Predicting the size of individual and group differences on speeded cognitive tasks

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An a priori test of the difference engine model (Myerson, Hale, Zheng, Jenkins, & Widaman, 2003) was conducted using a large, diverse sample of individuals who performed three speeded verbal tasks and three speeded visuospatial tasks. Results demonstrated that, as predicted by the model, the group standard deviation (*SD*) on any task was proportional to the amount of processing required by that task. Both individual performances as well as those of fast and slow subgroups could be accurately predicted by the model using no free parameters, just an individual or subgroup's mean *z*-score and the values of theoretical constructs estimated from fits to the group *SD*s. Taken together, these results are consistent with post hoc analyses reported by Myerson et al. and provide even stronger supporting evidence. In particular, the ability to make quantitative predictions without using any free parameters provides the clearest demonstration to date of the power of an analytic approach on the basis of the difference engine.

Although there exists a large body of research on cognitive abilities (for a review, see Carroll, 1993), this research has focused primarily on issues concerning the relative position of individual performances (e.g., whether those who score well on Test A also score well on Test B). There has been relatively little study, however, of what determines the absolute size of individual differences in performance. This may be partly because of problems inherent in comparing scores on different psychometric tests. These problems arise because different tests often measure performance on quantitatively (if not qualitatively) different scales. For example, how would one compare a difference in memory spans with a difference in vocabulary scores other than by using relative measures like *z*-scores or percentile ranks? In contrast, a major appeal of “chronometric” tests (Posner, 1978; Sternberg, 1977) is that they can be used to measure very different abilities on the same fundamental scale—time. Taking advantage of this property of chronometric tests, Myerson, Hale, Zheng, Jenkins, and Widaman (2003) recently proposed a model of diversity in speeded cognition, which they termed the *difference engine*. This model describes the interaction between individual differences in processing speed on the one hand and the amount of processing required by different tasks on the other, and the effect of this interaction on the absolute size of individual differences in performance.

The difference engine model (Myerson et al., 2003) assumes that processing may be represented as a series of

computational steps and that some individuals tend to perform all of these computations relatively quickly, whereas others tend to perform them all relatively slowly, reflecting the existence of a general cognitive speed factor. The time that individuals require for response selection and execution (i.e., the duration of the response component) is assumed to vary independently of their cognitive speed. On the basis of these assumptions, the difference engine model predicts (1) approximately linear relations between the response times (RTs) of any individual or subgroup and average performance for the group, with the regression lines for fast individuals having slopes less than 1.0 and positive intercepts and the regression lines for slow individuals having slopes greater than 1.0 and negative intercepts; and (2) an approximately linear relation between the diversity of performance on any task, as measured by the group *SD*, and the difficulty of the task, as indexed by the group mean RT. Moreover, the predicted relation between *SD* and RT leads to specific interpretations of the slope and intercept parameters for the regression lines describing individual and subgroup performance.¹

In order to evaluate these predictions, Myerson et al. (2003) reanalyzed data from previous studies. Although their analyses provided considerable support for the difference engine model, this support is limited by the fact that these analyses represented post hoc tests. In addition, most of the young adult data were collected at a highly selective private university and thus may not provide the

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best basis for evaluating a model of diversity. Finally, when Myerson et al. compared performance on verbal and visuospatial tasks in order to test the model's generality, they did so on the basis of small samples that precluded a factor analytic test of the assumption that these tasks actually tapped different abilities. The present study was designed to remedy these limitations. Specifically, we conducted an a priori test of the difference engine model on the basis of data collected at a state university with a diverse student body, using a sample size large enough to permit analyses designed to reveal whether the verbal and visuospatial tasks load on separate factors. In addition, this study conducted the first tests of the extent to which free parameters must be estimated in order to accurately predict performance using the difference engine model.

METHOD

Participants

Undergraduate students ($N = 137$) were recruited from a pool maintained by the Department of Psychology, Grand Valley State University, and received course credit for participation. All participants reported normal or corrected-to-normal vision. ACT scores were available for 91% of these participants (median ACT = 22). Scores ranged from below the 10th percentile up to the 99th percentile, indicating a wide range of ability among the participants.

Apparatus

Stimuli were presented using a Pentium computer and a 17-in. CRT monitor. Programs developed using SuperLab Pro controlled the presentation of stimuli, and responses were recorded using a six-button response pad (software and hardware by Cedrus Corp., San Pedro, CA).

Tasks

The test battery consisted of six RT tasks. Three of the tasks (category judgment, lexical decision, and rhyme judgment) were designed to assess verbal processing speed. The other three tasks (shape comparison, abstract matching, and visual search) were designed to assess visuospatial processing speed. Each task was made up of three conditions consisting of 24 trials. On each trial, participants indicated their decision by pressing either the leftmost or rightmost button on the response pad.

Category judgment task. On each trial, two words (drawn from the category norms published by Battig & Montague, 1969) were presented side by side in the center of the screen. Participants had to decide which word was an animal name. The three conditions differed in the types of items selected from the animal and non-animal categories: high-typicality items (e.g., *tractor* vs. *monkey*); low-typicality items (e.g., *hyena* vs. *zucchini*); subordinate items (e.g., *poodle* vs. *maple*).

Lexical decision task. On each trial, two four-letter strings were presented side by side in the center of the screen. Participants had to indicate which letter string was an English word. The three conditions differed in word frequency: high frequency (e.g., *lafe* vs. *home*); medium frequency (e.g., *claw* vs. *mong*); low frequency (e.g., *seep* vs. *murn*).

Rhyme judgment task. On each trial, one word (the sample) was presented directly above a pair of words presented side by side just below the center of the screen. Participants had to decide which of the two bottom words (e.g., *mush* and *wash*) rhymed with the sample (e.g., *hush*). The three conditions differed in the overlap among the orthography of the three words: the sample and its rhyme (but not the foil) were spelled identically except for the first letter (as in the previous example, where *hush* and *mush* were the rhymed words and *wash* was the foil); all three words were spelled differently (e.g., *rear* and *pier* rhymed, *were* was the foil); the sample and the foil (but not the rhyme) were spelled similarly (e.g., *mows* and *doze* were the rhymed words, *vows* was the foil).

Shape comparison task. On each trial, one object (the sample) was presented directly above a pair of objects that were presented side by side just below the center of the screen (top panel, Figure 1).

Figure 1. Sample stimuli from the three visuospatial tasks. The top panel depicts stimuli from the shape comparison task (from left to right: sample and matching object share color; all objects differ in color; sample and foil share color). The middle panel depicts stimuli from the abstract matching task (from left to right: sample and matching array share 3 dimensions, 2 dimensions, and 1 dimension). The bottom panel depicts stimuli from the visual search task (from left to right: set sizes of 10, 16, and 22). In all three panels, black, gray, and white represent different colors (e.g., in the bottom panel, the green target circle is represented by a gray circle, and the nontarget blue circles and green squares are represented by black circles and gray squares, respectively).

Participants had to decide which of the two bottom objects best matched the shape of the sample. The three conditions differed in the overlap among the colors of the objects: The sample and the match (but not the foil) shared the same color; all three objects differed in color; the sample and the foil (but not the match) shared the same color.

Abstract matching task. On each trial, one array (the sample) was presented directly above a pair of arrays that were presented side by side just below the center of the screen (middle panel, Figure 1). Participants had to decide which of the two bottom arrays best matched the sample and indicate their decision by pressing the corresponding button. Each array consisted of two, three, or four objects that also varied in terms of shape (triangle, circle, square) and color (red, green, yellow). The three conditions differed in the degree of overlap between the sample and its match: The sample was identical to the match on all three dimensions (number, shape, and color) but shared only two dimensions with the foil; the sample shared two dimensions with the match but only one dimension with the foil; the sample shared one dimension with the match but zero dimensions with the foil.

Visual search task. On each trial, two arrays of objects were presented side by side (bottom panel, Figure 1). The total number of objects in each array was always equal and half of the objects were always blue circles. The other objects were green squares, except that in one of the arrays, one of the green objects was a circle (the target). Participants had to decide which of the two arrays included the target. The three conditions differed in set size (i.e., number of objects in each array): 10, 16, and 22 objects.

Procedure

Participants were instructed to respond as quickly and as accurately as possible on all tasks. For each task, the test trials were preceded by specific instructions and 12 practice trials. The test trials consisted of 72 experimental trials preceded by 2 buffer trials (which were excluded from all analyses).

Each trial began with the presentation of an empty box or boxes in which the verbal or visuospatial stimuli would be presented. Following a 750-msec delay, the stimuli (i.e., words, shapes, or arrays of objects) for that trial appeared in the box or boxes simultaneously and remained on the screen until the participant responded or exceeded a time limit. A short beep was presented if a participant responded incorrectly or failed to respond within 15 sec (20 sec for the abstract matching and rhyme judgment tasks). For each task, trials from different conditions were randomized; the same randomized order was used for each participant. In addition, each participant performed the tasks in the same order (*rhyme judgment, abstract matching, category judgment, shape comparison, lexical decision, and visual search*). This order alternated tasks between the two domains to minimize the possibility of differential effects of practice and fatigue.

RESULTS AND DISCUSSION

After excluding 3 participants with incomplete data, 9 participants with extremely high error rates (i.e., greater than 40%), and 6 participants with abnormally long RTs (i.e., more than 3.5 *SDs* greater than the mean in at least one condition), analyses were conducted on data from the remaining 119 participants. Descriptive statistics for the six tasks are presented in Table 1, and the results of principal component and factor analyses of individuals' task mean RTs are presented in Table 2. Consistent with the difference engine model, principal component analysis revealed a general speed factor (which accounted for 63% of the total variance), and all tasks loaded heavily on this

Table 1
Mean Reaction Times (RTs, in Milliseconds)
and Error Rates (%), With Standard Deviations,
for Each Condition of the Six Speeded Tasks

Domain, Task, and Condition	<i>M</i>	<i>SD</i>	Error	<i>SD</i>
Verbal				
Category Judgment				
High typicality	688.7	126.5	1.1	2.7
Low typicality	785.5	161.6	3.0	4.3
Subordinate	961.9	230.7	7.4	6.7
Lexical Decision				
High frequency	849.8	146.4	1.3	2.6
Medium frequency	929.9	189.7	3.5	4.3
Low frequency	1,267.7	349.1	16.6	9.5
Rhyme Judgment				
Match similar spelling	1,314.1	299.9	3.1	5.0
All dissimilar spellings	1,423.8	350.2	4.6	7.0
Foil similar spelling	1,567.0	383.6	12.7	10.1
Visuospatial				
Shape Comparison				
Match shares color	633.8	114.8	1.8	3.3
All different colors	673.1	120.2	4.0	4.9
Foil shares color	701.3	126.1	3.3	4.8
Abstract Matching				
Share all dimensions	700.3	133.0	2.7	4.3
Share two dimensions	962.9	249.2	3.9	5.0
Share one dimension	1,065.6	287.6	3.3	4.1
Visual Search				
Set size 10	778.4	145.1	1.7	3.5
Set size 16	884.8	185.4	2.2	3.9
Set size 22	1,072.0	258.0	4.1	5.2

first principal component. Although the eigenvalue of the second principal component was less than 1.0, it explained an additional 13% of the variance, and the bipolar pattern of loadings was consistent with predictions: All the verbal tasks loaded negatively on the second component whereas all the visuospatial tasks had positive loadings. Varimax rotation was used to eliminate negative loadings and resolve a simple two-factor structure. All three visuospatial tasks loaded more strongly on one factor, whereas the three verbal tasks loaded more strongly on the other factor.

Consistent with the difference engine model (Myerson et al., 2003), there was an orderly, linear relation between the group *SD* for each task condition and the correspond-

Table 2
Factor Loadings From Principal Component Analysis of
Reaction Times on the Six Speeded Tasks and
Rotated Factor Loadings After Varimax Rotation of the
First Two Principal Components

Verbal and Visuospatial Tasks	Principal Components		Rotated Factors	
	1	2	1	2
Category judgment	.877	-.241	.843	.341
Lexical decision	.853	-.160	.775	.391
Rhyme judgment	.736	-.460	.864	.081
Shape comparison	.807	.191	.525	.642
Abstract matching	.837	.133	.584	.614
Visual search	.638	.661	.105	.912

Figure 2. The group SD as a function of the amount of processing, estimated as the mean RT minus 300 msec. The dashed line is the least squares best fitting proportional relation between these variables.

ing group mean RT, and as predicted, the intercept was negative ($SD = 0.313 RT_{avg} - 86.1$, $r^2 = .95$) and differed significantly from zero [$t(16) = -4.60$, $p < .001$]. A test for separate regressions revealed no significant differences between the parameters of lines fit to the verbal and visuospatial data: for the slopes [$t(14) = 1.71$, $p > .10$]; for the intercepts [$t(14) = 1.29$, $p > .10$]. According to the difference engine model, the equation for the linear relation between SD and mean RT is

$$SD = m (RT_{avg} - t_r), \quad (1)$$

where RT_{avg} and t_r represent the group mean RT and the duration of the response component, respectively.² Setting SD equal to zero and solving Equation 1 for RT_{avg} reveals that the x -intercept is equal to t_r . The x -intercept of the regression equation for the present data is 275 msec, consistent with the assumption that t_r represents the duration of the response component.

Equation 1 predicts that for any task the group SD will be proportional to the amount of cognitive processing required, where amount of processing is measured as the total decision latency minus the response component: $RT_{avg} - t_r$. This proportional relationship may be seen in Figure 2, which plots the group SD as a function of the group mean RT minus 300 msec, an estimate of the peripheral component of decision latencies frequently used in mathematical modeling and consistent with reaction times to highly discriminable stimuli (for a review, see Teichner & Krebs, 1974). Notably, this proportional relation involving only one free parameter (i.e., the slope) accounted for as much of the variance (95%) in the group SD as did the two-parameter linear regression equation with group mean RT as the predictor, providing strong support for the difference engine model's account of the determinants of diversity among individual performances.

Although it may not seem surprising that SD s increase with the mean, three points should be considered. First, SD s do not increase with the mean on all types of tasks, raising the question why they do so on speeded cognitive tasks. In fact, the diversity of scores on working memory tasks shows, if anything, the opposite trend (Jenkins, Myerson, Hale, & Fry, 1999). Second, SD s on speeded cognitive tasks do not merely show a tendency to increase; they increase in an extremely precise fashion. Third, although SD s increase with the mean RT, the increase is better described as being directly proportional to the amount of cognitive processing. Both the form and the precision of the relation between SD and amount of processing are unique to RTs, and call for a theoretical explanation. The difference engine model provides such an explanation, and goes on to develop the implications of the observed systematic variation in SD .

According to the difference engine model, the relation between SD and cognitive processing time is a fundamental one. The implications of this relation may be seen by considering an individual (i) who is consistently slower than the mean by 1.0 SD . For such a person, $RT_i = RT_{avg} + SD$, and based on Equation 1 we may substitute $m(RT_{avg} - t_r)$ for SD , simplify, and obtain $RT_i = (1 + m) \cdot RT_{avg} - mt_r$. More generally, if an individual's RTs differ from average by z_i standard deviation units,

$$RT_i = (1.0 + z_i m) RT_{avg} - z_i m t_r. \quad (2)$$

Equation 2 describes the regression of the RTs of an individual or subgroup on the average RTs for the group. Because fast individuals have negative z -scores, it is predicted that the slope ($1.0 + z_i m$) will be less than 1.0 and the y -intercept ($-z_i m t_r$) will be positive for such individuals. Slow individuals, who have positive z -scores, will have a slope greater than 1.0 and a negative y -intercept.

To test this prediction, we began by selecting subgroups (the bottom and top quartiles, 30 per group) from the 119 participants on the basis of their mean z -scores, averaged across all 18 conditions of the 6 tasks. These individual mean z -scores were highly reliable as evidenced by a correlation between z -scores for the odd and even conditions (based on the ordering of conditions in Table 1) that was greater than .95. Members of the bottom and top quartiles were consistently fast and slow, respectively, across all six tasks. All 30 members of the fast subgroup were faster than average on at least five of the tasks, and 26 of the slow subgroup members were slower than average on at least five tasks.

Regressing the mean RTs from the two subgroups for each condition on the average RTs for the corresponding conditions revealed orderly linear relations, as predicted by the difference engine model (see Figure 3); $r^2 = .97$ for the fast subgroup and $r^2 = .99$ for the slow subgroup. Consistent with the presence of a strong general speed factor, there were no significant differences between the verbal and visuospatial regression lines with respect to either slopes or intercepts (all t s < 1.12 , all p s $> .10$). As predicted, the slope of the regression of the fast sub-

Figure 3. RTs of the fast and slow subgroups as a function of the group mean RT. The dashed lines represent the predictions of Equation 2 on the basis of the subgroup mean z -scores and the parameter estimates from Equation 1. Vsp and Vrb stand for visuospatial and verbal, respectively.

group's RTs on all six tasks was significantly less than 1.0 and the y -intercept was positive (t s for both parameters > 2.74 , $ps < .05$), whereas for the slow subgroup the slope was significantly greater than 1.0 and the y -intercept was negative (t s for both parameters > 2.76 , $ps < .05$).

Just as the difference engine model's prediction of the relation between SD and mean RT is constrained by expectations regarding the duration of the response component, so too the model's predictions of the relation between individual and group mean RTs are constrained by the parameters of the relation between SD and mean RT, thereby permitting more rigorous evaluation of the model. Specifically, the parameters of Equation 2 are constrained by the parameter estimates for Equation 1, plus the mean of the z -scores for an individual or subgroup. For example, substituting the estimates of m and t_r (previously obtained by fitting Equation 1 to the group data) and the mean z -score for the fast subgroup (-0.912) into Equation 2 yields the prediction equation $RT_{fast} = 0.714 RT_{avg} + 78.5$, which accounted for 97% of the variance in the fast subgroup's RTs, as much as the regression equation with two free parameters. Similarly, substituting the obtained estimates of m and t_r and the mean z -score for the slow subgroup ($+0.992$) into Equation 2 yields the prediction equation $RT_{slow} = 1.311 RT_{avg} - 85.4$, which accounted for 99% of the variance in the slow subgroup's RTs, again as much as the regression equation with two free parameters. Note that the dashed lines in Figure 3 are these very prediction lines, using the same parameter estimates for both groups and differing only in mean z -scores, and were not fit to the data.

Recalling that a major goal of the difference engine was to predict the absolute size of individual differences, it should be noted that Equation 2 may be rewritten as

$$RT_i - RT_{avg} = z_i m (RT_{avg} - t_r). \quad (3)$$

Thus, the close correspondence between observed and predicted RTs seen in Figure 3 translates into the accurate predictions of the differences between the performance of the slow and fast subgroups and average performance presented in Table 3. Averaged across all tasks and conditions and both subgroups, the error in the size of the predicted difference was only 2.77% of the corresponding group's mean RT. Although Equation 2 may be preferred for regression analysis because of the reliability problems associated with difference scores, Equation 3 may be clearer conceptually because it reveals that the difference between average performance and that of an individual or subgroup is proportional to the amount of cognitive processing.

Further analyses were conducted to evaluate the difference engine model's predictions at the individual level. Consistent with Equation 2, strong linear relations (median $r^2 = .813$) were observed between individual RTs and group means. Also as predicted, regression lines for slow individuals tended to have negative intercepts, whereas those for fast individuals tended to have positive intercepts: Of the 43 participants with regression slopes greater than 1.10, 40 had negative intercepts and 48 of the 52 participants with slopes less than 0.90 had positive intercepts.

Moreover, the difference engine model accurately predicted the relationship between an individual's slope and mean z -score. As instantiated in Equation 2, the model predicts that the slope of the regression of an individual's RTs on the group mean RTs is equal to $1.00 + z_i m$, where m is the slope of the regression of group SD on mean RT. Regressing individual slopes on z -scores revealed a strong relation between the two measures [$r(117) = .610$, $p < .01$], but more importantly, the observed relation (slope = $1.00 + 0.285 z_i$) did not differ significantly from the predicted relation (slope = $1.00 + 0.313 z_i$; difference in $r^2 = .004$, n.s.). The data are shown in Figure 4; the dashed line is the predicted relation between slope and z -score. These results provide evidence that individual performance can be predicted from the difference engine model without using any free parameters and, instead, using only individual mean z -scores and the values of theoretical constructs (i.e., the parameters of Equation 1) estimated from group data.

One of the most important aspects of the present results is that, taken together, they demonstrate how the difference engine model makes it possible to predict so much on the basis of so little. Starting with the proportional relation between amount of processing and the diversity of individual performance on speeded cognitive tasks (Equation 1), one can predict the RTs of fast and slow subgroups, as well as the performance of individual participants varying considerably in cognitive ability. Equation 1 itself is derived from even more fundamen-

Table 3
Observed and Predicted Differences (and Errors As Percentages of the Group Mean
Reaction Times [RTs]) Between Average RTs and the Mean RTs for the Fast and Slow
Participant Groups (Predictions Were Made on the Basis of Equation 2)

Domain, Task, and Condition	Fast Subgroup			Slow Subgroup		
	Predicted	Observed	Error	Predicted	Observed	Error
Verbal						
Category Judgment						
High typicality	-118.5	-126.5	1.16	128.8	136.2	1.08
Low typicality	-146.2	-148.1	0.25	158.9	167.7	1.12
Subordinate	-196.6	-220.0	2.43	213.8	240.8	2.82
Lexical Decision						
High frequency	-164.6	-152.4	1.43	178.9	137.8	4.83
Medium frequency	-284.1	-343.6	4.70	308.8	338.4	2.33
Low frequency	-187.5	-196.1	0.93	203.8	189.6	1.52
Rhyme Judgment						
Match similar spelling	-369.7	-356.7	0.82	401.9	385.0	1.08
All different spellings	-328.7	-302.9	1.81	357.4	358.2	0.05
Foil similar spelling	-297.3	-276.5	1.58	323.3	331.0	0.59
Visuospatial						
Shape Comparison						
Match shares color	-122.1	-89.4	4.66	132.7	126.9	0.83
All different colors	-114.0	-103.6	1.55	123.9	126.8	0.42
Foil shares color	-102.8	-88.1	2.32	111.7	123.6	1.88
Abstract Matching						
Share all dimensions	-121.8	-129.0	1.03	132.4	156.2	3.39
Share two dimensions	-196.9	-257.2	6.27	214.1	280.4	6.89
Share one dimension	-226.3	-297.0	6.64	246.0	300.6	5.12
Visual Search						
Set size 10	-144.1	-137.0	0.92	156.7	113.2	5.58
Set size 16	-174.6	-146.2	3.21	189.8	124.9	7.33
Set size 22	-228.1	-171.6	5.27	248.0	184.0	5.97

Note—A negative difference means faster than average performance and a positive difference means slower than average performance; errors are given as absolute percentages.

tal assumptions that treat speeded cognition as a series of computational steps whose durations are correlated (Myerson et al., 2003), resulting in a general speed factor such as that which loaded highly on both the verbal and visuospatial tasks in the present study. It should be noted that the same predictions follow if the “steps” are defined as successive points in a continuous computation (e.g., each step represents the time spent accomplishing another X% of the computation), regardless of whether that computation is serial or parallel or a combination thereof, so long as the durations of the “steps” are correlated. Using computer simulations to validate their mathematical derivation, Myerson et al. showed that the existence of such correlations is key to modeling the pattern of individual differences in RTs.

Recently, Ratcliff, Spieler, and McKoon (2000, 2004) have argued that researchers should focus on models that deal with both speed and accuracy as well as with correct and error RT distributions. However, such models typically involve many free parameters (e.g., Ratcliff & Smith, 2004). The diffusion model, for example, has eight parameters, although the values of some parameters may be fixed in specific applications. The number of free parameters obviously contributes to the impressive ability of traditional molecular models to account for the details of performance on a single task (Ratcliff & Smith, 2004). Such models may be overparameterized, however, for

describing the highly regular molar patterns observed in mean RTs across tasks, individuals, and groups, just as the difference engine model is obviously underparameterized for describing more molecular details of performance on single tasks. Nevertheless, models with more parameters may be able to predict additional details of the molar patterns of individual differences in performance (e.g., error rates as well as RTs) if, as in the difference engine model, the parameters for a given individual (e.g., drift rates and boundary separations in the diffusion model) are assumed to be correlated across tasks.

At present, however, the only other model that specifically predicts both a linear relation between *SD* and group mean RT and a linear relation between RTs of fast and slow subgroups is the *rate-amount model* described by Faust, Balota, Spieler, and Ferraro (1999). The rate-amount model, like the difference engine model, assumes that individuals differ in processing rate and that tasks differ in the amount of processing required, but the rate-amount model also assumes that individuals differ in the amount of processing that they actually do on a given task. This last assumption suggests a way in which speed-accuracy trade-offs might be incorporated into models of individual differences in speeded processing, but the account of individual differences provided by the rate-amount model implies that incorporating such additional features into a model may come at a cost. That is,

Figure 4. Slopes from the regression of individual RTs on group mean RTs plotted as a function of individual mean z -scores. The dashed line represents the prediction of Equation 2 on the basis of individual mean z -scores and the estimate of the m parameter from Equation 1.

although the rate–amount model predicts the form of the empirical relations reported here, the parameters of the equations describing these relations are not always readily interpretable. Moreover, the model does not lead to specific quantitative predictions like those of the difference engine model (although it should be acknowledged that the purpose of the rate–amount model was quite different, as it was intended to provide a basis for statistical tests of small-scale deviations from large-scale patterns like those reported here, rather than being a theoretical model of these molar patterns).

Clearly, when a model is developed on the basis of abstract, general assumptions, such as those that underlie the difference engine model, one often gives up the possibility of using the model to understand some of the more specific aspects of the processing required by individual tasks. This trade-off between specificity and range of application may be seen also in more molecular models (e.g., diffusion and accumulator models) which, for example, do not formally distinguish between processes as different as signal detection and lexical decision (Ratcliff & Smith, 2004). Our present concern, however, was not with the computational processes underlying speeded performance, but at a higher level. Accordingly, we have taken the original equation for predicting individual and subgroup performance (Equation 2) and reformulated it (Equation 3) to more clearly reveal how the size of individual differences depends on the interaction of amount of processing and individual processing speed.

In contrast to more traditional models, the difference engine model provides a highly parsimonious account of higher level phenomena like those examined in the present study. The model is so parsimonious, in fact, that given the highly regular nature of these phenomena, we would venture to propose a rule of thumb to be used when parameter estimation is difficult or impossible: With typical

cognitive tasks, Equations 1–3 may be applied using mean z -scores and assuming that the group SD is one third of the cognitive processing time, which may be estimated as the average RT minus 300 msec (although the latter value is likely to vary slightly with the nature of the response and the age of the individual or group). This rule of thumb accurately describes the present data, and also does a good job of describing all of the data sets analyzed in Myerson et al. (2003). Further research is needed to delineate the boundary conditions of this rule and the network of regular relationships that follow from it, but we believe that, taken together, they provide a benchmark for theories of individual differences in speeded cognition.

AUTHOR NOTE

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REFERENCES

- BATTIG, W. F., & MONTAGUE, W. E. (1969). Category norms of verbal items in 56 categories: A replication and extension of the Connecticut category norms. *Journal of Experimental Psychology*, **80**, 1–46.
- CARROLL, J. B. (1993). *Human cognitive abilities: A survey of factor-analytic studies*. Cambridge: Cambridge University Press.
- FAUST, M. E., BALOTA, D. A., SPIELER, D. H., & FERRARO, F. R. (1999). Individual differences in information-processing rate and amount: Implications for group differences in response latency. *Psychological Bulletin*, **125**, 777–799.
- HALE, S., & JANSEN, J. (1994). Global processing-time coefficients characterize individual and group differences in cognitive speed. *Psychological Science*, **5**, 384–389.
- JENKINS, L., MYERSON, J., HALE, S., & FRY, A. F. (1999). Individual and developmental differences in working memory across the life span. *Psychonomic Bulletin & Review*, **6**, 28–40.
- MYERSON, J., HALE, S., ZHENG, Y., JENKINS, L., & WIDAMAN, K. F. (2003). The difference engine: A model of diversity in speeded cognition. *Psychonomic Bulletin & Review*, **10**, 262–288.
- POSNER, M. I. (1978). *Chronometric explorations of mind*. Hillsdale, NJ: Erlbaum.
- RATCLIFF, R., & SMITH, P. L. (2004). A comparison of sequential sampling models for two-choice reaction time. *Psychological Review*, **111**, 333–367.
- RATCLIFF, R., SPIELER, D., & MCKOON, G. (2000). Explicitly modeling the effects of aging on response time. *Psychonomic Bulletin & Review*, **7**, 1–25.
- RATCLIFF, R., SPIELER, D., & MCKOON, G. (2004). Analysis of group differences in processing speed: Where are the models of processing? *Psychonomic Bulletin & Review*, **11**, 755–769.
- STERNBERG, R. J. (1977). *Intelligence, information processing, and analogical reasoning: The componential analysis of human abilities*. Hillsdale, NJ: Erlbaum.
- TEICHNER, W. H., & KREBS, M. J. (1974). Laws of visual choice reaction time. *Psychological Review*, **81**, 75–98.

NOTES

1. A linear relation between the group SD and mean RT follows from positive linear relations between the RTs of individuals and average performance for their group (i.e., linear individual Brinley plots; see Hale & Jansen, 1994) if, and only if, the individual lines originate in a

small, well-defined region associated with fast RTs on very easy tasks. These individual Brinley plot lines necessarily imply the existence of a general cognitive speed factor. Moreover, the fact that they tend to cross the equality line close to a point with x and y values both approximately equal to the duration of the response component (see Figure 8 in Myerson et al., 2003), as do the lines for fast and slow subgroups (see Figures 1 and 2 in Myerson et al., 2003, and Figure 3 of the present study), implies the existence of an independent (i.e., relatively uncorrelated) factor associated with the individual differences in the duration of the response component. The difference engine provides a possible mechanism linking these phenomena and suggests theoretical interpretations of both individual and group regression parameters.

2. According to the difference engine (Myerson et al., 2003), the equation for the relation between SD and group mean RT is

$$SD = (r^{1/2}\sigma_c/\alpha) (RT - t_r).$$

The slope, $m = r^{1/2}\sigma_c/\alpha$, reflects both the correlations among processing step durations within a task (r), and the coefficient of variation for cognitive processing (i.e., σ_c/α , the between-subjects SD of processing step durations divided by the mean duration). For the derivation of this equation and an explanation of the logic underlying the mathematics, readers should see the Theoretical Development sections of Myerson et al. Unfortunately, there was a mistake in typesetting the Myerson et al. manuscript, and the equation given above is the correct statement of Equation 9 in the original article on the difference engine (as should be clear from inspection of Equation 8 in Myerson et al., 2003). See also the Erratum published in this issue (p. 542).

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