Aging and Individual Differences in Rapid Two-choice Decisions

Roger Ratcliff, Anjali Thapar, and Gail McKoon

The Ohio State University, Bryn Mawr College, and The Ohio State University

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Address correspondence to:

Roger Ratcliff,

Department of Psychology,

The Ohio State University,

Columbus, OH, 43210

Phone number: 614 292 7916

Fax number: 614 688 3984

email ratcliff.22@osu.edu

Abstract

The effects of aging on performance were examined in signal detection, letter discrimination, brightness discrimination, and recognition memory, with each subject tested on all four tasks. Ratcliff's (1978) diffusion model was fit to the data for each subject for each task and it provided a good account of accuracy and the distributions of correct and error response times. The model's analysis of the components of processing showed that aging had three main effects: the nondecision components of processing were slower and decision criteria were more conservative for 60-75 and 75-85 year old subjects than college students, but the quality of the evidence on which decisions were based was as good for some of the older subjects as for college students for some of the tasks. Individual differences among subjects in components of processing tended to be preserved across the tasks, as shown by strong correlations across the tasks in the parameters of the model that represent the components of processing. For example, if the evidence on which a subject's decisions were based was good in one task, it tended to be good in all four tasks.

Across a wide variety of tasks, research has shown that cognitive processing slows with age. Until recently, the most prominent account of this decline was the generalized slowing hypothesis, according to which either all cognitive processes slow with age or some general mechanism that contributes to many processes slows with age (e.g., Brinley, 1965; Cerella, 1994). Although the hypothesis has been favored by many researchers because it provides a relatively simple and intuitively appealing explanation of age-related decrements across many laboratory tasks as well as everyday behaviors, it has also been challenged on a number of fronts (Cerella, 1994; Fisher & Glaser, 1996; Fisk & Fisher, 1994; Myerson, Wagstaff, & Hale, 1994; Hertzog, 1992). One central problem is that the hypothesis does not allow the decision components of a task to be separated from the quality of the information upon which the decisions are based. Another is that the hypothesis has been focused on mean response times (RTs) for correct responses. The full set of data that need to be addressed includes accuracy and correct and error RT distributions (Ratcliff, Spieler, & McKoon, 2000). Recently it has been shown that Ratcliff's diffusion model (Ratcliff, 1978, 1988, 2002; Ratcliff & Rouder, 1998, 2000; Ratcliff & Smith, 2004; Ratcliff, Van Zandt, & McKoon, 1999) can handle the full set of data from two-choice tasks and additionally provide an analysis of the components of processing that underlie performance in a task and how they are differentially affected by aging (Ratcliff, Thapar, & McKoon, 2001, 2003, 2004; Thapar, Ratcliff, & McKoon, 2003). For this article, we tested the diffusion model in the aging domain by examining performance of individual subjects across four two-choice tasks, with college-age subjects, 60-75 year olds, and 75-85 year olds. The goal was to produce an analysis of individual differences as well as aging effects in components of processing. A key question was the extent to which the components of processing identified by the model are consistent for an individual across tasks.

The diffusion model assumes that fast two-choice decisions are made by a noisy process that accumulates information over time from a starting point toward one of two response criteria or boundaries, as in Figure 1, Panel B, where the starting point is labeled z and the boundaries are labeled a and 0. When one of the boundaries is reached, a response is initiated. The rate of accumulation of information is called drift rate (v), and it is determined by the quality of the information available from the stimulus. The better the information quality, the larger the drift rate toward the appropriate decision boundary and the faster and more accurate the response. Within trial variability in the accumulation of information results in processes with the same mean drift rate terminating at different times (producing RT distributions) and sometimes at different boundaries (producing errors). Speed-accuracy tradeoffs are modulated by the positions of the boundaries: moving boundaries closer to the starting point speeds responses and decreases accuracy. Response time distributions in two-choice tasks are positively skewed, which comes about naturally in the model by simple geometry: The increase in RT is larger if a lower value of drift rate is decreased by some amount than if a larger value of drift rate is decreased by the same amount. Besides the decision process, there are nondecision components of processing such as encoding and response execution (Figure 1, Panel B). These processes are combined in the model and their contribution to RT has mean T_{er} (Ratcliff & Tuerlinckx, 2002).

INSERT FIGURE 1 HERE

In the diffusion model, components of processing are assumed to vary from trial to trial. Variability in drift rate across trials (normally distributed with SD η) gives rise to error responses that are relatively slow compared to correct responses, and variability in starting point across trials (uniformly distributed with range s_z) gives rise to relatively fast errors. Whether errors are faster or slower than correct responses for an experimental condition depends on the relative amounts of drift rate and starting point variability, drift rate values, and boundary positions (Ratcliff et al., 1999). Across trial variability in T_{er} is uniformly distributed with range s_t.

The diffusion model serves to map performance characteristics onto underlying processes. From the probability of a correct response and the RT distributions for correct and error responses for each of the conditions in an experiment, the model extracts estimates of the quality of the stimulus information that enters the decision process for each condition (drift rate), the amount of information that must be accumulated before a decision can be made (boundary positions), the time taken by nondecision components of RT (T_{er}), and the amount of variability across trials in each of the processing components. In its initial applications to aging research, the key contribution of the diffusion model has been to identify which components are responsible for performance decrements in two-choice tasks for 60-75 year old subjects compared to college age subjects. In the five tasks that they examined, Ratcliff, Thapar, and McKoon (2001, 2003, 2004; Thapar, Ratcliff, & McKoon, 2003; hereafter collectively "RTM"), found that older subjects were usually slower than college subjects in the nondecision components of processing that are summarized by T_{er} and that older subjects usually set their response boundaries more conservatively than young subjects. One or both of these factors accounted for most of the difference in speed between the young and older subjects in all four experiments. Across trial variability in components of processing was generally not significantly different between the two groups of subjects. Most interesting was that drift rates did not differ significantly between the young and older subjects for four tasks: a signal detection task, masked brightness discrimination, recognition memory, and lexical decision (RTM; Ratcliff, Thapar, Gomez, & McKoon, 2004). Only for masked letter discrimination were the drift rates for the older subjects lower, in accord with psychophysical literature that has found decrements with age for higher spatial frequency stimuli (Spear, 1993). For all of the results just described, there were different subjects for each task. In this article, the subjects were the same for each task, and they included 75-85 year olds as well as 60-75 year olds. The goals were to test the application of the diffusion model with a broader range of subjects than previously and to examine whether the components of processing identified by the model are significantly correlated from one task to another for individual subjects.

Experiments

The first experiment used a signal detection task in which subjects were asked to decide whether the number of asterisks displayed on a computer screen was "large" or "small." The other three experiments' tasks were masked letter discrimination, masked brightness discrimination, and recognition memory. Following RTM, we expected response boundaries and T_{er} to vary with age in all four experiments. For the signal detection task, there are no perceptual or memory limits on the information available to the subjects and so, following Ratcliff et al. (2001), we expected that drift rates would not vary with age. For the other tasks, RTM found that drift rates were lower for 60-75 year olds only in masked letter discrimination. For 75-85 year olds, drift rates might also be lower in masked brightness discrimination and recognition memory.

Subjects had to meet the following inclusion criteria to participate in the study: a score of 26 or above on the Mini-Mental State Examination (Folstein, Folstein, & McHugh, 1975); a score of 15 or less on the Center for Epidemiological Studies-Depression Scale (CESD; Radloff, 1977); and no evidence of disturbances in consciousness, medical or neurological disease causing cognitive impairment, head injury with loss of consciousness, or current psychiatric disorder. There were no significant differences on any of these measures for the three groups of subjects: 10 young (college students from Northwestern University) subjects, 10 older (60-75) subjects, and 10 very old (75-85) subjects.

Each subject participated in 16 sessions, four sessions on each of the tasks, in the order signal detection, letter discrimination, brightness discrimination, and recognition memory. For each experiment, on alternating blocks of trials, instructions stressed that responses be either as accurate as possible or as fast as possible. Subjects were given feedback appropriate to the instructions: either accuracy feedback on each trial or a “too slow” message when RT was over 700 ms.

Signal Detection. For each trial, a number of asterisks between 1 and 100 was generated from a signal distribution, normal with mean 57.5, or a noise distribution, normal with mean 39.5, each with SD=14.4 (Ratcliff et al., 1999; Ratcliff et al., 2001, Experiment 1). The asterisks were placed in random positions in a 10x10 array of blank characters on a computer screen. Subjects were asked to decide whether the number of displayed asterisks was “large” or “small.” Accuracy feedback was given on all trials: If the number of asterisks was very large or very small, feedback indicated that “large” or “small”, respectively, was the correct response. For intermediate numbers of asterisks, feedback was probabilistic, sometimes indicating “large” and sometimes “small” as the correct response (Ratcliff et al., 2001). There were 12 blocks of 96 trials per session, 6 with speed instructions and 6 with accuracy instructions. For data analyses, the numbers of asterisks were grouped into eight experimental conditions such that the mean RTs and accuracy values were about the same for the stimuli within a group.

Letter Discrimination. For each block of trials, there were two target letters, continuously displayed on the top left and right corners of the computer screen. On each trial, one of the letters was displayed at the center of the screen for 10, 20, 30, 40, 50, or 60 ms and then masked as in

Thapar et al. (2003). A subject's task was to indicate which letter was presented. There were 12 blocks of 96 trials per session. Performance for the 40, 50 and 60 ms durations was near ceiling and so data from these conditions were combined into one condition for data analyses.

Brightness Discrimination. The stimuli were 64x64 squares of black and white pixels displayed on a grey background that totaled 320x200 pixels (Ratcliff et al., 2003). There were six levels of brightness for the squares, achieved with six values of the probability of a pixel being white (.350, .425, .475, .525, .575, .650) and a square was displayed for 50, 100, or 150 ms, followed by a mask made up of four 64x64 checkerboard patterns presented sequentially. Subjects were asked to decide whether each square was "bright" or "dark." There were 8 blocks of 144 trials per session.

Recognition Memory. The stimuli were high, low, and very low frequency words (Ratcliff, Thapar, & McKoon, 2004). There were 20 study-test blocks per session. For each block, the study list consisted of words displayed for 1 s each, 9 presented once and 9 presented three times, 3 high, 3 low, and 3 very low frequency in each case, and the immediately following test list consisted of the 18 studied words plus 18 new words, 6 high, 6 low, and 6 very low frequency. For each session, stimuli were chosen randomly without replacement from the three pools.

Results

Mean values of RT and accuracy were calculated for each subject and means of these means are shown in Figure 2. All subjects adjusted their performance according to instructions, but the young subjects were more willing to sacrifice accuracy for speed; they made 4-8% more errors with speed than accuracy instructions, whereas the older subjects made only 1-2% more errors. Otherwise, the main results were that accuracy rates for the 60-75 year olds were lower than for the young subjects for letter discrimination but not the other tasks, whereas accuracy rates for the 75-85 year olds were also lower for brightness discrimination and a little lower for recognition memory.

In the next paragraphs, we show first, that the model fit the data well for individual subjects for individual experiments, second, how components of processing (performance characteristics) change with age according to the model, third, we show that sensible and consistent interpretations of performance across the three age groups and the four tasks are provided by the model, and fourth, we examine whether components of processing are correlated for individuals across the four tasks.

INSERT FIGURE 2 HERE

For each subject individually for each experiment, the diffusion model was simultaneously fit to the probability of a correct response and the RT distributions for correct and error responses for all the conditions of the experiment. The fits of the model are constrained by several assumptions. First, subjects can adjust their response boundaries according to whether instructions emphasize speed or accuracy, but they cannot change drift rates. Drift rates are affected only by the quality of the information from a stimulus. Second, when subjects adjust response boundaries, they can separately adjust the distances from the starting point to the two boundaries. For the data presented here, the model fit well with the two distances set equal to each other (i.e., $z=a/2$), except for recognition memory. Third, it is assumed that T_{er} is constant across levels of stimulus difficulty and instructions. Although small differences in T_{er} might reasonably be assumed between, for example, speed versus accuracy instructions, little is added to the quality of the fits of the model to data and nothing significant would change in interpretations of the data. Finally, for the fits presented here, it was assumed that all the across trial variability parameters were constant across levels of stimulus difficulty and instructions.

For each experiment, there was one value of drift rate for each experimental condition or group of conditions. For the signal detection experiment, the four conditions for which “large” was the correct response had the same absolute values of drift rates as the four conditions for which “small” was the correct response, except that individual subjects set their criterion between the two at different points. To represent this bias, a parameter c was added to the model (Ratcliff et al., 2003) such that the value of c was added to each of the four drift rates for “large” stimuli and subtracted from the negatives of the four drift rates for “small” stimuli. For letter discrimination, there was one value of drift rate for each of the three shortest stimulus durations and a fourth value for the three longest durations combined. For brightness discrimination, the three brightness conditions for which the correct response was “bright” had the same absolute values of drift rates as the three conditions for which the correct response was "dark," except that, like the signal detection experiment, there was a bias parameter c. The three values of drift rate and c were different for the three stimulus durations. For the recognition memory experiment, there were nine drift rates, six for studied words (three levels of frequency, one or three presentations) and three for nonstudied words (levels of frequency). Also, the starting point z was an additional parameter because it was not equidistant between the two boundaries. The young subjects set the starting point nearer the "old" boundary by about 5% of total boundary separation and both groups of older subjects set the starting point nearer the "new" boundary by between 5 and 20%.

In addition to the parameters just mentioned, there were seven other parameters for each experiment: the distances between the response boundaries with speed instructions, a_s, and with accuracy instructions, a_a; the nondecision components of processing, T_{er}; the standard deviation in drift rate across trials, η; the range in starting point across trials, s_z; the range in the nondecision components of processing across trials, s_t; and the probability of contaminant "outlier" RTs p_o (less than .01 for all four experiments, see Ratcliff & Tuerlinckx, 2002). The parameter that represents variability in drift rate within a trial (s) is a scaling parameter, set to 0.1 as in previously published fits of the model. The same minimization routine as in previous diffusion model research was used to find the parameter values that produced the smallest chi-square value for the data for each subject for each experiment.

The full range of data that the model must accommodate and the quality of its fits to the data are usually presented in quantile probability functions (e.g., RTM), which display, for each condition in an experiment, the quantiles of the RT distributions for correct responses and error responses and the probabilities of the responses. They simultaneously show the relative speeds and accuracies of correct and error responses, as well as the shapes of the RT distributions, and how they covary across conditions. However, the number of functions required for the four experiments and three subject groups presented in this article would be large (40 panels), so instead goodness of fit was summarized statistically. Table 1 shows the means of the chi-square values produced by the minimization routine, the degrees of freedom for the chi-square, and the number of free parameters for each experiment. For N experimental conditions, 10 quantile RTs (5 correct and 5 error), and a model with M parameters, the number of degrees of freedom is df =N(12-1)-M.

INSERT TABLE 1 HERE

Overall, the model fit the data well, as well as for the studies with the same tasks with college age and 60-75 year old subjects published by RTM. To allow comparison of the chi-square values across the experiments reported here, they were divided by their respective degrees of freedom. The resulting values were 2.6, 2.1, 2.4, and 2.2 for the signal detection, letter discrimination, brightness discrimination, and recognition memory experiments, respectively. These values, as well as the chi-square values in Table 1, are similar to those from the RTM experiments (except for letter discrimination for which there were about 50% more observations here than in Thapar et al., 2003). Although the mean chi-square values in Table 1 are larger than the .05 significance level, the numbers of degrees of freedom and numbers of observations are so large that even small deviations between model and data lead to significant chi-square values (see Ratcliff et al., 2004 for further discussion).

Interpreting the Data through the Diffusion Model

Age Effects. Figure 3 and Table 2 show which components of processing changed with age, and which did not. For older subjects for all four tasks, boundaries widened and nondecision components of processing slowed. For the 60-75 year olds, the quality of the information upon which their decisions were based (drift rates) was as good as for the young subjects, except in letter discrimination. For the 75-85 year old subjects, drift rates were worse in brightness discrimination and recognition memory as well as in letter discrimination. Across trial variability in drift rate tended to be larger for the older subjects in the discrimination tasks. For the 60-75 year olds, the results replicate RTM except that the boundary separation values were larger here than in Ratcliff et al. (2003). The larger nondecision components of processing and wider response boundaries for the older subjects mapped into longer overall RTs, augmented in some of the experiments by lower drift rates.

INSERT FIGURE 3 AND TABLE 2 HERE

Mapping Components of Processing into Performance. For each subject in each experiment, we computed correlations between their data-- specifically, the mean values of accuracy, correct RT, and error RT across experimental conditions-- and the parameter values from the best fits of the model to their data. This was done only for conditions with speed instructions because the data and parameter values were much less consistent across experiments with accuracy instructions, apparently because of individual differences in how accuracy instructions were interpreted. The correlation averaged over subjects and experiments between T_{er} and correct RT was .78, between boundary separation and correct RT, .75, and between drift rate and accuracy, .74, with a critical value for p=.05 of .27[1]. This means that slower subjects tended to have longer values of T_{er} and higher values of a_s, and that more accurate subjects had higher values of drift rate. Among the other correlations, only that between drift rate and η was significant (.66). The others were: correct RT and drift, -.29; accuracy and T_{er}, .18; accuracy and a_s, .22; and accuracy and correct RT, -.05. The correlations between error RTs and the parameter values followed those for correct RTs because error and correct RTs correlated .93. For the college age and 60-75 year old subjects, this pattern of correlations matches that obtained in earlier studies.

Individual Differences Across Experiments. We examined whether the model parameters were consistent across experiments for individual subjects by computing the correlations between each pair of experiments for each parameter. With four experiments, this yields six correlations for each of the three groups of subjects and these are shown in Figure 4. Averaging across pairs of experiments and subject groups, the correlations were: a_{sp}=.45, a_{ac}=.13, T_{er}=.48, η=.08, s_z=-.02, drift=.54, and s_t=.07. The critical value for the correlation coefficient is .44 (computed using a Monte Carlo method which mimics the multiple correlations and averages across subject groups). Thus, the values of a_{sp}, T_{er}, and drift rates were reasonably consistent across experiments for individuals, whereas the values of the other parameters were not (for the variability parameters, this was partly because of high variability in their estimates, Ratcliff & Tuerlinckx, 2002).

INSERT FIGURE 4 HERE

General Discussion

The diffusion model fit all the data from all four tasks simultaneously, and it did so at the level of individual subjects who varied across a wide range of performance levels. The model's analyses of performance characteristics for college and 60-75 year old subjects replicated those from earlier studies in which different subjects participated in each different task.

The model's interpretations of the components of processing indicate that response accuracy is mainly a function of the quality of the evidence from a stimulus and that response speed is mainly a function of decision boundaries and, to some degree, nondecision components of processing. Individual differences in components of processing were significantly correlated across experiments, and this was true for college students, 60-75 year olds, and 75-85 year olds. A subject who was slow in one task because of slow nondecision components of processing or conservative response criteria tended to be slow in the other tasks for the same reason. A subject who was accurate in one task because of large values of drift rate tended to be accurate in the other tasks for the same reason.

For aging research, the results are important in showing that the much slower responses of older adults compared to young adults in cognitive tasks can be due mainly to conservative response criteria, accompanied by relatively small slowdowns in nondecision components of processing. For the tasks studied here, differences in the quality of the evidence available from the stimuli between college and 60-75 year old subjects appeared only for letter discrimination and they were small. Differences in the quality of the evidence between college and 75-85 year old subjects appeared for three of the four tasks (letter discrimination, brightness discrimination, and recognition memory), but again they were small. The significant correlations across tasks suggest that these components of an individual's processing are not task-specific, but instead are significantly consistent across tasks.

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Footnote

[1]The critical value for r for $p=.05$ and 10 subjects is .55. With 21 r's tested (all combinations of 3 data values and 4 parameters), the critical value is raised to .81, but because the averages over 12 experiments were computed, the critical value is lowered to .27. The critical values were obtained using 10,000 Monte Carlo simulations, exactly mimicking the multiple comparisons and averages over experiments.

Table 1: Goodness of Fit Values for the Diffusion Model

	Chi Square Goodness of Fit Averaged Over Subjects		
Task	Young Subjects	Older Subjects	Very Old Subjects
Signal detection	460	413	409
Letter discrimination	172 (84)	181 (119)	127
Brightness discrimination	869 (680)	945 (951)	919
Recognition memory	435 (368)	323 (431)	408

Note. The degrees of freedom and number of parameters for the signal detection task were 164 and 12, for the letter discrimination task, 77 and 11, for the brightness discrimination task, 376 and 19, and for the recognition memory task, 180 and 18. The numbers in parentheses in the table are the average chi square values from previously published experiments (Thapar, Ratcliff, & McKoon, 2003; Ratcliff, Thapar, & McKoon, 2003, 2004).

Table 2: Effects of Aging on Components of Processing: Parameters of the Diffusion Model

Task	Parameter differences for 60-75 year olds versus young subjects				Parameter differences for 75-85 year olds versus 60-75 year olds			
	a_s	T_{er}	v	η	a_s	T_{er}	v	η
Signal detection	higher	longer	n.s.	n.s.	n.s.	longer	n.s.	n.s.
Letter discrimination	higher*	longer	lower*	higher*	higher	longer*	n.s.	higher
Brightness discrimination	higher	longer	n.s.	higher	n.s.	n.s.	lower	n.s.
Recognition memory	higher	longer	n.s.	n.s.	higher	longer*	lower*	n.s.

Note. Significance of the differences were computed using simple t-tests. Asterisks indicate marginally significant effects (.05<p<.10) and n.s. indicates nonsignificant effects: the other differences were significant p<.05. Note that for young versus older subjects, the results for a_s (boundary separation for the speed condition), T_{er} (nondecision component of processing), and v (drift rate) replicated results from RTM (apart from a_s for brightness discrimination).

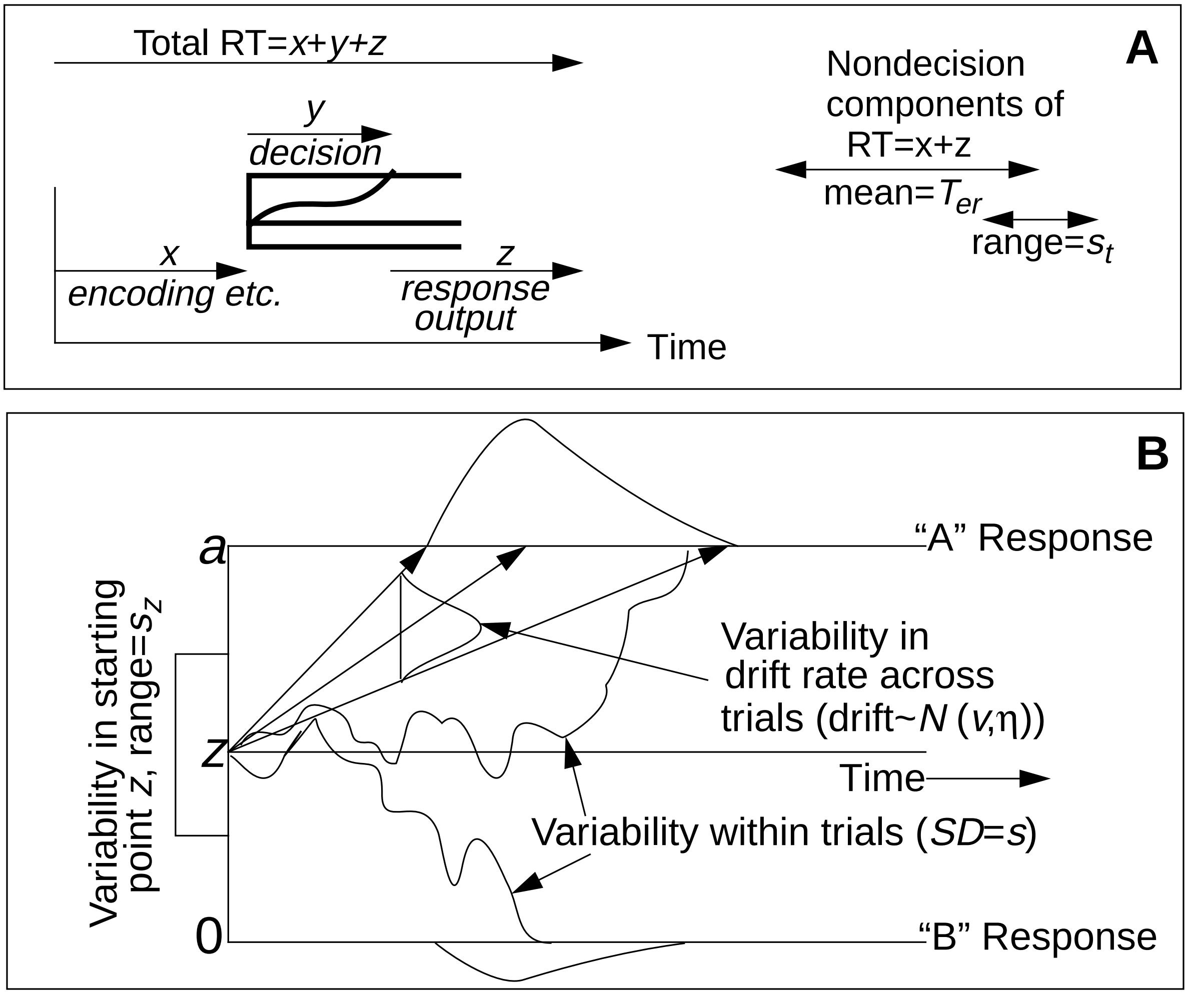
Figure Captions

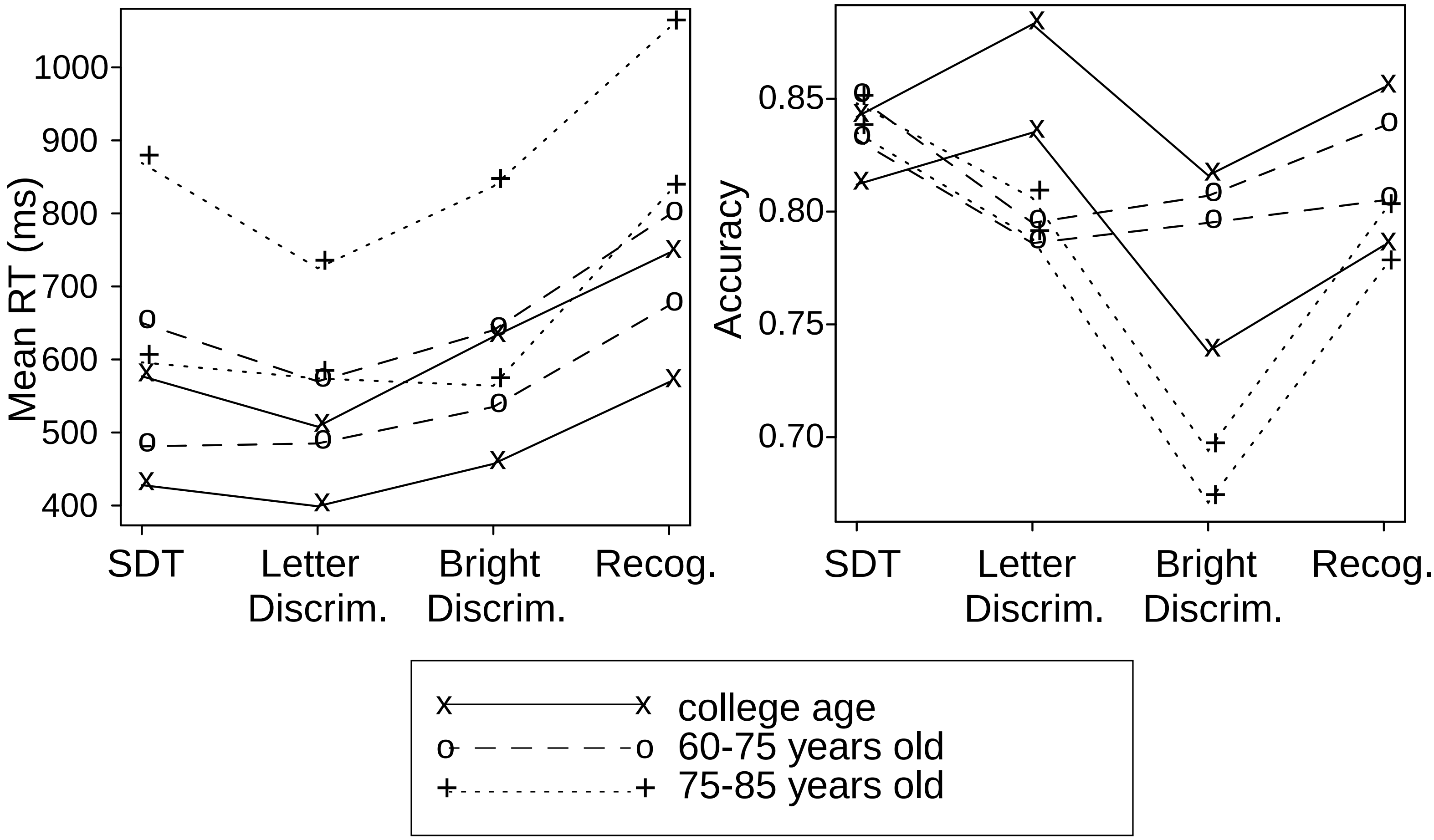
Figure 1. An illustration of the diffusion model. Parameters of the model are $\underline{a}$=boundary separation, $\underline{z}$=starting point, T_{er}=nondecision components of RT, η=SD in drift across trials, s_z=range of the distribution of starting point (z) across trials, $\underline{v}$=drift rate, s_t=range of the distribution of nondecision times across trials, $\underline{s}$= SD in variability in drift within trials.

Figure 2. Mean values of correct RT and accuracy averaged over subjects and experimental conditions for each task for each group of subjects. For both mean RT and accuracy, the top line of the pair of lines for each group is for conditions with accuracy instructions and the bottom line is for conditions with speed instructions.

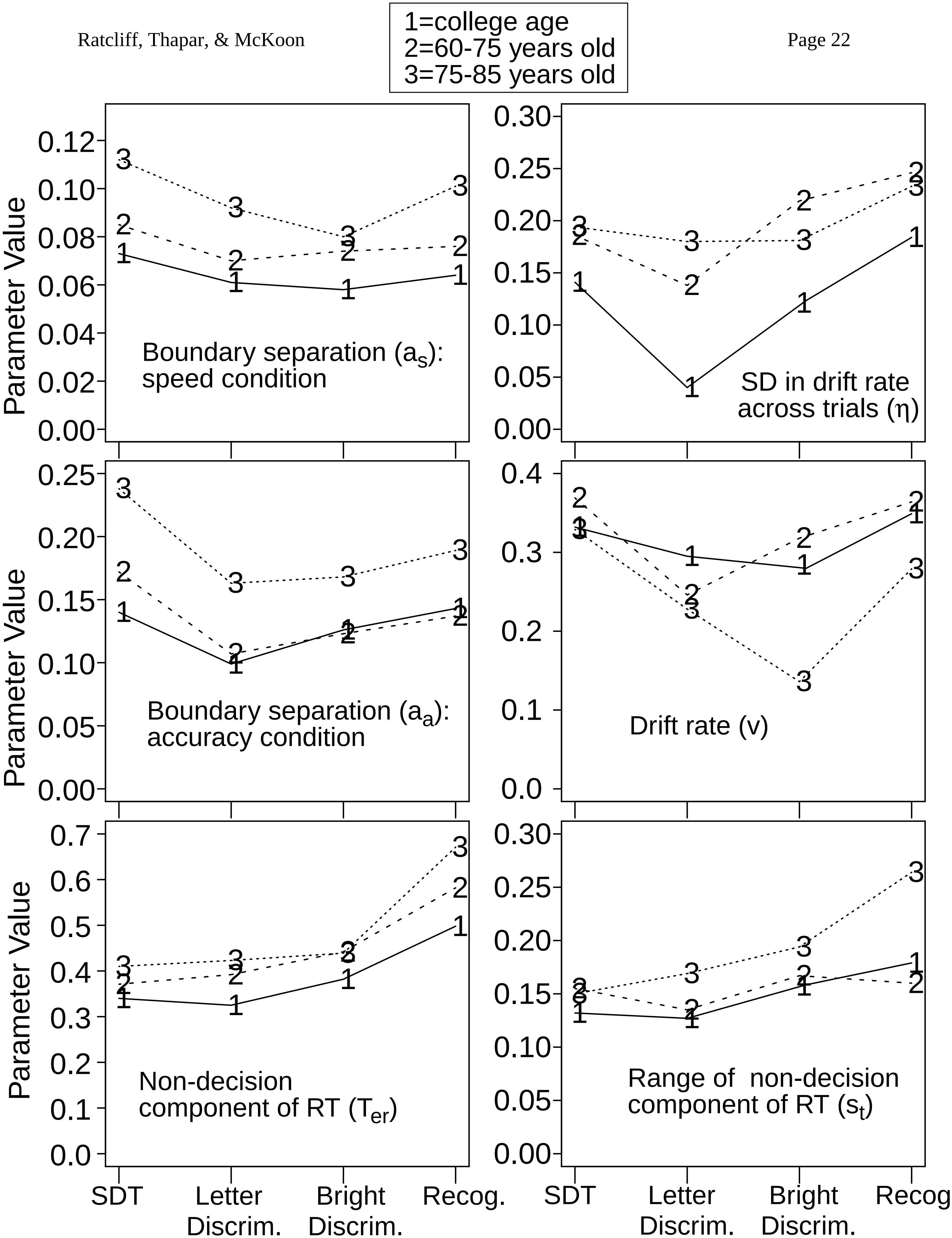
Figure 3. Mean parameter values averaged across subjects and conditions for each task and subject group. Values of $\underline{s}_{\underline{z}}$ were between 0.004 and 0.008 for the letter discrimination experiment and between 0.021 and 0.040 for the other experiments.

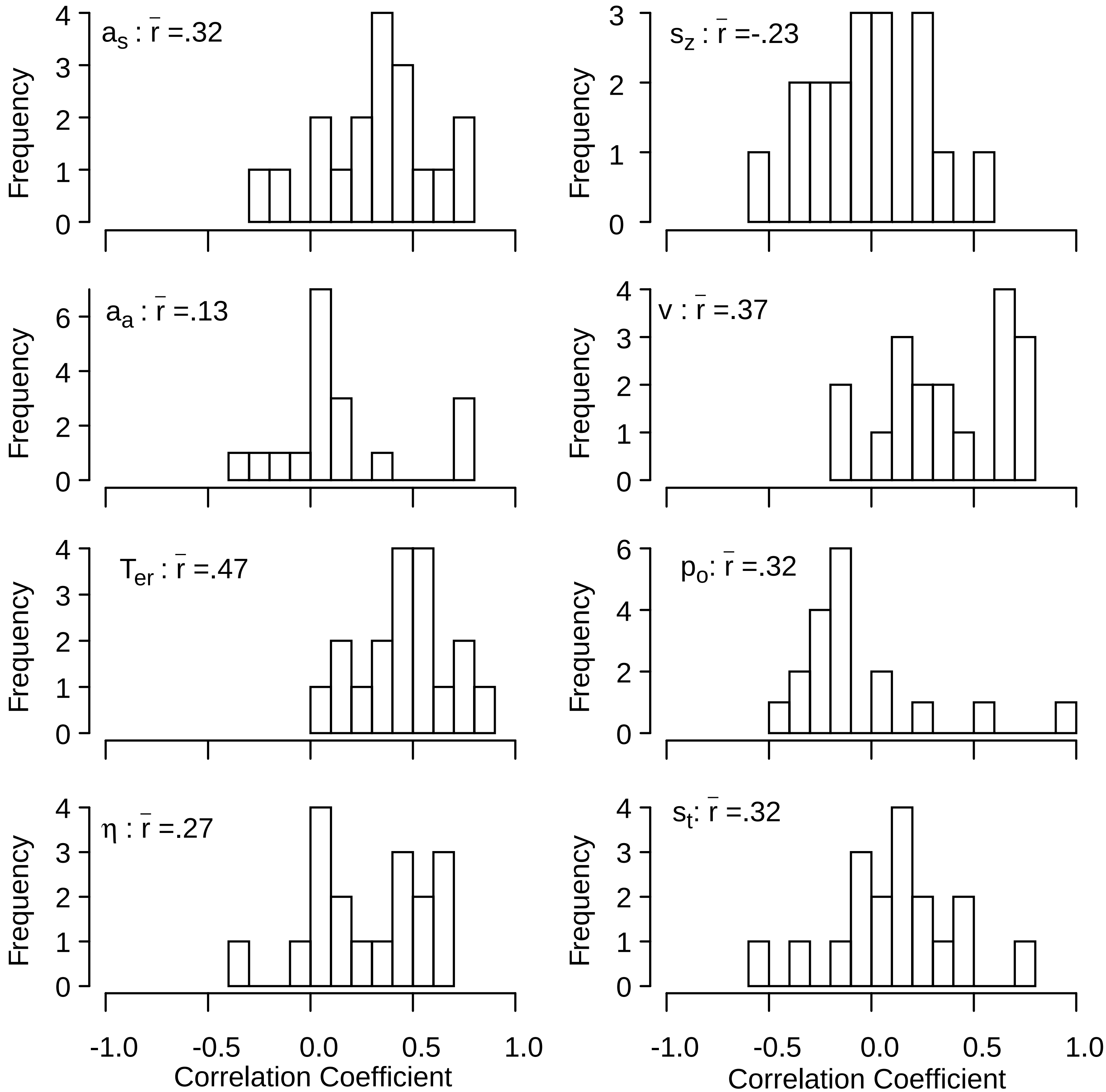
Figure 4. Histograms of correlations for parameter values of the model across all pairs of the 4 experiments and across the 3 subject groups. The mean values of the correlation are shown and the critical value of the correlation is .44.


A
Total RT=x+y+z
y
decision
x
encoding etc.
z
response output
Time
Nondecision components of RT=x+z
mean=T_{er}
range=s_t
B
a
z
0
"A" Response
"B" Response
Variability in starting point z, range=s_z
Variability in drift rate across trials (drift~N (v,η))
Time
Variability within trials (SD=s)



1000
900
800
700
600
500
400
Mean RT (ms)
0.85
0.80
0.75
0.70
Accuracy
SDT
Letter Discrim.
Bright Discrim.
Recog.
college age
60-75 years old
75-85 years old


1=college age
2=60-75 years old
3=75-85 years old
Parameter Value
Boundary separation (a_s): speed condition
SD in drift rate across trials (η)
Boundary separation (a_a): accuracy condition
Drift rate (v)
Non-decision component of RT (T_{er})
Range of non-decision component of RT (s_t)
SDT
Letter Discrim.
Bright Discrim.
Recog.



a_s : $\bar{r}$ =.32
s_z : $\bar{r}$ =-.23
a_a : $\bar{r}$ =.13
v : $\bar{r}$ =.37
T_{er} : $\bar{r}$ =.47
p_o: $\bar{r}$ =.32
η : $\bar{r}$ =.27
s_t: $\bar{r}$ =.32
Frequency
-1.0 -0.5 0.0 0.5 1.0
Correlation Coefficient