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Daniel H. Spieler

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Daniel H. Spieler
Stanford University, CA, USA

Researchers in cognitive ageing seldom take advantage of explicit quantitative models of information processing to account for age differences in cognition. Where quantitative models have been used, these models typically remain silent about the details of information processing. The lack of explicit cognitive models has consequences for the interpretation of a number of empirical results. Using a specific class of models called random walk models, I review evidence showing that the empirical relations taken as support for global age-related changes are consistent with a number of possible age effects on information processing. In addition, I demonstrate that these models can be used to account for age differences within the context of individual experiments and such modelling has important implications for the interpretation of age differences in performance.

The central point that I argue for in this paper is not novel (Fisher & Glaser, 1996; Newell, 1973; Ratcliff, Spieler, & McKoon, 2000) but it is one that bears some reiteration, especially within the field of cognitive ageing. The point is that valid conclusions about the nature of age differences in cognition require the use of explicit information processing models that make quantitative rather than simply qualitative predictions. Quantitative modelling is particularly critical to research progress in cognitive ageing because of the unique inferential problems associated with using cognitive psychological paradigms in the context of between-group comparisons.

Requests for reprints should be addressed to D.H. Spieler, Department of Psychology, Stanford University, Stanford CA 94305-2130, USA. Email: spieler@psych.stanford.edu

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In arguing for the importance of quantitative modelling in cognitive ageing, I will explore two specific instances where the lack of explicit information processing models led to a misunderstanding of what specific empirical results imply about age differences in cognition. First, I turn to the question of whether age differences in cognition are best characterised as general and global in nature or as a set of process-specific age effects. Second, I examine the role of modelling in the interpretation of the results of individual experiments. I turn first to the issue of general versus process-specific ageing.

EMPIRICAL EVIDENCE FOR GENERAL AGE EFFECTS

Older adults are slower than younger adults. While this statement is simple, the implications are not. Suppose (e.g., Faust, Balota, Spieler, & Ferraro, 1999) that for any task there is some amount of information that needs to be processed. Further assume that experimental manipulations influence the amount of information to be processed. Now assume that individuals (and groups) differ in the rate at which that information is processed. The changes in response time (RT) in response to experimental manipulations will be greater for the slow compared to the fast information-processing group (Cerella, 1985; Myerson, Hale, Wagstaff, Poon, & Smith, 1990; Salthouse & Somberg, 1982).

Creating a scatter plot (Brinley plot; Brinley, 1965) of young and old mean RTs for a set of conditions and tasks demonstrates this nicely. When the data is plotted in this manner, a striking regularity emerges. As shown in Figure 1, the mean RTs for younger and older adults are generally linearly related, and the function relating the two generally has a slope around 1.5 and a negative intercept (e.g., Brinley, 1965; Cerella, 1985; Salthouse & Somberg, 1982). Note also that the variance accounted for by this linear relationship is typically in excess of 90% (frequently over 95%).

This empirical relationship has been demonstrated across a wide range of tasks, conditions, and participant samples, suggesting that given the mean RT results from a group of younger adults, it may be possible to predict the speeded performance for a group of older adults. Because these data points are drawn from a range of tasks and conditions that tap a range of cognitive processes, age differences can be predicted with little regard for the specific processes and knowledge structures used in any individual task.

Following Cerella (1985) and Ratcliff, Spieler, and McKoon (2000), we can make this more explicit by developing a linear model of age-related slowing. If RT is a function of difficulty x with a minimum RT b even

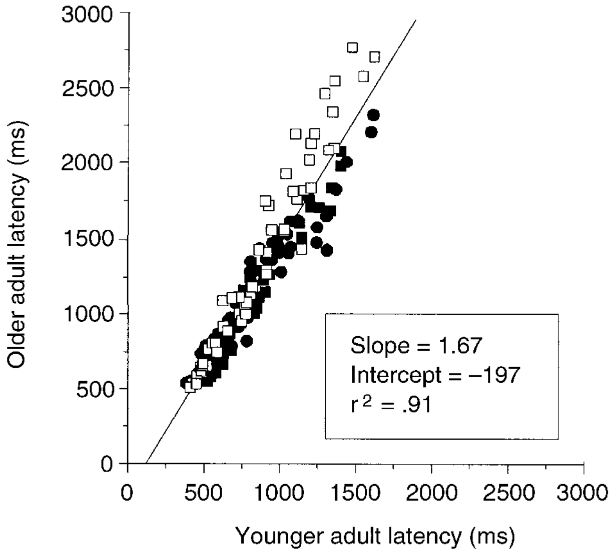

Figure 1. Brinley plot demonstrating the common result of linear relationship between young and older adult mean RTs. The different symbols represent different sets of tasks.

when processing is extremely easy, then:

$$RT = ax + b$$

Suppose that x remains constant with age but what changes is a and b. Thus

$$RT_{young} = a_{young}\, x + b_{young}$$

and

$$RT_{old} = a_{old}\, x + b_{old}$$

and using algebra to eliminate x we get:

$$RT_o = \frac{a_o}{a_y} RT_y + b_o - \frac{b_y a_o}{a_y}$$

Note that this function has a form exactly like the one observed in most Brinley plots, with a slope of a_o/a_y and an intercept of $b_o - b_y a_o/a_y$. This very simple derivation suggests that we should obtain slopes greater than one when $a_o > a_y$.

This linear model suggests that we might account for a wide range of empirical results in a very simple and elegant way. However, this formulation provides little information about what is actually influenced by the ageing process. It says only that older adults show a greater change in RT compared to younger adults in response to changes in difficulty.

INFORMATION-LOSS MODEL

Providing a more specific framework accounting for the general slowing results, Myerson et al. (1990) formulated a model intended to provide a quantitative account for the empirical Brinley plots and provide a mechanism for the influence of ageing on information processing. Within the model, the total time between the onset of a stimulus and an individual's response is the RT. This RT is the sum of a number of individual processing stages or steps.

$$RT = \sum T_k$$

The time for each individual processing stage, T_k is a function of the amount of information available at that stage, k.

$$T_k = \frac{D}{I_k}$$

where $I_k = I(1 - p)^k$ with D as a constant. The I_k defines the amount of information available at stage k, and p represents the loss of information at each processing stage. Thus, if there is less information available, then the amount of time required to complete that stage increases. Finally, the assumption is that a certain amount of information is lost at each processing stage. For example, as tasks become more complex, they require more processing stages, and with more processing stages, the amount of information lost increases. This loss of information parameter, p, is the parameter assumed to change with age. The model gives rise to a Brinley plot that is actually a positively accelerated power curve although within the range of RTs typically examined, the approximation to a linear function is quite high.

In both the linear model and the information-loss model, the primary goal has been to account for age differences in general, and empirical Brinley plots specifically. To varying degrees, these two models remain silent about any aspects of underlying processing not required by the between group comparisons.

In the linear model and the information-loss model, ageing influences a single parameter which in turn influences the type of Brinley function. The function that relates the young and older adults' performance provides the estimate of the model parameter (e.g., information loss or "difficulty"). If all points fall along a single function, then only a single parameter value is required, and if data points are better fit by two functions, then two parameter values are needed. Framing the research question in this way places considerable weight on the Brinley plot as a method for elucidating the nature of age differences in performance. The assumption is that the Brinley plot provides a way to determine how many parameters or parameter values are needed to adequately account for age effects. A single Brinley function suggests a single parameter or parameter value, and this in turn suggests a unitary influence of ageing on cognition.

To justify the central role for the Brinley plot method, it is not sufficient to show that a model can be formulated that is consistent with this interpretation of the Brinley plot. One should also show that Brinley plots constrain the interpretation of age effects in alternative but plausible models of information processing. Ideally these would be models that do not make a priori assumptions about the nature of age effects. In other words, the case for generalised slowing accounts would be greatly strengthened by showing not only that empirical Brinley plot results are consistent with general slowing models, but that the empirical Brinley pattern is inconsistent with a range of alternative models. If this empirical result is compatible with a number of plausible models, then no individual model gains much support by fitting these empirical results. To explore the constraint imposed by results of empirical Brinley plots, I turn to a traditional class of models commonly used in cognitive psychology and that are applicable to many of the tasks in which age effects have been examined.

RANDOM WALK MODELS OF INFORMATION PROCESSING

Random walk models, like other sequential sampling models (see Luce, 1986, for a review), make general assumptions about how information accumulates for a response. Assume a simple case where the task is a simple binary decision between two different responses based on the identity of a stimulus. This task could be a recognition memory judgement, a perceptual discrimination task, or any other choice task. Two basic parameters define the speed and accuracy of a decision. First, there is an amount of information that is necessary to make a decision, in other words, the response criterion. Second, there is the rate at which information accumulates toward a response. Following others (Luce, 1986; Ratcliff, 1978, 1988), I will refer to this as drift rate. In a binary decision, information is consistent with one of the response alternatives, moving the decision process toward the corresponding response boundary and away from the alternative, resulting in a relative decision criterion. At stimulus onset, the process starts equidistant from each response boundary, reflecting no bias for one response or another. (Response biases can easily be modelled but generally experiments are designed to discourage such biases).

Drift rate represents the quality or strength of information entering into the decision process. High drift rates result in the decision process moving quickly to one of the response boundaries while a low drift rate results in a slow rate of approach to the response criterion. The name "drift rate" gives the impression that this represents a speed parameter, but it is more accurately represented in terms of signal detection (for extensive discussion, see Luce, 1986; Ratcliff, 1978). If we assume that at each point in time, the information entering the decision process is either drawn from a signal or noise distribution and the decision process is an ideal observer attempting to minimise both misses and false alarms, then drift rate is directly analogous to the separation between the signal and noise distributions, d'. When the signal and noise distributions overlap considerably, the resultant drift rate will be relatively low and when the signal and noise distributions are far apart, the drift rate will be high.

On the assumption that the random walk is a model of the decision process and the response time includes time for other processes, there is a third parameter representing the residual time (Tr) and acts as an additive constant.

There is reason to believe that the parameters of the model tap real processes because it is possible to identify experimental manipulations that have selective influences on these parameters. For example, there are a range of manipulations that would seem to influence the quality of information entering the decision process and, as expected, these manipulations are modelled as changes in drift rate. Examples of these manipulations include perceptual noise (Ratcliff & Rouder, 1998) and ambiguity in categorisation (Ratcliff, Van Zandt, & McKoon, 1999). Moreover, instructions to individuals to emphasise either speed or accuracy or that bias individuals towards one of the response alternatives influence response criteria. Finally, this class of models has found support from recordings of neural activity in monkeys (Hanes & Schall, 1996).

RANDOM WALK MODELS AND BRINLEY PLOTS

Given the importance of Brinley functions, an obvious starting point is to demonstrate that this class of models can at least generate linear Brinley

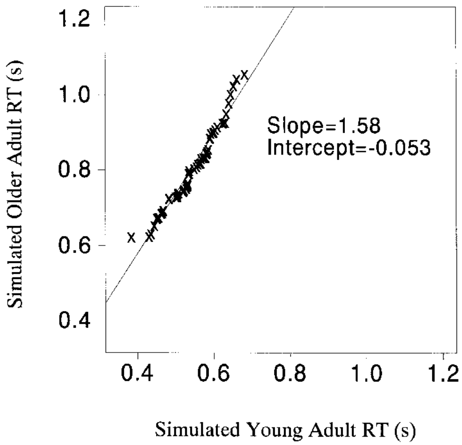

Figure 2. Brinley plot of mean RTs for simulated young and older adults using the diffusion model (adapted from Ratcliff, Spieler, & McKoon, 2000).

functions that are commonly found. As shown in Figure 2, this class of models is able to do so (Ratcliff, Spieler, & McKoon, 2000).

Brinley plots suggest that differences in overall response time have implications for the expected effect size for an experimental manipulation. Thus we might expect a slower group to show larger effect sizes. Exactly this scaling property is built into the general slowing models discussed earlier. The drift rate parameter in random walk models also exhibits such a relationship between speed and effect sizes. This is best demonstrated in signal detection terms. If the signal and noise distributions are already far apart, then increasing the separation further is likely to have only a small effect. However, if the two distributions overlap substantially, then even a small increase in separation will have large effects on performance. Similarly, if drift rate is already high, a further increase in drift rate because of some experimental manipulation will decrease RT only slightly, but at lower drift rates, a small increase in drift rate will result in a large decrease in RT. This is shown in Figure 3, where the faster group has a higher drift rate and the slower group has a lower drift rate and some experimental manipulation is assumed to result in an equal change in drift rate in the two groups. Ratcliff, Spieler, and McKoon (2000) showed that if young and old differ in drift rate overall, and experimental manipulations have identical effects on drift rate for both young and old, the diffusion model will produce a linear Brinley plot with a slope greater than unity and a negative intercept. Importantly, depending on the size of the experimental manipulations, changes only in

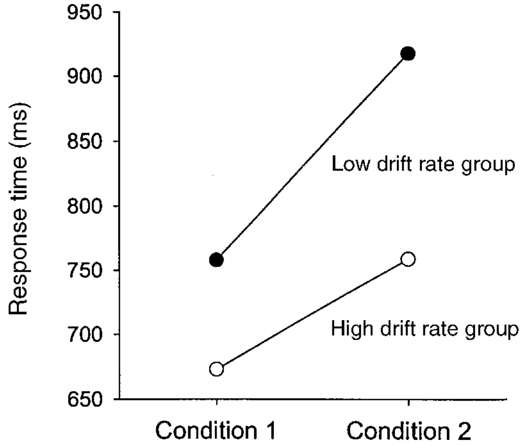

Figure 3. Example of overadditive interaction in slower group if both condition differences and group differences occur in drift rate.

drift rate can generate a range of Brinley slopes and intercepts. The actual slopes and intercepts depend on the size of the overall age difference in drift rate and the size of the differences in drift rate across conditions.

While the Brinley functions are influenced by age differences in drift rate, it is not possible to work backwards from the Brinley function to random walk parameters. The Brinley function does not sufficiently constrain the model parameters. For example, response criteria also influence RTs generated by random walk models. We (Ratcliff, Spieler, & McKoon, 2000) have shown that age differences solely in response criterion can also generate linear Brinley plots with a range of possible slopes and intercepts. There is an important distinction between drift rate and response criterion. While the effect of changes in drift rate on RT depends on the overall value of drift rate, the effect of changes in response criterion on RT is the same throughout the range of the parameter (e.g., Figure 4). Equal changes in response criterion for simulated young and old result in equal changes in RT for simulated young and old. One might think of this in terms of moving the finish line in a race (assuming constant speed of the runners).

These results lead to two insights. First, interpretations of age differences in the effect of some experimental manipulation depend on what parameter is influenced by the experimental manipulation and by the nature of the overall age difference in processing. If an experimental

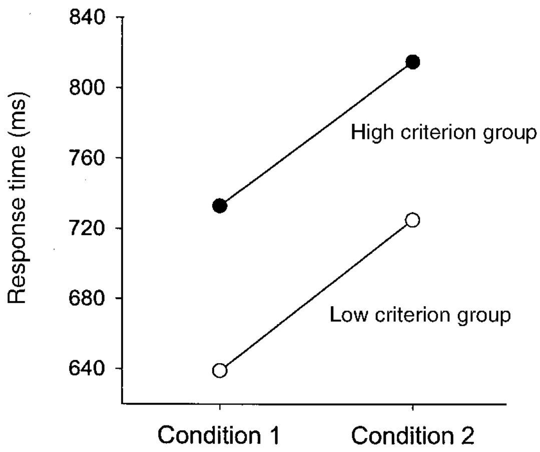

Figure 4. Example of additive effects if difference between conditions are in response criterion.

manipulation has a primary influence on an individual's criterion, then age differences in effect size may map closely onto age differences in underlying processing. Alternatively, if an experimental manipulation influences drift rate, then the interpretation of age differences in the effect of some experimental manipulation depends critically on how the overall age difference is modelled. Second, if a given linear Brinley plot can be generated by assuming age differences solely in drift rate or solely in response criterion, then a single linear Brinley function drawn from a range of tasks and conditions may reflect a heterogeneous mixture of age differences in drift rate and age differences in response criterion. Thus, while models attempting to account for age differences in cognition should be consistent with the empirical Brinley plots, these results alone are inadequate in determining the number or type of influences that ageing exerts on information processing.

CONSTRAINTS ON MODELLING OF AGE EFFECTS

If the random walk models can generate linear Brinley plots with changes either in response criterion or drift rate, then this suggests that the Brinley plots place insufficient constraint on these models and it suggests that additional empirical results are needed to adequately constrain these models. These constraints come from two sources.

Changes in model parameters have implications for the shapes of response time distributions and how those distributions differ across conditions. To characterise empirical RT distributions, it is common to use a mathematical function that, if successfully fit to the data, provides a description of the RT distribution via the parameters of the function. Ratcliff (1979) and many others (Heathcote, Popiel, & Mewhort, 1991; Hockley, 1984; Hohle, 1965; Luce, 1986) have shown that a convolution of a Gaussian and an exponential distribution, the ex-Gaussian, is generally successful in fitting empirical response time distributions from a range of experimental paradigms. Fitting the ex-Gaussian distribution yields three parameters that define the shape of the distribution. The parameters μ and σ are from the Gaussian distribution and reflect the leading edge and symmetric variability of the distribution, whereas the exponential parameter τ reflects the slow tail of the distribution (this is more of a heuristic rather than a definition because τ is influenced by RTs at other points in the RT distribution as well).

Figure 5 demonstrates how changes in the parameters of the random walk influence the shapes of the RT distribution as captured by the ex-Gaussian parameters. As the drift rate decreases, mean RT increases and this increase is particularly apparent in the slow tail of the RT distribution as reflected by the τ parameter. Figure 6 shows changes to the RT distribution as a result of changes in response criterion. Note that in this case, the change in mean RT is reflected as changes primarily in the μ

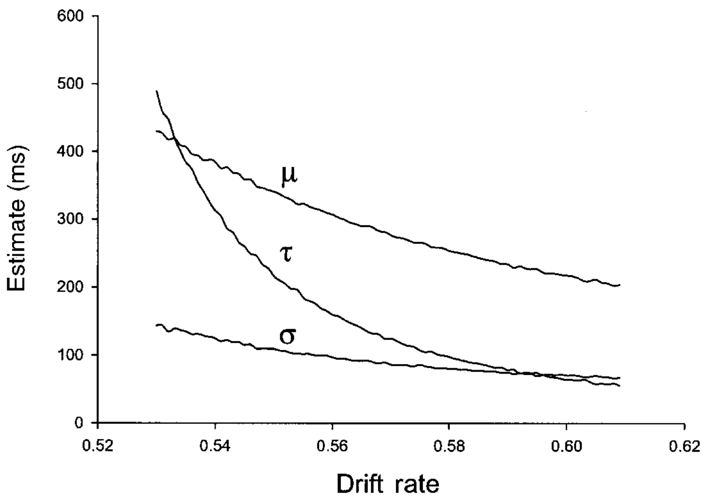

Figure 5. Relation between ex-Gaussian parameters and drift rate.

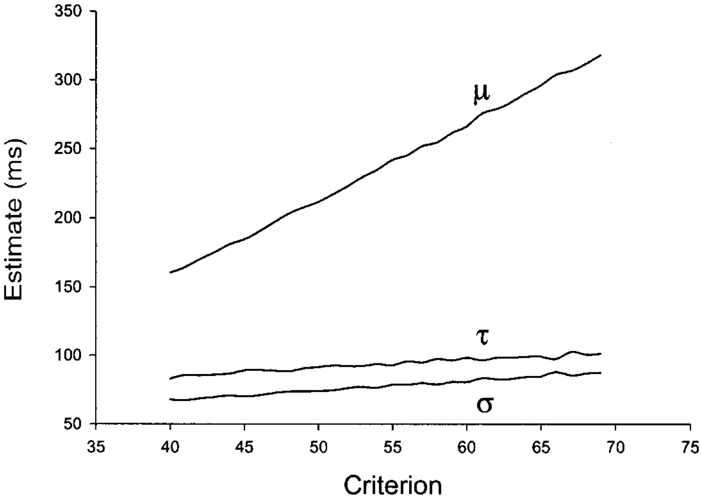

Figure 6. Relation between ex-Gaussian parameters and response criterion.

parameter. Thus, while drift rate influences the skew and variability of the RT distribution, response criterion tends to shift the RT distribution. As a result of these different influences of drift rate and response criterion, knowledge of how response time distributions differ across groups or across conditions provides an important constraint on the model. Of course, this also means that these models may not only account for effects on the mean of the RT distribution, but also for effects on the shape of the distribution.

A second source of constraint is error rates. If a decrease in drift rate is analogous to an increase in the overlap between the signal and noise distributions, a decrease in drift rate will result in slower RTs and an increase in the error rate. Increasing RTs may also result from increases in response criterion but the result will be a decrease in the error rate. For practical purposes, error rates under 5% across all conditions provide less constraint because a proportion of errors might arise from inappropriate response mapping or lapses in attention that are not directly related to the decision process modelled by the random walk. In practice, error rates will tend to be most informative when above the 10% range. This need not be a serious liability because this means that the random walk models are likely to be most informative in the range of error rates that can be particularly problematic for other information-processing models. Indeed, these models turn the liability of differential error rates and the possibility of speed–accuracy trade-offs into an asset because error rates help distinguish between changes in performance due to drift rate versus response criterion.

There are three possible outcomes from the application of these information-processing models. First, we may find that age differences are localised to one parameter. For example, across a wide range of circumstances, age differences may consistently be solely and uniformly in drift rate. This outcome is unlikely because of the relationship between model parameters such as response criterion and drift rate and error rates. Age differences solely in one of these parameters would enforce considerably more uniformity of age differences in RT and error rates than seems present in the literature. Lower drift rates in older adults with equal response criteria in young and old will generally result in larger error rates for older adults than for younger adults. However, we know that in some domains, age differences are present primarily in RT (e.g., many attentional paradigms), whereas in other domains, age differences are present to varying degrees in both RT and error rates. Moreover, in most studies, participants are instructed to minimise error rates. This will generally induce a negative correlation between drift rate and response criterion as individuals with low drift rates adopt more stringent response criteria. Thus it seems unlikely that age differences will be captured by a single parameter.

Second, the models may show that there is a single general transformation of the model parameters for younger adults that are able to fit older adults across a range of tasks and conditions. However, there is at least one instance in which young and old exhibit equal drift rates while old adopt more stringent response criteria (Ratcliff, Thapur, & McKoon, in press) and one case in which young and old show equal response criteria but different drift rates (Spieler & Balota, 2000). Nonetheless, it may be premature to rule out this second possibility, as it remains to be seen whether these results are exceptions to, rather than examplars of, the actual rule.

Third, we may find that what appeared to be a general relationship between young and old performance evaporates into a variety of age effects that are highly dependent upon the task and the sample of subjects used. It may be the case that in processing domains such as memory, age differences are modelled solely in drift rate; in some domains, age differences are perhaps solely in response criterion; in others, age differences are some various mixture of drift rate and response criteria. There is some preliminary evidence that appears to make this a likely outcome (e.g., Ratcliff, Thapur, & McKoon, in press; Spieler & Balota, 2000).

LOCAL ACCOUNTS IN COGNITIVE AGEING

In most experimental studies that include comparisons between younger and older adults, age differences are not observed in the context of a wide range of tasks with large samples of subjects. Rather, as is the case for most studies in cognitive psychology, a limited series of experiments is conducted with relatively small sample sizes. These experiments generally focus on one domain or one experimental paradigm. This approach makes it particularly difficult to test the traditional general slowing argument that relies on empirical relations from a range of tasks and conditions. In contrast, explicit information processing models allow us to capture age differences in conjunction with traditional task analyses, and allow for the interpretation of age differences in performance within the context of individual experiments. To demonstrate this, I turn to recent modelling efforts in which we examine the issue of age differences in Stroop performance (Spieler & Balota, 2000).

AGE DIFFERENCES IN INHIBITION

One of the landmark papers in cognitive ageing was a paper published by Hasher and Zacks (1988) that drew on a range of empirical results to suggest that older adults suffer from a decreased ability to suppress competing information. The inhibitory deficit framework was immediately applicable to a large range of tasks. Many of the tasks that appear to implicate inhibitory processing involve presenting individuals with distracting or competing information. In studies where RT is the primary dependent measure, the prediction is generally that older adults will show larger interference effects than do younger adults. Qualitatively, this is the identical prediction of generalised slowing. Indeed, across many experimental paradigms, evidence for an inhibitory deficit is also qualitatively consistent with generalised slowing (e.g., Connelly, Hasher, & Zacks, 1991; Gerard, Zacks, Hasher, & Radvansky, 1991; Spieler, Balota, & Faust, 1996).

As a specific example of this, take the Stroop task (Stroop, 1935). In this task, participants are required to name the colour in which a word is printed. In the conflict condition, the word names a nonmatching colour (e.g., BLUE printed in green), and the conflict between the colour and the word results in a slowing of colour naming compared to a neutral condition in which the word is colour unrelated (e.g., DOG printed in green). Efficient performance in this task requires suppressing the processing of the word information in order to name the colour. A deficit in the efficiency of inhibition should result in an increase in the processing of the word information and an increase in the size of the interference effect. Consistent with the inhibitory deficit account, older adults evidence larger Stroop interference effects than do younger adults (Comalli, Wapner, & Werner, 1962; Panek, Rush, & Slade, 1984; Spieler et al., 1996). Because this is also consistent with generalised slowing, it is common to try to show that the interference effects are larger or slower than some construal of generalised slowing. Unfortunately, this strategy is rarely successful because most general slowing models are not predictive but rather attempt to account for data after the fact. This gives the model a high amount of flexibility making it difficult to obtain empirical results that clearly refute general slowing (Perfect, 1994).

It is possible to translate a claim about inhibitory processing deficits into predictions about how random walk model parameters may differ across groups. The reasoning is as follows. Any Stroop trial can be seen as a selection between a word and colour response. The two boundaries in the random walk corresponds to the colour and word in the display. Sampling information from the word dimension moves one closer to the word boundary and sampling information from the colour dimension moves one closer to the colour boundary. Because the neutral condition contains word information not directly related to an appropriate response, there is less sampling of word information in the neutral condition and more in the incongruent condition. Thus, interference in the Stroop task is modelled as a reduction in drift rate in the incongruent relative to the neutral condition.

An application of a random walk model to Stroop performance in younger adults showed that the random walk model was able to account for these results (Spieler, Balota, & Faust, 2000). Recently we (Spieler & Balota, 2000) revisited the results of an experiment looking at Stroop performance in young and older adults (Spieler et al., 1996). In the original study, Spieler et al. (1996) also examined RT distributions from younger and older adults. The basic pattern is shown in Table 1. The older adults showed a much larger interference effect than did the younger adults. The increase in the interference for the older adults relative to the younger adults was evidenced as a large increase in interference in the τ parameter of the ex-Gaussian. It is this data that we sought to fit using the random walk model. There are three things to note about these data that suggest some general differences in random walk parameters for the two groups. First, there is a large difference between young and old in the leading edge of the distribution. Second, older adults show more variability and greater skew in the distributions than younger adults. Third, error rates (not shown) were nearly asymptotic ($\sim$3%). The greater variability and skew suggest that older adults have a lower overall drift rate than do the younger adults. However, the age difference in the leading edge of the distribution is greater than is obtained solely by drift rate differences suggesting that there are age differences in both drift rate and *Tr*. Assuming equal response criteria, the random walk fits to the young and old data are shown in Table 1.

TABLE 1
Ex-Gaussian parameter estimates reported in Spieler et al. (1996) and corresponding random walk fits

	Neutral	*Incongruent*	*Effect*
Young adult data			
μ	608	659	51
σ	64	87	23
τ	64	100	36
Young adult model fit			
μ	609	658	49
σ	68	81	13
τ	64	101	37
Old adult data			
μ	811	878	67
σ	93	97	4
τ	98	195	97
Old adult model			
μ	810	875	65
σ	81	102	21
τ	100	196	96

Young parameters: *Tr* (400, 50); drift rate = .103–.078, response criterion = 57; old parameters: *Tr* (630, 50); drift rate = .079–.054, response criterion = 57.

For these results, the older adults had lower drift rates but surprisingly the best fit resulted by assuming that both groups were equally influenced by interference, with a change in drift rate of 0.025. This modelling result is inconsistent with our original account that argued support for an age deficit in inhibitory control. Indeed, these results argue against age differences in the processes that underlie Stroop performance.

One interpretation of these results is that age differences in the Stroop task are simply a result of overall differences between young and old and have nothing to do with the specific processes tapped by this task. In other words, our interpretation sounds quite similar to a general slowing account. Here it might be necessary to distinguish between general slowing *models* and general slowing *perspectives*. General slowing models are concerned with empirical relations between young and old adult performance (in practice this typically just means RT) across a range of tasks and conditions. I and others (e.g., Fisher & Glaser, 1996; Ratcliff, Spieler, & McKoon, 2000) have shown that such empirical relations underdetermine the nature of age differences. However, these models will be nearly impossible to disprove or even address in the context of a single experiment. In this case, these specific results have little to say about the status of general slowing models.

General slowing perspectives are more difficult to define. One perspective emphasises that age differences across a range of processing domains will be accounted for by a small number of explanatory constructs. The results of any individual study are unlikely to dissuade anyone committed to such a perspective although there are preliminary data suggesting age differences in drift rate (Spieler & Balota, 2000) but not response criterion, and age differences in response criterion (Ratcliff, Thapur, & McKoon, in press) but not drift rate. An alternative point of emphasis from a general slowing perspective is that the influence of experimental manipulations in different groups is related to group differences in overall RT. The present results may be quite consistent with this perspective although it is not clear that such a scaling of response times is a general phenomenon.

Rather than attempt to argue whether these results, or any other results, violate a general slowing perspective, it may be more useful to focus on what the present modelling perspective offers, particularly for researchers interested in cognitive theories of ageing. These models are not theories but are implementations of theoretical accounts of how processing is performed within a task. As such, the emphasis in this form of modelling remains on traditional task analyses. The models provide a way of translating our interpretation of how processing is performed in a task into an account of performance. In this case, performance includes a range of dependent measures including mean RT, RT distributions, error rates, and error RTs.

The class of models discussed here, specifically sequential sampling models, are unlikely to cover the entire range of tasks that have been identified as tapping executive control processes. In particular, tasks that involve complex problem solving and reasoning are likely to require alternative models such as that discussed by Meyer, Glass, Mueller, Seymour, and Kieras (this issue). Regardless of the particular model used however, the goal remains the same. Through the application of these models where appropriate, and in the development and use of alternative models where necessary, the goal is a formal and quantitative statement about how processing takes place and how this processing is influenced by ageing. The result is a theoretical account of some aspect of cognition and of how cognition is influenced by the ageing process.

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