*Psychonomic Bulletin & Review*
*2007, 14 (5), 1007-1009*

# NOTES AND COMMENT

## Individual differences on speeded cognitive tasks: Comment on Chen, Hale, and Myerson (2007)

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*Chen, Hale, and Myerson (2007) recently reported a test of the difference engine model (Myerson, Hale, Zheng, Jenkins, & Widaman, 2003). This test evaluated whether the standard deviation (SD) is proportional to the amount of processing—that is, mean reaction time (RT)—in a speeded cognitive task. We show that this evaluation is not a test of the model because its finding is a consequence of relationships in the data. We argue any model structure that produces increasing values of RT as a function of difficulty, with different slopes for different individuals, necessarily produces a correlation between SD and mean RT. We illustrate this with a different model structure—that is, the diffusion model proposed by Ratcliff (1978)—showing that it produces a fan out between fast- and slow-group means and produces the correlation between SD and mean RT that matches the empirical result.*

Myerson, Hale, Zheng, Jenkins, and Widaman (2003) introduced the difference engine model as "a theory of diversity in speeded cognition," accounting for group and individual differences in reaction time (RT) for speeded cognitive tasks. The two key assumptions of the model are that processing of information is represented as a series of computational steps and that some people tend to perform these individual steps quickly, whereas others tend to perform them slowly. That is, among a group of participants performing the same task, this individual speed difference in carrying out each of these processing steps produces differences in individual mean RTs.

Given these individual differences, one can always split the group into fast and slow subgroups, and then compute their respective mean RTs. If difficulty varies across conditions, mean RTs for individuals, subgroups, and groups should increase with difficulty. In a recent article, Chen, Hale, and Myerson (2007) reported results from six RT tasks where regression of mean RTs—from fast and slow subgroups for each of their 10 difficulty conditions—on overall group mean reaction time produced a linear relation between subgroup mean RT and group mean RT (see Chen et al.'s Figure 3). In addition, Chen et al. also reported a linear relation between the group mean and group standard deviation (*SD*) computed from RTs from each difficulty condition. They claim these findings support the difference engine model's predictions.

The relation between group *SD* (Equation 1) and group mean RT is a "fundamental one" for the difference engine model (Chen et al., 2007) because variability in performance is typically measured as group *SD* (Myerson et al., 2003, p. 268). In this commentary, we show that the two predicted linear relations—first, between subgroup mean RT and a group mean RT, and, second, between group *SD* and group mean RT—arise as a mathematical consequence of individual mean RTs increasing at different rates as a function of difficulty. As a result, finding these relations as predicted by the difference engine model cannot serve as a valid test of the model.

As given in Chen et al. (2007), the precise relationship between *SD* and mean RT (MRT), according to the difference engine model, is described by

$$SD = \left(r \cdot \frac{1}{2}\sigma_{\mathrm{c}}/\alpha\right)\left(\mathrm{MRT} - t_{\mathrm{r}}\right), \tag{1}$$

where $r$ represents the correlation among processing-step durations within a task. That is, for $r$ near 1, if one step is short, the next is short, and if one step is long, the next is long. The ratio $\sigma_c/\alpha$ is the within-task, between-subjects standard deviation in processing-step durations divided by the mean processing-step duration. The quantity ($\mathrm{MRT} - t_r$) is the task mean RT minus the time required for response selection and execution.

Chen et al. (2007) contend that this relationship between *SD* and mean RT is of particular interest for speeded cognitive tasks. However, this relationship is not a result unique to speeded cognitive tasks. For example, suppose that in a 10-km race, 5 runners average $8 \pm 2$ km/h and 5 other runners average $12 \pm 2$ km/h. After running 1 km, the faster group is on average 2.5 min ahead of the slower group ($M_f \approx 5.0$, $SD_f \approx 0.2$; $M_s \approx 7.5$, $SD_s \approx 0.5$). By Kilometer 5, the spread between fast and slow has increased to about 12.5 minutes ($M_f \approx 25.0$, $SD_f \approx 1.2$; $M_s \approx 37.5$, $SD_s \approx 2.6$), whereas at the end of the race it reaches 25 min ($M_f \approx 50.0$, $SD_f \approx 2.3$; $M_s \approx 75.0$, $SD_s \approx 5.3$). Thus, the more kilometers that are run, the greater the difference in mean time and in *SD* between fast and slow groups.

Chen et al. (2007) also noted that *SD*s "increase in an extremely precise fashion" as a function of mean RT. This linear increase has also been previously shown in Hale, Myerson, Smith, and Poon's (1988) Figure 1 and in Faust, Balota, Spieler, and Ferraro's (1999) Figure 7. In an earlier article, Myerson et al. (2003) argued that such precise increase is not due to the positive relationship between group mean RT and group *SD*—as noted above; nor is it a result, they claim, of comparing slow and fast quartile subgroups. To substantiate these claims,

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they ran three sets of simulations, generating RTs for 65 pseudosubjects in 10 difficulty conditions. They then split these subjects in fast and slow quartiles, and compared the regression lines from slow and fast subgroup mean RTs on overall group mean RT. When group *SD* in RT was held constant across difficulty conditions, their simulated data showed no fan out at all, which was taken to support their claim that the precise increase is not due comparing subgroups. However, by setting group *SD* to a constant positive value for all pseudosubjects, they ensured that the slopes of the mean RT regression lines for slow and fast subgroups would have the same values; that is, the lines would be parallel. If subgroups have similar rates of increase in mean RT across difficulty conditions, those slope values will be near 1, as reported in Myerson et al. (2003, p. 264).

In the simulations, when individual *SD*s and mean RTs varied among pseudosubjects, Myerson et al. (2003) observed a fan out between subgroup mean RTs. When participants or groups of participants produce different mean RTs and *SD*s—a result usually observed in speeded cognitive tasks—the rate at which mean RT increases across conditions differs for slow and fast subgroups. More specifically, mean RTs will increase at a lower rate for faster participants than slower participants, producing longer mean RTs and larger *SD*s for the latter group. In short, the correlation between increase in mean RT and increase in *SD* occurs because individual mean RTs increase at different rates across difficulty conditions. Thus, the larger the difference in *SD* and mean RT between subgroups, the larger the fan out that will be produced. This is found in data from Ratcliff, Thapar, and McKoon (2001), for example, where fan out is larger for accuracy than speed conditions.

Chen et al. (2007) report that only the difference engine model and the rate–amount model (for its description, see Faust et al., 1999) can predict the linear relations between *SD* and group mean RT and between mean RTs of slow and fast subgroups. However, we claim that this is a natural consequence of the fact that mean RTs fan out as mean increases. In particular, if all participants have the same floor RT and some have longer RTs than others, across conditions, then mean RTs must fan out. Also, if participants have different floors but they are not too different from one another, then mean RTs will still fan out—unless all RTs change by the same amount going from a fast to a slow participant. Sequential sampling models naturally produce the fan out in mean RT if model parameters vary from subject to subject (see Ratcliff & Smith, 2004, for a review of some of the most prominent sequential sampling models applied to cognitive tasks). In the diffusion model (Ratcliff, 1978), as well as in other sampling models, an increase in boundary separation between the decision criteria leads to increase in mean RTs, with the longer RTs increasing more than the shorter RTs. Figure 1 shows the result of a simulation demonstrating this result. The parameters of the diffusion model were chosen to be typical of fits to experimental data, and were allowed to vary from subject to subject, with *SD*s about the same as those from fits to experimental data (Ratcliff, Gomez, & McKoon, 2004; Ratcliff, Thapar, & McKoon, 2001, 2003; Thapar, Ratcliff, & McKoon, 2003). As mean RT increases, the spread across subjects increases, and the *SD* increases. The correlation between group *SD* and group mean RT was .998. The bottom panel of the figure shows the result from splitting mean RTs from the simulated subjects into 0fast and slow halves. The means for the three conditions

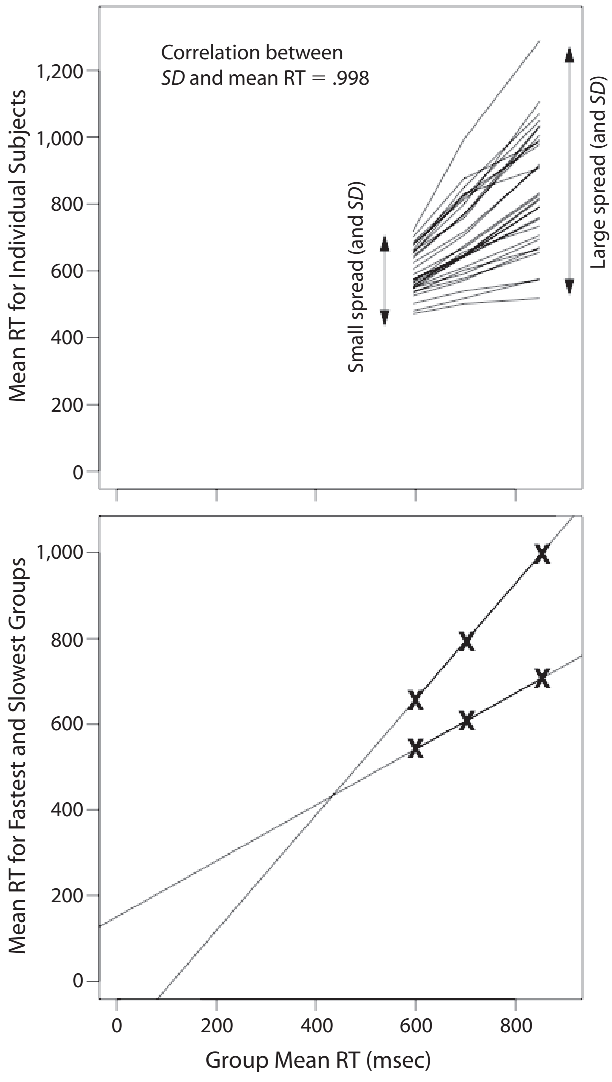


**Figure 1. Diffusion model simulation results from 30 simulated subjects, with 400 observations per condition. The top panel shows correlation between group standard deviation and group mean reaction time (RT). The bottom panel shows the result from splitting mean RTs from the simulated subjects into fast and slow halves. Parameters were chosen to be typical of fits to experimental data: boundary separation, $a = 0.16$; mean drift rates, $\nu_1 = 0.45$, $\nu_2 = 0.3$, $\nu_3 = 0.15$, within-trial variability in mean drift rates, $\eta = 0.08$; nondecision component, $T_{er} = 0.4$; variability in nondecision component, $s_t = 0.1$; and starting point, $z = a/2$. The across-subjects variabilities in $\nu_{1,2,3}$, $a$, and $T_{er}$ were respectively set to 0.07, 0.03, and 0.02, and within-trial variability was set to $s = 0.1$.**

for the fastest and slowest subgroups were plotted against the group mean, providing exactly the same regularity showing in Chen et al.'s Figure 3.

Chen et al. (2007) argue that sequential sampling models are overparameterized in accounting for the kinds of simple regularities presented in their article. We have shown that if any reasonable assumptions are made about variability across subjects in parameter values (by "reasonable," we mean assumptions that are similar to those in fits to experimental data, e.g., Ratcliff et al., 2004; Ratcliff et al., 2001, 2003; Thapar et al., 2003), then the relationships presented by Chen et al. are an automatic consequence of the sequential sampling model. Moreover, the relationships themselves do not support any strong tests of the models, because, if mean RT increases as a function of difficulty for each participant (on average), and the slower the participant the larger the increase, then the standard deviation will increase with mean. This is not a consequence of the model, rather, it is another way of describing the fan out in the data.

In summary, we have shown that the effect purportedly validating the difference engine model is a mathematical relationship inherent in data from speeded cognitive tasks. That is, if one assumes something about the source of individual differences (e.g., nonhomogeneity in participants) and that there exists a floor on RT, then the proportional relationship between *SD* and mean RT is a consequence of mean RT increasing with difficulty at different rates for different participants. Therefore, finding this relationship in behavioral data does not support the difference engine model. In addition, we have also shown that a model with different architecture, the diffusion model (Ratcliff, 1978), accounts for the same relationship with no extra assumption or parameter.

## AUTHOR NOTE

We thank Anne MacGilvray, Gail McKoon, and Jeff Starns for comments on the manuscript. Correspondence related to this article may be sent to R. Ratcliff, 291B Psychology Building, Department of Psychology, Ohio State University, 1835 Neil Avenue, Columbus, OH 43210.

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(Manuscript received November 15, 2006;
revision accepted for publication December 19, 2006.)