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Age Differences in Central (Semantic) and Peripheral Processing: The Importance of Considering Both Response Times and Errors

Philip A. Allen, Martin D. Murphy, Miron Kaufman,
Karen E. Groth, and Ana Begovic

In this project we examined the effect of adult age on visual word recognition by using combined reaction time (RT) and accuracy methods based on the Hick–Hyman law. This was necessary because separate Brinley analyses of RT and errors resulted in contradicting results. We report the results of a lexical decision task experiment (with 96 younger adults and 97 older adults). We transformed the error data into entropy and then predicted RT by using entropy values separately for exposure duration (thought to influence peripheral processes) and word frequency (thought to influence central processes). For exposure duration, the entropy–RT functions indicate that older adults show higher intercepts and slopes than do younger adults, suggesting an encoding decrement for older adults. However, for word frequency, older adults show higher intercepts but not steeper slopes than younger adults. Older adults thus show a peripheral processing decrement but not a central processing decrement for lexical decision.

THERE were two goals in this study. First we wished to determine if past studies using a lexical decision, semantic memory task would be replicated when more rigorous methods are used. Earlier studies of lexical decision processing have typically observed age decrements in peripheral processing but not central processing (e.g., Allen, Madden, & Crozier, 1991; Allen, Madden, Weber, & Groth, 1993; Allen, Sliwinski, & Bowie, 2002; Allen, Sliwinski, Bowie, & Madden, 2002; Allen, Smith, et al., 2002, although cf. Balota & Ferraro, 1993, 1996 who found somewhat different results for a naming task). We assume that lexical decisions consist of word encoding, lexical access (in which letters strings are matched to representations stored in long term semantic memory), a stimulus decision stage, a response selection decision stage, and response execution (Allen, Sliwinski, Bowie, & Madden, 2002; Allen, Smith, et al., 2002; Monsell, Doyle, & Haggard, 1989). We assume that the input and output processes (encoding and response execution) are peripheral processes and that the lexical access, stimulus decision, and response selection processes are central processes (Allen et al., 1993, Allen, Sliwinski, Bowie, & Madden, 2002; Cerella, 1985; Sternberg, 1967). We assume the present exposure duration manipulation to manipulate word encoding a periph eral process (Carr & Pollatsek, 1985), whereas we assume word frequency effects to measure lexical access a central process (Monsell et al., 1989).

Our second goal was to develop a method of analysis that would include both response time (RT, or speed) and accuracy (error) measures as critical components of analyses instead of just speed or error measures. Cognitive psychology assumes that both RT and accuracy or errors are involved in a speed accuracy trade off (Luce, 1986; Pachella, 1974). That is, the more processing time taken to make a decision, the more accurate the decision up to an asymptotic RT.

Previously, we developed an entropy model of age differ ences in spatial memory (Allen, Kaufman, Smith, & Propper, 1998a, 1998b). Our conclusion from these studies was that older adults' increased entropy levels result in less efficient molar memory networks. By entropy, we mean the level of disorder in the information processing system. This earlier research was based entirely on accuracy data (i.e., entropy is computed from accuracy data). A related approach is the oscillator based as sociative recall model (or OSCAR model; see Brown, Preece, & Hulme, 2000; Maylor, Vousden, & Brown, 1999). However, both the entropy model of Allen and colleagues and the OSCAR model of Brown and colleagues and Maylor and colleagues are based on a single dependent variable. Our goal in the present study was to develop a methodology that would allow examination of both RT and accuracy data in the same analysis. This methodology allows both dependent variables to be modeled with continuous variables.

Although the time accuracy methodology of Kliegl, Mayr, and Krampe (1994) allows us to examine the onset, rate of increase, and asymptotic task performance of estimated processing time (using accuracy data) across age (also see Madden & Allen, 1991; Salthouse & Somberg, 1982), we decided not to use this method because it does not use both RT and errors as continuous variables. Because we were particularly interested in using both accuracy and RT as continuous variables in the same analysis, time accuracy methods would not suffice.

We could also use a Brinley plot (Brinley, 1965) to model the present data. The Brinley method plots older adults' data on the *y* axis and younger adults' data on the *x* axis. Although Brinley plots are typically used for modeling RT (e.g., Cerella, 1985), they can be used to model errors as well (e.g., Verhaeghen & Marcoen, 1993). We could produce separate Brinley plots for both RT and errors, although this would still

not allow us to analyze RT and error data simultaneously. One potential solution would be for us to plot RT on the *y* axis and errors or accuracy on the *x* axis, drawing younger and older adults' functions separately. We could then interpret the resulting slope and intercept data by using Sternberg's additive factor logic (Roberts & Sternberg, 1993; Sternberg, 1967). That is, intercepts would measure peripheral processes (e.g., encoding and response execution) and slopes would measure central processes (e.g., memory retrieval, memory comparison, and response selection). Researchers of aging have also interpreted intercepts and slopes from RT based Brinley plots as indices of peripheral and central processes, respectively (Allen, Smith, Jerge, & Vires Collins, 1997; Cerella, 1985). The advantage of the error RT plot is that researchers take both error and RT data into consideration rather than just using RT data and assuming that error data do not confound results.

However, the error RT plot methodology has three potential limitations. First, researchers of aging have not developed a theoretical justification for why error rate and RT are hypothesized to be positively correlated. Although these researchers certainly have used error rate as a primary dependent variable in research reports, we know of no theoretical discussion of how RT and errors are hypothesized to be related in the relevant literature. It appears that it is implicitly assumed that RT and errors are both performance measures that are positively correlated (except in the case of a speed accuracy trade off). Unlike the basic experimental literature (e.g., Hick, 1952; Hyman, 1953), however, research ers of aging have not explicitly discussed the relationship between RT and errors.

Second, error data tend to be "noisy." For example, the variance accounted for by age when an error dependent variable is used is much lower than that when RT is used (Verhaghaen & Marcoen, 1993). Third, RT and errors show a curvilinear rather than linear relation (Hyman, 1953). We believe that we can alleviate all of these difficulties by using the Hick Hyman law (Hick, 1952; Hyman, 1953; Shannon & Weaver, 1949).

Hick–Hyman Law

The Hick Hyman law states that RT is a monotonically increasing function of the amount of information in a stimulus (Hick, 1952; Hyman, 1953). Here, we define information as the amount by which uncertainty must be reduced (e.g., Garner, 1962). Using this information theory definition, we find that "the amount of information which a message conveys is an increasing function of the number of possible messages from which that particular message could have been selected" (Hyman, 1953, p. 188). Given that entropy generally increases with the amount of stimulus information, RT should increase as entropy increases (entropy is the level of disorder, or uncertainty, in a system).

We model entropy (in this case, internal noise) rather than stimulus information (measured in bits and referred to as external noise; see Krueger, 1978) in the present study in order to address age differences. Consequently, the present concep tual application of entropy uses internal noise (entropy resulting from information processing; Krueger, 1978) rather than stimulus defined external noise (Hick, 1952; Hyman, 1953), although the quantitative methods are identical for both types of noise.

Hick–Hyman Equations

A fundamental assumption in information theory is that RT is a monotonically increasing function of the amount of information in the stimulus (Hick, 1952; Hyman, 1953; Shannon & Weaver, 1949). Although the Hick Hyman law makes an accurate prediction in many cases involving serial processing, it does not do so for parallel unlimited capacity processing in which RT is not affected by an increasing stimulus load. However, it should be noted that parallel unlimited capacity processing in humans is quite rare (see Miller, 1982, for potential examples). See Luce (1986), Townsend and Ashby (1983), and Miller (1982) for suggestions on how to model unlimited capacity, parallel processing data. Individuals should be careful, though, when using diffusion models (e.g., Ratcliff, 1981), because of the "boundary problem," although Ratcliff, Thapar, Gomez, and McKoon (2004) have recently applied a diffusion model to aging. RT is predicted to increase as the amount of information processing system entropy increases. The regression equation describing this relationship is

$$\mathrm{RT} = t_1 + t_2 S, \tag{1}$$

where the t_1 parameter is the *y* intercept of the function and the t_2 parameter is the slope of the function. The S variable reflects the level of disorder, or entropy, in the information processing system. Entropy for a subject for a particular stimulus condition with a set of possible outcomes X_j, where $j = 1, \ldots N$, is defined as (Allen et al., 1998a; Hyman, 1953)

$$S = -\sum_{j\ 1}^{N} p_j \ln p_j, \tag{2}$$

where p_j is the relative frequency of outcome X_j.

In the present study, we use Equations 1 and 2 to analyze data from a lexical decision experiment (a semantic memory task). We compute entropy, S, by using the frequency of two possible trial outcomes, that is, correct answers, p_{correct} (hits), and incorrect answers, $p_{\text{incorrect}}$ (misses), to a given stimulus (hit and miss rates sum to 1.0 because they are conditional probabilities that a target word is present):

$$S = -p_{\text{correct}} \ln(p_{\text{correct}}) - p_{\text{incorrect}} \ln(p_{\text{incorrect}}). \tag{3}$$

Entropy is typically computed using hits and false alarms, but we use hits and misses in this study because misses are errors obtained from words whereas false alarms are errors obtained from nonwords. Given that word frequency is not a meaningful manipulation for nonwords, and we are interested in modeling word frequency effects, we used errors from words rather than errors from nonwords.

When entropy is plotted as a function of a stimulus variable (we used exposure duration and word frequency), the intercept is an index of those processes that are not affected by the variable. Typically these processes are executed only once (e.g., response execution) and they are peripheral. The slope is an index of the processes that are affected by the stimulus variable (lexical access in the case of word frequency and encoding for exposure duration; see Hyman, 1953). Slope may measure central or peripheral processes, depending on the type of process affected by the variable. Word frequency affects lexical

access, a central process; exposure duration should affect encoding, primarily a peripheral process. When a variable affects the complexity or amount of processing required, the effect appears in the slope, whether the process affected is central or peripheral.

Conceptual Issues Revisited

The present Hick Hyman function methodology has the potential to solve a key problem with error RT functions (keep in mind that entropy involves a log transformation of errors). The Hick Hyman law applied to the entropy based models of Smolensky (1986) and Allen and colleagues (1998a) provides a theoretical explanation for why errors and RT tend to be positively correlated. Namely, both dependent measures are affected by the disorder of the information processing system. As the disorder of the system increases, the performance decreases. Consequently, the Hick Hyman function methodol ogy is based on theoretical mechanisms that can explain why RT and errors are typically correlated positively.

Age Differences in Lexical Decision Research and the Present Study

Earlier lexical decision task research has suggested that older adults show peripheral process age differences (e.g., larger case mixing effects) but no appreciable central process age differences (e.g., older adults show at least as efficient lexical access as younger adults; see Allen et al., 1991, 1993; Allen, Lien, Murphy, Sanders, & McCann, 2002; Allen, Sliwinski, & Bowie, 2002; Allen, Sliwinski, Bowie, & Madden, 2002; Allen, Smith, et al., 2002c).

Our goal in the present study is to determine if the same pattern of age differences is present for peripheral and central semantic processes when both RT and error or entropy data are examined simultaneously as when RT and errors are used as separate dependent variables. Earlier research has found that, for a semantic memory task such as a lexical decision task, there are age differences in RT intercept but not in slope for word frequency (Allen, Sliwinski, & Bowie, 2002), suggesting that age differences appear more strongly in peripheral than central processes. We now model both dependent measures in the same analysis, and, consistent with prior work, we expect age differences primarily in peripheral processes.

Exposure duration, in contrast, ought to affect perceptual encoding a peripheral process (e.g., Allen, Smith, Lien, Weber, & Madden, 1997; Carr & Pollatsek, 1985; Dobbs, Friedman, & Lloyd, 1985; Sternberg, 1967). As exposure duration decreases, stimulus uncertainty increases along with the processing requirements of the task. The additional image normalization required for encoding with short exposure durations should lead to longer latencies or decreases in accuracy. As a result, we expect age differences in peripheral processing to be reflected in both intercept and slope of the entropy function.

We examine both traditional Brinley plot analyses (for both RT and word errors misses) as well as accuracy RT and entropy RT functions. Two issues of interest are (a) whether analyzing both measures of performance provides a clearer measure of overall performance relative to separate Brinley plots, and (b) whether entropy RT functions provide greater precision than accuracy RT functions.

METHODS

Participants and Apparatus

We tested 96 younger adults (age, $M = 22.2$ years; range = 17 43 years) and 97 older adults (age, $M = 71.1$ years; range = 60 87 years). We did not use additional data from 4 younger adults and 12 older adults because these participants had at least one empty cell in the five longest exposure durations. The younger adults were psychology undergraduates who partici pated for course credit. The older adults were community dwelling individuals who had no known history of neurological dysfunction. Each older adult was paid $20 for participation. All participants reported that they were in good physical health and had visual acuity of at least 20/40. Data on years of education, vocabulary, and Digit Symbol Substitution subtests of the Wechsler Adult Intelligence Scale Revised (WAIS R; Wechsler, 1981) were collected.

Older adults showed significantly higher vocabulary subtest scores (44.4) than younger adults (38.3), $t(191) = -5.67$, $p < .001$, and more years of education (older = 15.2 years, younger = 14.0 years), $t(191) = -3.51$, $p < .001$. However, younger adults exhibited higher Digit Symbol Substitution task scores (68.7) than did older adults (50.1), $t(191) = 13.01$, $p < .001$, as well as better visual acuity (younger = 20/20.1, older = 20/25.4, according to the Rosenbaum pocket vision tester), $t(191) = 8.92$, $p < .001$.

We tested participants individually on personal computers. We used Micro Experimental Laboratory software (Schneider, 1988). Participants responded by using the left and right arrow keys (located in the lower right corner of the keyboard), which they pressed with the index and middle fingers of their right hand. Half of the participants responded "word" by pressing the left arrow key, and the remaining half of the participants responded "word" by pressing the right arrow key. Each letter in the display subtended a visual angle of approximately 0.28° horizontally and 0.56° vertically. Participants viewed the stimuli from 50 cm away from the monitor, and stimuli showed luminance values of 25 cd/m^2.

There were a total of 24 practice trials and 864 experimental trials (432 word and 432 nonword trials) in the lexical decision experiment. We took the present words and nonwords from the stimulus set developed by Allen, Wallace, and Weber (1995). From each word, we formed a corresponding nonword by changing one letter (e.g., "loose" to "loost"). The six different exposure durations were 400 ms, 300 ms, 200 ms, 150 ms, 100 ms, and 68 ms (144 trials per exposure duration block). However, performance was very close to 50% (chance) for the 68 ms exposure duration condition, so we excluded data from this condition from further analysis. This exclusion resulted in 720 usable experimental trials rather than 864. We varied word frequency by using four categories obtained from Kucera and Francis (1967): very high (240 1,016 occurrences), medium high (151 235 occurrences), low (40 54 occurrences), and very low (1 5 occurrences). We blocked exposure duration (using six different presentation orders across participants), and we varied word frequency, stimulus type (word vs nonword), and word length (four, five, and six letters) randomly within each

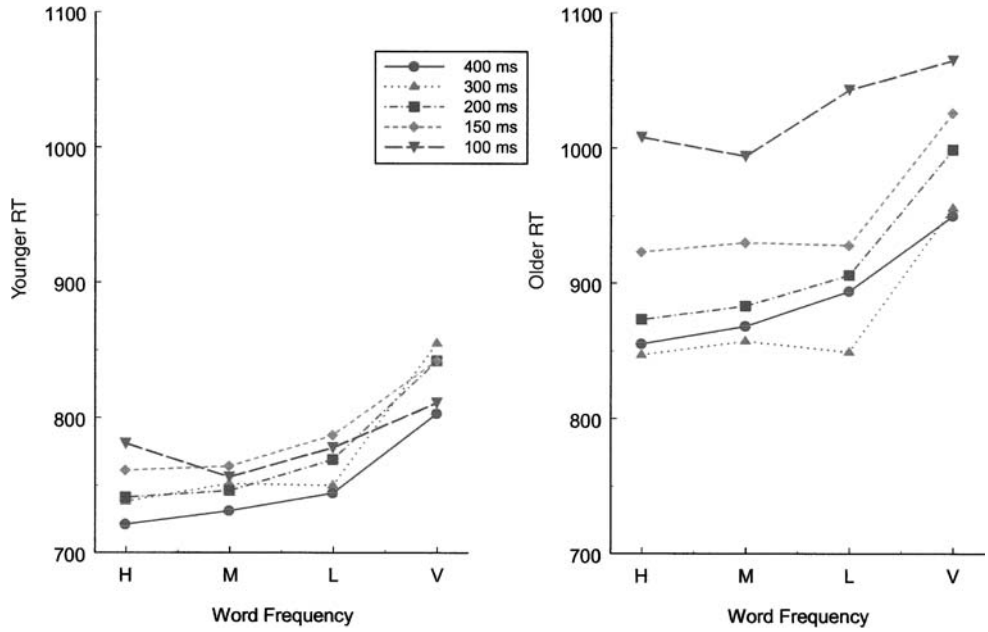

Figure 1. Response time (RT) data, plotted as a function of word frequency (H high, M medium, L low, and V very low frequencies) and exposure duration (100 ms, 150 ms, 200 ms, 300 ms, and 400 ms).

block (although there were equal numbers of trials within each of the randomly ordered conditions within each block). Thus, there were 18 trials in each of the 5 (exposure duration) × 4 (word frequency) × 2 (stimulus type) condition cells in the pre sent analyses. Age group was the only between subjects factor.

Results

Lexical Decision Latency Data

We report correct latency and error data in Figures 1 and 2, respectively. We emphasize the word data because word frequency is not interpretable for nonwords. We analyzed latency by using a mixed 5 (exposure duration) × 4 (word frequency) × 2 (age group) design. We collapsed across word length because previous research found smaller effects for word length than word frequency (e.g., Spieler & Balota, 2000), and collapsing decreased the likelihood of empty cells.

There were main effects for age, $F(1, 191) = 43.80$, $p < .001$ (younger mean RT = 773 ms, older mean RT = 933 ms); exposure duration, $F(4, 764) = 16.95$, $p < .001$ (100 ms = 905 ms, 150 ms = 870 ms, 200 ms = 845 ms, 300 ms = 826 ms, 400 ms = 821 ms); and word frequency, $F(3, 573) = 214.19$, $p < .001$ (very high = 825 ms, medium = 828 ms, low = 845 ms, very low = 915 ms). Older adults took longer to respond than younger adults, latencies increased as exposure duration decreased, and latencies increased as word frequency increased. There were also Age × Exposure duration [$F(4, 764) = 9.92$, $p < .001$] and Word frequency × Exposure duration [$F(12, 2292) = 5.07$, $p < .001$] interactions, but the Age × Word frequency interaction was not statistically significant [$F(3, 573) = 1.29$, $p = .28$]. The Age × Exposure duration interaction occurred because older adults showed a larger cost for briefer exposure duration (100 ms = 1027 ms, 400 ms = 892 ms; difference = 135 ms) than did younger adults (781 − 750 = 31 ms). The Word frequency × Exposure duration interaction resulted from a smaller word frequency effect for the shortest exposure duration (difference between highest and lowest word frequencies: 100 ms exposure duration = 45 ms, 150 ms = 92 ms, 200 ms = 114 ms, 300 ms = 113 ms, 400 ms = 89 ms; see Figure 1).

Error Data

We also conducted the analogous analyses for the error data (see Figure 2). There were main effects for age, $F(1, 191) = 12.75$, $p < .001$ (younger mean percent error = 18%, older = 14%); exposure duration, $F(4, 764) = 357.89$, $p < .001$ (mean percent error at 100 ms = 35%, 150 ms = 18%, 200 ms = 13%, 300 ms = 9%, 400 ms = 7%); and word frequency, $F(3, 573) = 478.34$, $p < .001$ (mean percent error, very high = 9%, me dium = 13%, low = 14%, very low = 26%). There was also an Age × Word frequency × Exposure duration interaction, $F(12, 2292) = 3.96$, $p < .001$, that resulted because younger adults showed a relatively larger word frequency effect for middle exposure durations than older adults. The key finding from the error data, though, was the existence of an Age × Word frequency interaction, $F(3, 573) = 35.50$, $p < .001$ (younger errors for word frequency: high = 13.2%, medium = 13.5%, low = 15.0%, very low = 31%; older errors: high = 12.0%, medium = 12.0%, low = 12%, very low = 21%), in which older adults showed a significantly smaller word frequency effect than did younger adults.

Signal detection theory analyses. It could be that there are differential age effects in decision criteria (Green & Swets, 1966) that might make the sensitivity data difficult to interpret. In order to examine this issue, we used nonparametric signal detection theory sensitivity (A', range = 0 1; larger values represent

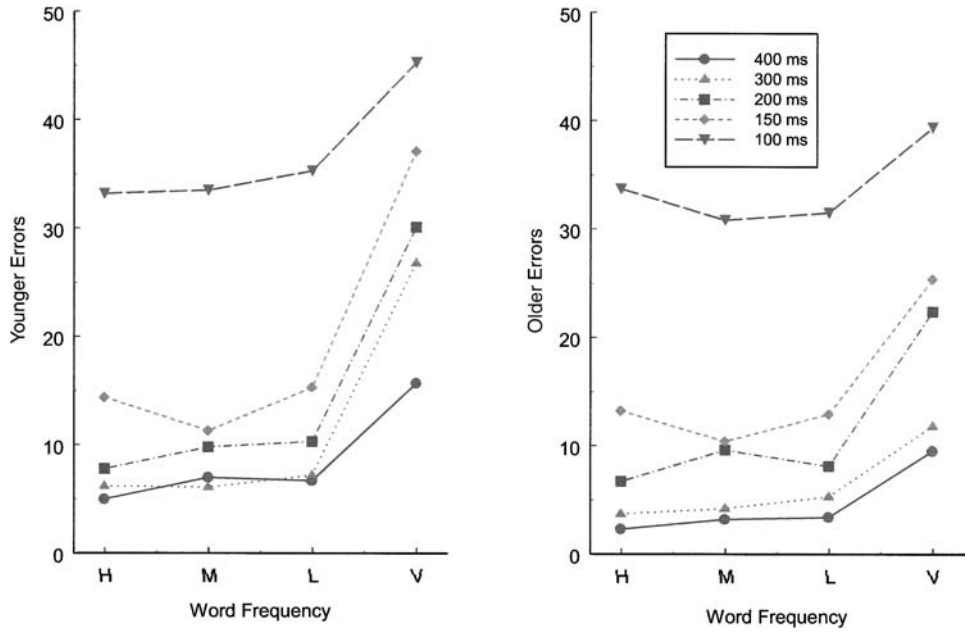

Figure 2. Error data, plotted as a function of word frequency (H high, M medium, L low, and V very low frequencies) and exposure duration (100 ms, 150 ms, 200 ms, 300 ms, and 400 ms).

higher sensitivity) and decision criteria (b'', range = 1 to −1; negative scores reflect a liberal response bias) measures (Snodgrass & Corwin, 1988). Because these analyses have potential implications for entropy analyses to be reported separately by exposure duration and word frequency, we conducted the signal detection analyses separately by exposure duration and word frequency. For these analyses, we use both word and nonword accuracy data. A' (sensitivity) and b'' (decision criterion) are based on hit (responding "word" to a word item) and false alarm (responding "word" to a nonword item) data, using formulas suggested by Snodgrass and Corwin (1988).

The A' and b'' conditional means are available from us on request. For sensitivity analysis conducted on word frequency, there was a main effect of word frequency, $F(3, 573) = 194.87$, $p < .001$ (high = .89, medium = .89, low = .89, very low = .85), as well as an Age × Word frequency interaction, $F(3, 573) = 23.70$, $p < .001$ (younger range in sensitivity: high = .89, very low = .83; older range: high = .90, very low = .87). For the exposure duration sensitivity analysis, there was a main effect for exposure duration, $F(4, 764) = 478.87$, $p < .001$ (A' values: 400 ms = .95, 300 ms = .94, 200 ms = .90, 150 ms = .86, 100 ms = .67), but no other effects approached statistical significance (ps > .20). There were no main effects of age on sensitivity.

In the nonparametric word frequency decision criteria analyses, there were main effects for age, $F(1, 191) = 10.82$, $p < .001$ (b'': younger = −.10, older = −.18), and word frequency, $F(3, 573) = 197.01$, $p < .001$ (b'': high = −.23, medium = −.26, low = −.20, very low = −.11), as well as an Age × Word frequency interaction, $F(3, 573) = 3.48$, $p < .001$. The main effect for age showed that older adults were more liberal in their response criterion; the main effect for word frequency occurred because higher frequency letter strings had a more liberal response bias than did lower frequency strings, and the Age × Word frequency interaction occurred because the liberal bias for higher frequency items was more pronounced for older adults. For the exposure duration response bias data, older adults showed a more liberal overall response bias than younger adults, $F(1, 191) = 32.19$, $p < .001$ (b'': younger = −.05, older = −.20); response bias became less liberal as exposure duration decreased, $F(3, 573) = 11.49$, $p < .001$ (b'': 100 ms exposure duration = −.06, 150 ms = −.09, 200 ms = −.08, 300 ms = −.09, 400 ms = −.21); and older adults showed a relatively stronger liberal bias as exposure duration increased than did younger adults, $F(3, 573) = 4.99$, $p < .001$.

Consequently, the sensitivity results are not qualified by the response bias results in the critical exposure duration condition. That is, there were no age differences in sensitivity as a function of exposure duration, and there were no age differences in response bias for the briefest exposure duration. In general, younger adults showed little evidence of bias, whereas older adults were biased somewhat toward responding "word."

Brinley plot analyses for word RT and errors. The best fitting, single parameter linear Brinley function (using 20 data points formed from the crossing of word frequency with exposure duration) for the present RT data is as follows: Older RT = 1.27 (Younger RT) − 51 (R^2 = .51; see Figure 3). Although the amount of variance accounted for by function is somewhat lower than that observed in previous studies, the 1.27 slowing ratio is similar to the 1.46 slowing ratio observed by Cerella (1985) in his classic meta analysis of age related slowing. However, the best fitting, single parameter linear Brinley error function is as follows: Older misses (errors for words) = .86 (Younger misses) − 1.31 (R^2 = 92; see Figure 4). That is, older adults actually showed better performance on the

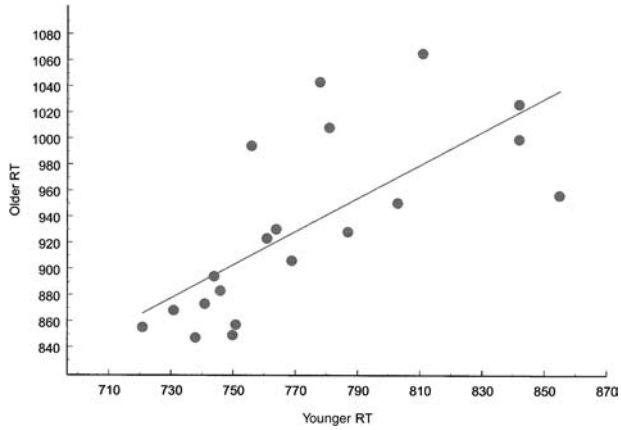

Figure 3. Brinley plot for older adults' (*y* axis) and younger adults' (*x* axis) response time (RT) data, using the 20 data point means obtained from crossing word frequency (high, medium, low, and very low frequencies) and exposure duration (100 ms, 150 ms, 200 ms, 300 ms, and 400 ms).

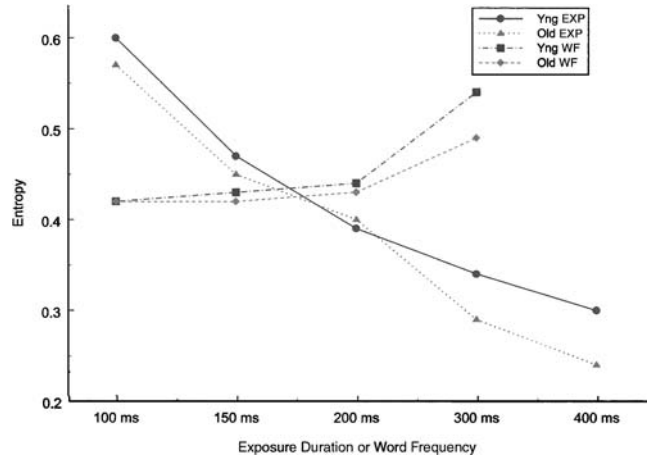

Figure 5. Entropy data, plotted as a function of age group (younger and older), word frequency (high, medium, low, and very low frequencies), and exposure duration (100 ms, 150 ms, 200 ms, 300 ms, and 400 ms). EXP exposure duration; WF word frequency.

error analysis but poorer performance on the RT analysis. These results present a strong justification for why looking at a single dependent variable in isolation can be misleading.

Entropy analyses (see Equation 3). We analyzed the entropy data as a function of age group separately for both word frequency and exposure duration (see Figure 5). We do this so that we can examine the effects of word frequency and exposure duration separately. For the word frequency analysis, there was a main effect for frequency, $F(3, 573) = 264.63$, $p < .001$, indicating a word frequency advantage (high, $S = .42$; medium, $S = .43$; low, $S = .43$; very low, $S = .51$) as well as an Age × Word frequency interaction, $F(3, 573) = 15.71$, $p < .001$ (S, younger: high = .43, medium = .43, low = .44, very low = .54; older: high = .42, medium = .42, low = .43, very low = .49). It should be noted that by using an analysis of variance approach we are using an additive model of aging, even though this is probably an overly simplistic view of aging (see, e.g., Faust, Balota, Spieler, & Ferraro, 1999). However, the observed Age × Word frequency interaction is still inconsistent with a complexity model because this interaction is subadditive with increasing age. That is, older adults showed smaller word frequency effects suggesting more efficient lexical access. These results are consistent with those observed by Allen, Lien, et al. (2002), who used a dual task methodology in which Task 2 consisted of a lexical decision task.

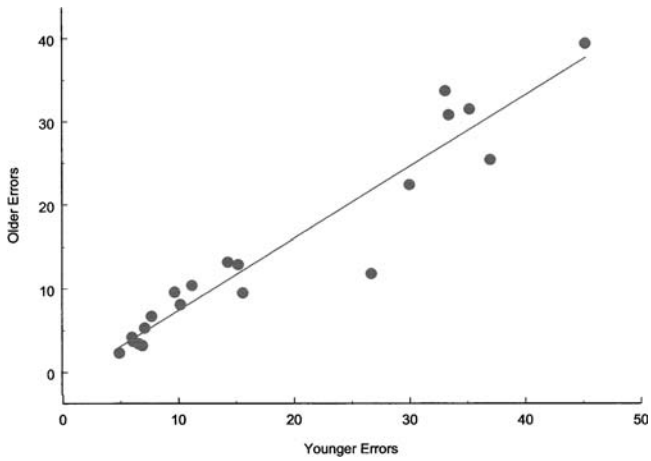

Figure 4. Brinley plot for older adults' (*y* axis) and younger adults' (*x* axis) error data, using the 20 data point means obtained from crossing word frequency (high, medium, low, and very low frequencies) and exposure duration (100 ms, 150 ms, 200 ms, 300 ms, and 400 ms).

There was no main effect for age. Younger adults showed a relatively larger increase in entropy for lower frequency words relative to older adults.

For the exposure duration analysis, younger adults showed slightly higher entropy levels, $F(1, 191) = 6.44$, $p < .05$ (S: younger = .42, older = .39); entropy decreased as exposure duration increased, $F(4, 764) = 511.31$, $p < .001$ (S: exposure duration for 100 ms = .59, 150 ms = .46, 200 ms = .39, 300 ms = .32, 400 ms = .27); and older adults, relative to younger adults, showed a larger increase in entropy as exposure duration decreased, $F(4, 764) = 2.71$, $p < .05$ (S: younger: 100 ms = .60 − 400 ms = .30 = .30; older: 100 ms = .57 − 400 ms = .24 = .33).

We formed entropy RT functions for each participant separately across exposure duration and word frequency (by regressing RT on entropy). Note that entropy RT functions are an implementation of the Hick Hyman law (see Equation 1). Our main goal was to examine slopes of the function predicting latency from entropy. If, as we hypothesized, older adults show peripheral but not central process decrements in semantic processing (e.g., Allen, Sliwinski, & Bowie, 2002; Allen, Sliwinski, Bowie, & Madden, 2002), then older adults should show steeper entropy RT slopes than younger adults for exposure duration but not for word frequency. For the slope analysis with word frequency, there was no effect for age (younger slope = 543, older slope = 625), $F(1, 191) = .39$, $p =$

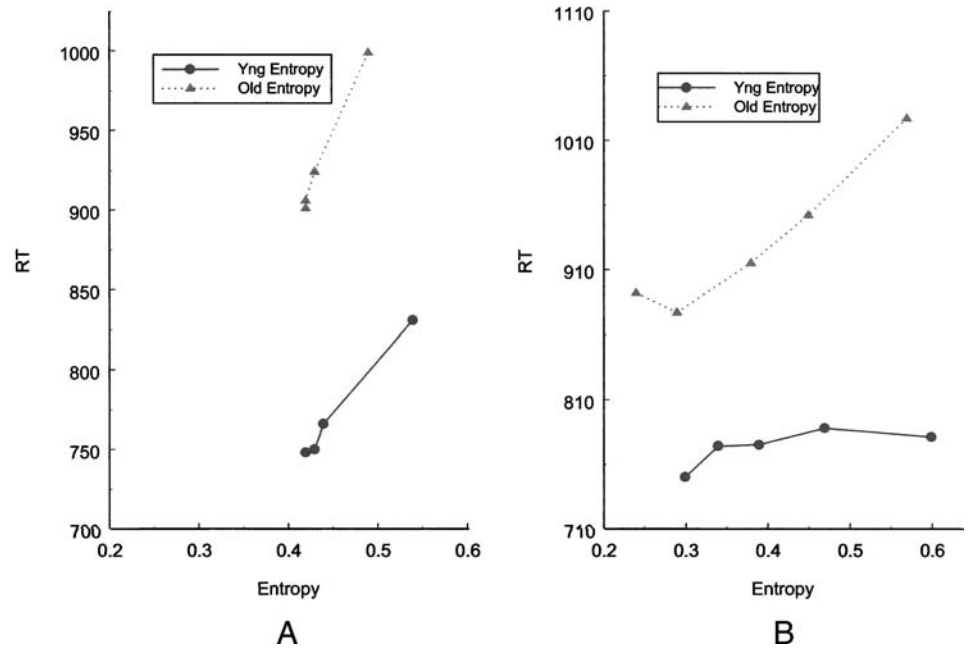

Figure 6. Entropy response time (RT) functions for word frequency (**A**) and exposure duration (**B**).

.53 (see Figure 6A). However, for the entropy RT slope analysis for exposure duration, older adults did show a significantly steeper slope, $F(1, 191) = 19.48$, $p < .001$ (younger slope = 51, older slope = 476; see Figure 6B). Although it may appear that we are testing an additive model of cognitive aging, we do not believe that this is the case because we are testing slopes that are based on a linear model (a multiplicative model with an additive constant).

In order to determine if these slopes interacted, we conducted a 2 (age) $\times$ 2 (slope type: word frequency vs exposure duration) mixed analysis of variance. This analysis did reveal an Age $\times$ Slope type interaction, $F(1, 191) = 4.55$, $p < .05$. Slopes were approximately parallel across age group for word frequency, but exposure duration slopes for older adults were significantly steeper than those for younger adults; see Figure 6B. (Figures 6A and 7A appear to show a slightly steeper slope for word frequency for older adults than for younger adults. However, this is not the case. For entropy RT slopes, younger adults

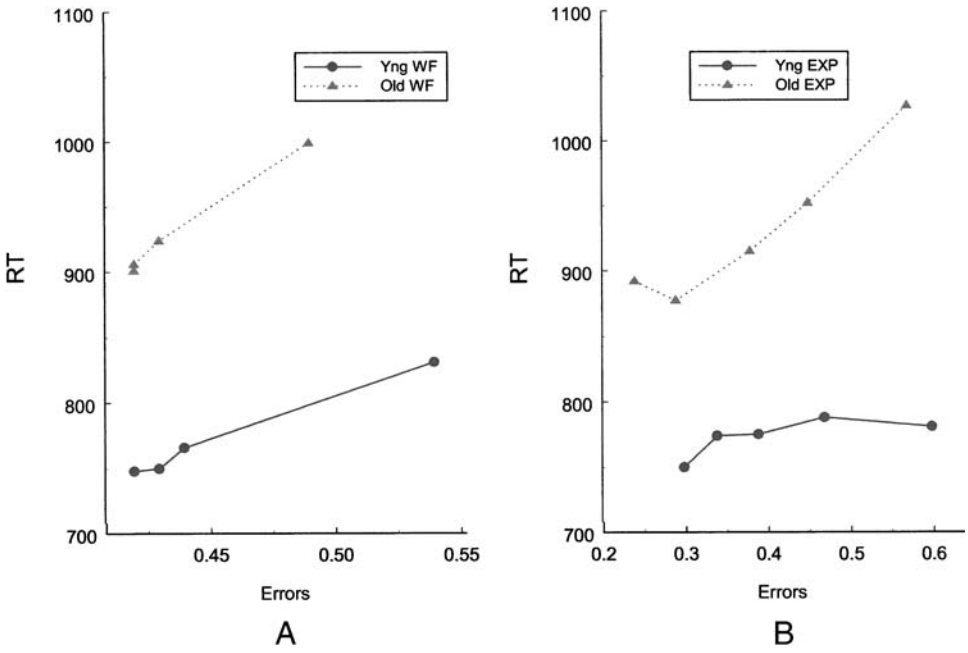

Figure 7. Error response time (RT) functions for word frequency (**A**) and exposure duration (**B**) for both younger and older adults. WF word frequency; EXP exposure duration.

show a mean slope of 543 with $SD = 421$, whereas older adults show a mean slope of 625 with $SD = 1{,}218$. For the error RT slopes, younger adults show a mean slope of 493 with $SD = 408$, whereas older adults show a mean slope of 624 with $SD = 916$).

With regard to the fit of the entropy RT functions (using the overall mean of individual equations), the r^2 for the frequency data was 0.67 and 0.49 (for younger and older adults, respectively), and the r^2 for the exposure duration data was 0.15 and 0.48 (for younger and older adults, respectively). Note that the variance accounted for estimates are based on individual scores rather than on group means traditionally used to form Brinley plots (e.g., Cerella, 1985). The use of individual regression equations to compute r^2 values results in substantially lower values but provides a measure of individual differences that are not available when group means are used.

Error RT functions. An important issue with regard to methodological parsimony is whether we need to transform errors into entropy values. This method would be simpler if we could use error RT functions rather than entropy RT functions. We reanalyzed the present data by using error (misses) RT derived slopes for each individual and then analyzed these slopes across age group (young and older adults) and slope type (exposure duration and word frequency). For the slope analysis with word frequency, there was no effect for age (younger slope = 493, older slope = 624); $F(1, 191) = 1.63$, $p = .20$ (see Figure 7A). However, for the entropy RT slope analysis for exposure duration, older adults did show a significantly steeper slope; $F(1, 191) = 10.35$, $p < .01$ (younger slope = 196, older slope = 674; see Figure 7B). In the 2 (age) $\times$ 2 (slope type: word frequency vs exposure duration) analysis of variance, the Age $\times$ Slope type interaction, $F(1, 191) = 3.68$, $p = .0565$, did not reach significance. As with the entropy RT analysis, slopes were approximately parallel across age group for word frequency, but exposure duration slopes for older adults were somewhat steeper than those for younger adults however, the error data were not as reliable as the entropy data, resulting in a dilution of the age difference in slopes across exposure duration. With regard to the fit of the error RT functions (using the overall mean of individual equations), the r^2 for the frequency data was 0.76 and 0.59 (for younger and older adults, respectively), and the r^2 for the exposure duration data was 0.08 and 0.43 (for younger and older adults, respectively).

Do We Need the Entropy Transform? An important issue concerns whether it is necessary to transform errors into entropy so that the Hick Hyman law can be applied to research on aging. Although the Age $\times$ Slope type interaction was significant for the entropy RT function analysis, it was not for the error RT function analysis; however, we still have not confirmed why this occurred. To examine this issue, we used the 20 means from crossing word frequency with exposure duration to determine whether linear and quadratic components would be significant for separate analyses conducted on younger and older adults. The rationale is that typically RT and errors show a curvilinear (quadratic) relationship, whereas entropy and RT show a linear relationship (Hyman, 1953). For the error RT regression analyses (using errors to predict RT), younger adults showed significant linear [$F(1, 19) = 22.23$, $p < .05$] and quadratic [$F(1, 19) = 4.95$, $p < .05$] terms, and older adults showed significant linear [$F(1, 19) = 152.24$, $p < .001$] and marginally significant quadratic [$F(1, 19) = 4.10$, $p = .0589$] terms. However, for the entropy RT regression analyses (using entropy to predict RT), neither younger [$F(1, 19) = 0.28$, $p = .60$] nor older [$F(1, 19) = 1.58$, $p = .23$] adults showed evidence of a significant quadratic term, although both showed a significant linear term: $F(1, 19) = 33.50$, $p < .001$ and $F(1, 19) = 207.27$, $p < .001$, respectively. Because the existence of a curvilinear term has potentially confounding effects on interactions (e.g., Ganzach, 1997), the entropy RT functions (which have a linear relationship between variables) do appear to be a preferable method over error RT functions (which tend to have a curvilinear relationship between variables). If one does use error RT functions, then one should use quadratic regression.

Discussion

In the present study we applied the Hick Hyman methodology (entropy RT functions) to research on aging. This methodology allows both RT and errors or entropy to be modeled together as continuous variables. We also replicated and extended earlier research on peripheral process and central process age effects for a common lexical task (lexical decisions), using a large sample size and entropy RT functions.

Latency and accuracy data. Older adults were slower and showed a greater cost for decreased exposure durations than did younger adults for RT analyses, although older adults were more accurate and exhibited higher levels of recognition sensitivity (see earlier text on signal detection performance). Furthermore, older adults actually showed significantly smaller word frequency effects. This suggests that older adults actually carried out lexical access more rapidly particularly for lower frequency words than did younger adults (also see Allen, Smith, et al., 2002). Finally, older adults were actually somewhat more liberal in their response bias (b'') than were younger adults for both the word frequency and exposure duration data (see earlier text). This is an important finding because response bias effects cannot be used to account for the differential age effects observed for word frequency (older adults showed shorter lexical access) and exposure duration (older adults showed a greater cost for faster exposure duration indicating slower perceptual encoding), because older adults showed a similar pattern of response bias for both word frequency and exposure duration, yet older adults showed a performance decrement for exposure duration but not for word frequency.

Brinley plots. Brinley plots for RT showed age related slowing similar to that reported by Cerella (1985), but Brinley plots for miss errors showed poorer performance on the part of younger adults. These results based on relatively large samples of younger ($n = 96$) and older ($n = 97$) adults suggest that relying on just RT data can result in a biased interpretation of one's data. To address this issue, we analyzed RT and error data (either as miss errors or as log transformed entropy) together.

Entropy RT functions. Older adults showed steeper entropy RT slopes for exposure duration but not for word frequency (see Figures 6A and 6B). These entropy RT functions

were formed by using five exposure durations or four word frequency entropy values to predict the analogous RT values for these conditions (and the slopes were obtained separately for each participant). These semantic task results are quite different from earlier entropy analyses done for spatial memory tasks (Allen et al., 1998a, 1998b). Specifically, for spatial memory, older adults showed greater increases in entropy for central processes than did younger adults, whereas in the present semantic task, older adults did not show a decrement for central processes for a lexical task. Indeed, older adults actually showed more efficient lexical access performance than did younger adults. However, even for the present lexical task, older adults continued to show a substantial decrement in perceptual encoding as measured by the age decrement in exposure duration. Thus, the present study largely replicates past RT studies that have also observed no age differences in semantic memory (e.g., Allen et al., 1991, 1993; Balota & Ferraro, 1993, 1996; Madden, Pierce, & Allen, 1993), but significant age differences in nonlexical memory (e.g., Burke & Light, 1981; Light, 1991; also see Allen, Sliwinski, Bowie, & Madden, 2002; Lima, Hale, & Myerson, 1991; Mayr & Kliegl, 2000; and Verhaeghen, Kliegl, & Mayr, 1998, for simultaneous comparisons of semantic and nonsemantic tasks). However, the presently observed differential age effects across processing stage provide an additional theoretical framework for interpreting such age differences a framework that uses both RT and error data as continuous measures. That is, the Hick Hyman law provides the conceptual justification for why RT and errors (actually entropy) should have a linear relationship.

Note that for exposure duration and word frequency, the steeper the entropy RT slope, the better that entropy predicts RT. Thus, older adults are more affected by the entropy induced by exposure duration than are younger adults, but younger and older adults are equally affected by entropy induced by word frequency.

Error RT functions. Although entropy RT functions were more sensitive to age differences in exposure duration than were error RT functions, both methods resulted in the same pattern of results. In the present error RT function analyses, the Age $\times$ Slope type interaction was not statistically significant (although it was approaching significance, $p < .06$), although this analogous interaction was statistically significant for the entropy RT function analysis. Consequently, although the entropy RT method is slightly more sensitive, we believe that the error RT function method is also quite applicable to many data sets and is still preferable to the use of just RT alone. Therefore, a central finding from this article is that it is important to consider both RT and entropy or errors (preferably in a composite analysis) rather than solely RT.

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