For SAMPLE 2 rejected subject data, the two values are 79.95% and 98.07%, respectively. Certainly, the hypothesis of elevated variability is not supported overall; rather, another explanation is required to account for the bad fit.

With regard to the third hypothesis, that is, the edited data from both samples should demonstrate similarity of IQ × RT and *SD* correlations, Table 5 presents the median RT × WAIS scale score correlation matrix.

For SAMPLE 1, a correlation equal to or greater than ±.29 and ±.39 is significant at $p < .05$ and $p < .01$ one-tailed, respectively (33 degrees of freedom). For SAMPLE 2, these values are ±.31 and ±.42, respectively (28 degrees of freedom). For the subtests of the WAIS, there is some appreciable fluctuation in the values of the correlations between samples. Overall, SAMPLE 1 is providing a strong relationship between PICTURE ARRANGEMENT, BLOCK DESIGN, and the median RTs. However, the correlations between the FULLWAIS score and the Median RT for each condition are suggestive not only of a relationship between IQ and RT, but also of a consistency of values not observed in Jensen's data. The correlations between the variability parameters and the WAIS scores are given in Table 6.

Once again, the WAIS subscale relationships tend to be sample specific but not as markedly as those reported in Table 5. Whereas in Table 5 few of the correlations were significant in both samples for any pair of variables, there are now six variable pairs whose values both exceed the $p < .05$ level. In addition, the variable pair whose variables are both functions of all the other RT and IQ variables—σRT and FULLWAIS—have correlations that are effectively equal in both samples of data. Finally, computing the regression of the mean median RT on the number of bits of information for the corrected, edited data for both

TABLE 5
Median RT × WAIS Correlations Using the Corrected, Edited Data

VARIABLE	FULLWAIS	VOCAB	ARITHM	PICTARRNG	BLOKDESN
0 BITS RT	−.37*	−.19	−.07	−.39**	−.47**
	−.29	−.01	−.24	−.25	−.22
1 BIT RT	−.48**	−.35*	−.23	−.47**	−.58**
	−.29	−.13	−.35*	−.14	−.13
2 BITS RT	−.47**	−.37*	−.21	−.42**	−.55**
	−.29	−.20	−.37*	−.07	−.12
3 BITS RT	−.48**	−.33*	−.17	−.36*	−.58**
	−.29	−.15	−.39*	−.07	−.11

VARIABLE	VERBAL TOTAL	PERFORMANCE TOTAL	INFORMATION	DIGIT SPAN
0 BITS RT	−.28	−.42**	−.23	−.19
	–	–	–	–
1 BIT RT	−.42**	−.50**	−.37*	−.30*
	–	–	–	–
2 BITS RT	−.40**	−.50**	−.28	−.31*
	–	–	–	–
3 BITS RT	−.36*	−.56**	−.27	−.32*
	–	–	–	–

VARIABLE	COMPREHENSION	SIMILARITIES	PICTURE COMPLETN	OBJECT ASSY.	DIGIT SYMBOL
0 BITS RT	−.32*	−.26	−.31*	−.33*	−.41**
	–	–	–	–	–
1 BIT RT	−.47**	−.36*	−.37*	−.41**	−.48**
	–	–	–	–	–
2 BITS RT	−.47**	−.34*	−.33*	−.40**	−.50**
	–	–	–	–	–
3 BITS RT	−.43**	−.21	−.44**	−.51**	−.46**
	–	–	–	–	–

Note. The upper values are for SAMPLE 1, the lower values for SAMPLE 2
* = Significant $p < .05$ one-tailed
** = Significant $p < .01$ one-tailed

SAMPLES 1 and 2 yielded intercepts of 289.15 and 305.29, respectively. The slopes were 30.25 and 25.66, respectively. There was no evidence to support a significant difference between the slopes and intercepts at $p < .05$ two-tailed (for the total samples of 46 and 40 subjects, both the intercepts and slopes were significantly different at $p < .05$ two-tailed).

Overall, the two sets of corrected, edited data from SAMPLES 1 and 2 tend to agreement marginally more than in the total sample data. However, the main effect of the editing procedure has been to increase the size of most RT parameter

TABLE 6
RT Variability × WAIS Correlations Using the Corrected, Edited Data

VARIABLE	FULLWAIS	VOCAB	ARITHM	PICTARRNG	BLOKDESN
0 BITS *SD*	−.46**	−.38*	−.26	−.38*	−.46**
	−.55**	−.46**	−.48**	−.15	−.33*
1 BIT *SD*	−.27	−.17	−.15	−.39**	−.26
	−.21	−.13	−.33*	−.17	−.01
2 BITS *SD*	−.43**	−.30*	−.33*	−.46**	−.58**
	−.20	−.29	−.28	.09	.04
3 BITS *SD*	−.35*	−.12	−.35*	−.33*	−.39**
	−.39*	−.05	−.40*	−.30	−.31*
σRT	−.53**	−.31*	−.42*	−.53**	−.59**
	−.52**	−.33*	−.56**	−.23	−.27

VARIABLE	VERBAL TOTAL	PERFORMANCE TOTAL	INFORMATION	DIGIT SPAN
0 BITS *SD*	−.42**	−.45**	−.29*	−.18
	–	–	–	–
1 BIT *SD*	−.23	−.31*	−.22	−.01
	–	–	–	–
2 BITS *SD*	−.37*	−.44**	−.34*	−.21
	–	–	–	–
3 BITS *SD*	−.28	−.33*	−.23	−.28
	–	–	–	–
σRT	−.45**	−.53**	−.37*	−.28
	–	–	–	–

VARIABLE	COMPREHENSION	SIMILARITIES	PICTURE COMPLETN	OBJECT ASSY.	DIGIT SYMBOL
0 BITS *SD*	−.43**	−.43**	−.31*	−.35*	−.43**
	–	–	–	–	–
1 BIT *SD*	−.23	−.18	−.23	−.11	−.36*
	–	–	–	–	–
2 BITS *SD*	−.44**	−.30*	−.25	−.46**	−.30*
	–	–	–	–	–
3 BITS *SD*	−.25	−.04	−.37*	−.33*	−.04
	–	–	–	–	–
σRT	−.44**	−.27	−.44**	−.46**	−.32*
	–	–	–	–	–

Note. The upper values are for SAMPLE 1, the lower values for SAMPLE 2
* = Significant $p < .05$ one-tailed
** = Significant $p < .01$ one tailed

× WAIS subtest/FULLWAIS correlations. With regard to the third hypothesis, the statistical equivalence of the slope and intercept values is a strong indicator of some lawfulness within the data.

Comparability of our data with those made available by Jensen (1982b) is the test of the fourth and final hypothesis that was introduced in Section 3 in "Results." section. Examination of Table 1 in Jensen (1982a) provides two sets of median RT versus bits regression intercept and slope parameters. For a sample of 218 vocational college students, the mean intercept was 348.7 and the slope 34.1, with a 0-bits *SD* of 48.8. For a sample of 280 university students, these values were 299.4, 28.0, and 29.8, respectively. For our edited data in SAMPLE 1, these values were 289.15, 30.25, and 29.87, and in SAMPLE 2, they were 305.29, 25.66, and 37.78, respectively. These values are sufficiently similar to suggest that a psychophysical phenomenon is being assessed.

Correlating median RT with the FULLWAIS score for each condition of 0, 1, 2, and 3 bits of information does not yield values at all comparable with those given by Jensen (1982a; Figure 9). As can be seen from Table 5, both SAMPLES 1 and 2 tend toward a flat zero slope function. In Jensen's figure, both samples of data have definitely increasing correlations as the number of bits increases.

Correlating the slope and intercept parameters, from the regression of median RT on bits, with the FULLWAIS scores in SAMPLES 1 and 2 yielded the following values: for SAMPLE 1, these correlations were −.08 and −.42, respectively. For SAMPLE 2 data, these values were −.06 and −.29, respectively. The intercept correlations were almost identical to the 0-bits RT × FULLWAIS correlations as presented in Table 5. However, the slope correlations are effectively zero, in complete disagreement with Jensen's data and verbal assertion (1982a, p. 110). "Both the intercept and slope of the regression of RT on bits of information in the Hick paradigm are correlated with *g*." (Jensen [1982b] reported a significant [$p < .01$] correlation of −.41 between the Ravens Advanced Progressive Matrices and RT slope and an insignificant correlation of +.15 with the intercept using 50 university students). There can be no doubt that our results do not support Jensen's findings with regard to the correlation of IQ and the median RT slope and intercept parameters.

Lastly, the correlation of σRT with the FULLWAIS scores yields an appreciable elevation of Jensen's value computed from the same 50 university students. Jensen quoted a correlation of −.35 (uncorrected for IQ range restriction); our values were −.53 and −.52 for SAMPLES 1 and 2, respectively. Certainly, we are in agreement with Jensen over the importance of performance variability and its association with IQ scores.

With regard to the comparability of results, a pattern appears to be emerging that is suggestive of a replication of the psychophysical parameters of slope and intercept computed from the regression of median RT on bits of information. However, the results concerning correlations between IQ and RT parameters do not replicate as well. This is perhaps a function of the different measures of IQ used by Jensen and ourselves, the disparate nature of the sample compositions (students, schoolchildren, and adults), and small sample sizes used in general. What is certain is that failure to fit Hick's Law is not solely a function of response variability.

The last bivariate correlational analysis concerns the relationship of Personality variables with RT parameters. Correlating the seven Personality scale scores with the variability, speed, and %fit parameters yielded few $p < .05$ two-tailed, statistically significant, correlations. The cross-sample comparisons indicated a wide variation of correlation values, with some correlations changing sign between samples; e.g., correlating Venturesomeness with σRT in SAMPLE 1 and 2 gave coefficients of $-.40$ and $-.15$, respectively; however, for the 0-, 1-, 2-, and 3-bit condition *SD*s, the correlations were $-.19$, $-.13$, $-.41$, and $-.34$ in SAMPLE 1. For SAMPLE 2 these values were $+.16$, $-.34$, $+.23$, and $-.33$. With such variation in the correlations, it was felt unwise to attempt to interpret the results (the means and *SD*s on all the scales were not significantly different from one another). The data for the two samples were subsequently combined and the results recomputed; however, only 8 correlations out of the 84 possible were significantly different from zero at the $p < .05$ two-tailed level, with the largest correlation of $-.33$ being observed between the 3-bit condition *SD* and Venturesomeness. The next largest value was that between σRT and Psychoticism, with a value of $-.30$. All the remaining significant values were less than $\pm.30$ and involved only Psychoticism or Venturesomeness.

The correlation of age with the *SD*s of RTs, σRT, and %fit within both SAMPLES 1 and 2 yielded some rather large, although unreplicated, statistically significant correlations ($p < .05$ two-tailed tests). For SAMPLE 1, 4 significant correlations were observed. The four variables were 0 bits median RT (0.49), 1 bit median RT (0.39), median RT versus bits regression intercept (0.49), and %fit (-0.37). For SAMPLE 2, the *SD* of RTs for the 0-bits condition correlated .37 with age. In addition, correlations of $-.42$, $-.36$, and $-.47$ were observed between age and the FULLWAIS, ARITHMETIC, and BLOCK DESIGN WAIS variables, respectively. Age was subsequently partialed out of the correlations between the WAIS scores and the speed and variability RT parameters. This had little or no effect; the significant correlations remained significant. Thus, with regard to the correlations between the WAIS scores and the RT measures, we may conclude that age is not a significant mediating variable within our two samples of data.

In order to examine the dimensional characteristics of the data, a principal components analysis was undertaken. So as to provide some stability for the multivariate statistics, the two samples of corrected, edited data were combined into a joint sample of 65 subjects. The variable range was restricted to the four main RT speed parameters (median RT for 0, 1, 2, and 3 bits), the five variability parameters (*SD* of RTs for 0, 1, 2, and 3 bits, and σRT), and the five WAIS scale scores. Although the σRT parameter is provided by a direct linear combination of the four *SD* values and the FULLWAIS score provided almost as directly, the correlation matrix retained its gramian properties of nonsingularity with positive eigenvalues. Three tests of factor extraction quantity were used, the Velicer MAP test (Velicer, 1976), the Kaiser factor alpha criterion (Kaiser, 1960, 1965), and AUTOSCREE (a computer implementation of Cattell's scree test (Barrett & Kline, 1982). The first three eigenvalues from this analysis were 6.216, 2.075, and 1.402 accounting for 44.4%, 14.8%, and 10.01%, respectively. The MAP and AUTOSCREE tests indicated 3 factors for extraction; the Kaiser alpha indicated a minimum of 2, with the third eigenvalue α equal to a marginal 0.31. Given the size of the first eigenvalue in relation to the others, there was an obvious suspicion that a general factor solution might perhaps be optimal. However, designating the 14 variables as a scale and computing the coefficient alpha yielded a coefficient of size 0.595. Although coefficient alpha is not strictly a direct measure of variable homogeneity (Green, Lissitz, & Mulaik, 1977; Hattie, 1984), it is nevertheless a useful guide as to its likelihood. Thus, with such a low value indicated, it was felt that the adoption of a general factor solution could not be upheld in this present analysis. Therefore, a hyperplane maximized direct oblimin (Jennrich & Sampson, 1966, 1979; Barrett & Kline, 1980) rotation was implemented on the first three components. The δ parameter was swept from -40.0 to $+0.5$ in steps of 0.5, the hyperplane bandwidth set at ± 0.10. In this way, a maximized simple structure solution was obtained. Table 7 provides the rotated component loadings for the solution and, for interest, the loadings on the first unrotated component.

From examination of Table 7, one overriding feature is apparent; that is, the 5 intelligence-test variables consistently load on a component separate from the RT performance variables. However, these components are correlated to a fair extent as might be expected from the previously cited zero-order correlation analyses. The three-component solution appears to clearly show separation between RT speed and variability measures, although these components are correlated +.33. It is impossible to compare the component analysis results with Jensen's (1980) factoring of data from 50 university students as the bulk of the variables are not common between his and our studies. However, while we share Carroll's (1979) concern that the extraction of a general factor is a somewhat liberal procedure given the loading pattern in Jensen's matrix, Carroll's factorial solution itself is not optimal.

Finally, using the joint sample data from the above analysis, it was proposed to compute the multiple R of the speed and variability RT parameters with the FULLWAIS scores. However, due to the high intercorrelations between the individual *SD*s of RTs for condition, and between the median RTs for each condition, it was felt that the mean of both the speed and variability parameters might be more appropriate variables. Thus the mean of the median RTs ((RT1 + RT2 + RT3 + RT4)/4) was computed accordingly, the σRT parameter being already available. The mean RT was then correlated both with the FULLWAIS

TABLE 7
Rotated Principal Component Loadings and Associated Statistics

Variable	1st Principal Component Factor 1	3 Component Solution Factor 1	Factor 2	Factor 3
0 BITS RT	**.659**	**.937**	−.020	−.122
1 BIT RT	**.765**	**.910**	−.026	.058
2 BITS RT	**.792**	**.864**	−.035	.140
3 BITS RT	**.718**	**.786**	−.090	.062
0 BITS *SD*	**.676**	**.339**	−.243	**.345**
1 BIT *SD*	**.487**	.055	.134	**.800**
2 BITS *SD*	**.615**	**.334**	−.069	**.450**
3 BITS *SD*	**.507**	−.113	−.176	**.687**
σRT	**.824**	.166	−.157	**.856**
FULLWAIS	**−.775**	−.084	**.938**	−.033
VOCABULARY	**−.512**	.029	**.851**	.132
ARITHMETIC	**−.624**	.065	**.736**	−.199
PICT. ARRNG	**−.552**	−.101	**.508**	−.149
BLOCK DESN	**−.700**	−.147	**.811**	.012
HYPERPLANE COUNT	0	4	5	4
VARIANCE	6.216	3.665 $\delta = -0.5$	3.454	2.575

Factor correlations: 1 with 2 = −.28; 1 with 3 = .33; 2 with 3 = −.31.
Note. For ease of interpretation, variables with loadings > ±.30 are set bold face.

score and with the σRT parameter. The correlations were −.41 and .53, respectively, both values significant at the $p < .01$ level two-tailed. (The correlation between the σRT parameter and the FULLWAIS scores was −.50.) Given the high correlation between the mean RT and σRT parameters, there was little purpose in computing a multiple R. However, for the sake of possible future analyses in this area, a multiple R was computed purely for reference purposes. The value was 0.53, with a shrunken size of 0.52 significant beyond the $p < .01$ level.

DISCUSSION

The main features of the results from all the analyses implemented are:

1. The inclusion of subjects who have a %fit coefficient of determination value (computed from the regression of median RT on bits of information) of less than about 60% depress nearly all correlational relationships between RT parameters and the WAIS scores. The effect of these data is basically that of statistical noise, tending to increase disparity between all parameters within the two samples of data.

2. The reason or reasons why the poor-fit subjects do not perform as expected by Hick's Law is not clear within our two data samples. Increased response variability is only a partial explanation.
3. The heuristic correction made for extraordinarily long RTs within any one condition certainly tends to improve all variable intercorrelations. While this is not an optimal algorithm, it was shown to be impartial and unbiased in its effects.
4. In a series of tests of four specific hypotheses proposed upon the basis of the expected properties of Hick's Law and its relationship to cognitive performance, the evidence suggested that the measurement characteristics specifically defining the law are probably correlated only marginally and nonsignificantly with cognitive performance as assessed by the WAIS. Certainly, the slope of the regression line computed (see Section 1) does not correlate with the WAIS scale scores; nor do the *SD*s of RTs have a positively increasing slope in the manner of Jensen's data. In addition, the plot of the median RT × FULLWAIS correlations against each bit of information does not yield a positively increasing slope as suggested by Jensen's results. However, the specific slope and intercept parameters computed from the regression of median RT on bits were statistically equivalent between our two samples of data. In addition, these values were very similar to Jensen's published data from 280 university students.
5. Generally higher RT × WAIS score relationships were observed between those RT parameters assessing performance variability rather than performance speed. The most consistent and high values observed across both samples of data were between the FULLWAIS score and the mean of the *SD*s for each RT condition (σRT). Our results suggest a higher zero-order relationship than Jensen has previously indicated.
6. Examination of the effects of age on the RT × WAIS correlations demonstrated that age could not be considered a significant mediating variable within our two samples of data.
7. The relationship of personality variables to the RT parameters was minimal except for the correlations between Psychoticism, Venturesomeness, and the RT variability measures. Although considerable cross-sample size fluctuations were present, there was, nevertheless, the indication that Venturesomeness might correlate around −.30 with σRT. However, since this is the first such result, it is essential to replicate it before attempting any interpretation. Given the sign similarity of correlations in the two samples of data, it would be expected to replicate, although the size of the correlation may render it conceptually, if not statistically, insignificant.
8. The results obtained from a principal components analysis, using the speed and variability RT parameters with the five WAIS scores, suggested that a single general component was not an optimal psychometric solution. While RT speed and variability parameters are related to the WAIS scores, unidimensionality of the variables was not clearly apparent.

Overall, the results differ markedly from Jensen's published data with regard to the correlations between RT parameters and intelligence test scores. While directionality of correlations was mostly preserved, size was not. In addition, unlike Jensen's data, fit to Hick's Law was not universal. While it is natural to question the abnormality or otherwise of our data, the apparent cross-sample consistency in most parameter and correlational values suggests that our data are reasonably valid and internally consistent. Given this fact, the major difference between our results and Jensen's data is that the correlations between slope, intercept, and IQ are completely different. To reiterate, Jensen reports a −.41 correlation between the Ravens test and RT slope, and a value of +.15 with the intercept (using 50 university students). Our results indicated a correlation between slope and FULLWAIS for SAMPLES 1 and 2 of −.08 and −.06, respectively. The intercept correlated −.42 and −.29, respectively, with the FULLWAIS scores. Given the high positive correlation between intercept and 0 bits median RT (.97 and .98 for SAMPLES 1 and 2), it would be impossible for our data to have produced a positive intercept × IQ correlation (note that the correlations between slope and intercept are comparable to those given in Jensen [1982a], Table 2). Unfortunately his sample of 50 university students cannot be taken as representative of the other samples of data. Certainly, the 0-bit RT × IQ correlations differ markedly from Lally and Nettlebeck's data and from a sample of 39 female ninth-graders' data (Jensen & Munro, 1979).

On the whole, our data support a general speed–IQ paradigm (Eysenck, 1967), but not the particular form given to it by Jensen and the Erlangen school. Their version requires two deductions to be verified which we fail to replicate, namely the slope–IQ correlations, and the increase in correlation betwen RT and IQ as number of bits increases. However, as Carroll (in press) has pointed out, Jensen's own data do not always support his position, and the German data too often fails to do so (Amelang, 1985; Bieger, 1968). Unless more convincing evidence on these points can be produced, we cannot accept the specific model addressed by Jensen and the Erlangen school (Eysenck, 1985).

The main problem generated by our data concerns Hick's Law. Our data preclude the assertion that Hick's Law is a fundamental psychophysical law in the tradition of, say, Stevens' loudness estimation power function (Stevens, Guirao, & Slawson, 1965). A third sample of subjects' data collected prior to the reported data by a different investigator (within our laboratory) also yielded about 27% of a sample of 28 subjects as poorly fitting Hick's law. (We have, of course, checked the measurement equipment and analysis software for errors, but nothing so obvious was apparent.) Editing and correcting the data in the manner indicated here does indicate that some lawfulness exists within the paradigm, but this is confined mainly to the intercept and slope parameters from the regression of median RT on bits. These two parameters appear constant not only between our two samples but also within and between Jensen's data and our own. However, an explanation has to be forthcoming to determine why some subjects do not perform as expected by Hick's Law. The data above do not provide more than a partial explanation in terms of excessive response variability. Our next study will attempt to remedy this situation.

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