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Chapter Number & Title – Chapter 10, Methods for Studying Memory Differences Between Young and Older Adults

Effects of aging have long been an interesting topic in memory research due to the well-known fact that memory functions deteriorate with normal aging. The causes of this deterioration have been studied by employing various methods, including measures for time-scale of memory or the accuracy of reported episodic events. This chapter reviews methods for measuring slowing in cognitive processes through a joint evaluation of response time and accuracy. We consider both empirical and theoretical procedures. Finally, a cognitive model of aging was reviewed as an example case by which test the mechanisms of memory deterioration. Every section in this chapter ends with a practical advice for researchers interested in applying each method.

Methods for Studying Memory Differences Between Young and Older Adults

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Methods for Studying Memory Differences Between Young and Older Adults

One of the most common complaints by adults, especially by older adults, is poor memory. Typically, they complain about poor episodic memory, or memory for the events in life, the focus of this chapter. Examples of episodic memoires include remembering that you took medication this morning, remembering what you had for dinner last Tuesday, and remembering where you put the car keys. Other forms of memory (e.g., procedural which is colloquially called muscle memory, semantic memory or knowledge, etc.) are preserved or even sometimes improve with age. Decades of research showed that episodic memory functions weaken with advancing age (see, Naveh-Benjamin & Ohta, 2012, Light, 1991, and Salthouse, 2009, for a review). However, measuring memory to evaluate these claims in applied settings or in the laboratory is a challenge. One challenge is that the time-scale of memory (i.e., speed of retrieval), rather than memory per se, may undergo age-related changes. A second challenge is that what people claim to remember is not a direct report of the experienced events, but rather a description that may include accurate memories, approximate reconstruction, as well as false memories. Age-related changes in memory may affect any number of processes, and studying each of these processes poses different methodological constraints. The objective of this chapter is to review different methodologies that have been used to measure age-related decline in human episodic memory with a specific focus on the challenge of measuring different aspects of memory, including the timing of memory processes.

Memory fidelity and bias

In everyday assessments of memory, people tend to focus on memory for prior experiences, or episodic memory. For example, common complaints are failing to remember where the car keys were placed, or failing to remember if medication was taken. This focus on accuracy (or lack thereof) for experienced events is intuitive but fails to consider the complexity of memory. In particular, this focus ignores bias. Consider the case of remembering whether or not medication was taken. One important property is the fidelity of the actual memory, and the other is the willingness to endorse a feeling of familiarity as a true memory. The willingness to claim a memory as true is called response bias. Response bias can differ for different types of memoranda, different people, and different circumstances. For example, in the case of medication, if the medication in question is life-saving, then it would be wise to carefully calibrate response bias, such that when in doubt, err on the side of caution. That is, in the absence of strong detailed memory for taking today's medication, it is best to claim absence of a memory rather than to endorse a weak memory. Studies reporting measures of fidelity and response bias often show that older adults are more conservative in their willingness to report a memory than young adults, even when fidelity of memories are similar between the groups (e.g., Criss, Aue, & Kilic, 2014; Poon & Fozard, 1980; Ratcliff & Starns, 2010). In order to evaluate both the fidelity and bias of memory, it is necessary to measure both hit rates (correct memory for studied targets) and false alarm rates (incorrectly endorsing memory for unstudied foils) using a task such as single item or associative recognition. Based on both these values, nonparametric measures of fidelity (A' – *A* prime) and bias (B'' – *B* prime prime) can be computed as follows, where H is the hit rate and F is the false alarm rate (Stanislaw & Todorov, 1999)

$$A' = .5 + \frac{(\mathrm{H}-\mathrm{F})(1+\mathrm{H}-\mathrm{F})}{4\mathrm{H}(1-\mathrm{F})} \text{ when } \mathrm{H} \geq \mathrm{F}$$

$$B'' = \frac{\mathrm{H}(1-\mathrm{H}) - \mathrm{F}(1-\mathrm{F})}{\mathrm{H}(1-\mathrm{H}) + \mathrm{F}(1-\mathrm{F})} \text{ when } \mathrm{H} \geq \mathrm{F}$$

Likewise, in a recall task, it is necessary to report both the percent of correctly recalled memories as well as the total number of recalled memories (both corrects and intrusions). Measures of accuracy and precision can be computed from these values. Accuracy is simply the percent of correctly recalled memories (e.g., if 4 of 10 items on a study list are recalled, accuracy is 40%). Precision takes into account both accuracy and the willingness to report anything as a memory. In the example above, the participant might recall 8 items with 4 being correct and 4 being intrusions. Here, precision is the number of correctly recalled items divided by the total number of output or 4/8=50%. This indicates rather poor precision in discriminating between accurate versus false memories.

Practical Advice

It is best to consider the full report of memories including incorrectly endorsed memories in order to evaluate both memory fidelity and response bias. Memory accuracy is typically the focus of interest. However, metrics of accuracy can be best understood in the context of corresponding metrics measuring response bias.

Is slowing of processing speed specific to memory functions or generalizable to all cognitive functions?

Early studies of aging mainly focused on the slowing of information processing as people age and investigated not only the decline in accuracy but also the decline in the speed of information processing (Birren, 1965; Birren, Woods, & Williams, 1980; Brinley, 1965). Reaction time measures were the center of interest in aging studies because the hypothesized neural slowing with advancing age could be most easily measured by changes in response latency (Birren, 1965). As slowing of reaction time is one of the most prominent findings in cognitive aging, the main cause of age-related deficits including memory functions has been hypothesized to be a result of overall slowing of neural processes (see Birren & Fisher, 1995, for a review). In other words, all cognitive processing might slow with age, leading to a general decline. This lead to questions whether age-related deterioration is specific to memory functions or whether this deterioration could be generalized to all cognitive systems (Salthouse, 1996; Verhaegen, Marcoen, & Gossens, 1993; Zacks, Hasher, & Lee, 2000).

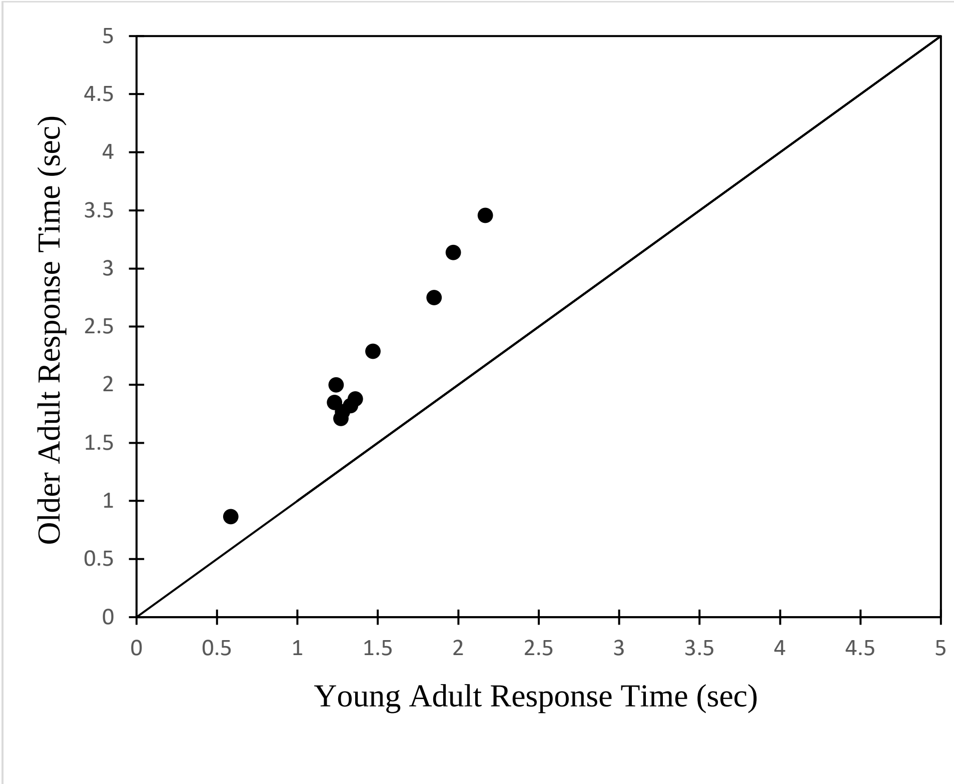

Figure 1: Example Brinley plot. Circles represent mean response time of the older adults plotted against mean response time of the young adults (data based on Myerson, Adams, Hale, and Jenkins, 2003).

It was Brinley (1965) who first plotted mean response latency of older adults as a function of mean response latency of young adults in a given task. In these so-called Brinley plots (see Figure 1), the slope of the best fitting regression line exceeds 1, suggesting that response latency is slower for older adults than young adults, and this pattern was observed across a wide range of tasks. The plots point to a simple explanation; that is, performance by older adults was simply a transformation of performance by young adults.

In a meta-analysis, Cerella, Poon, and Williams (1980) evaluated whether a single factor (e.g., task complexity) would be sufficient to account for the slowing of processing in older adults by fitting linear models to Brinley plots constructed by plotting task-task pairs (rather than person-person pairs). The question that they were interested in was whether slowing in reaction times was proportional to task complexity. That is, when a task becomes more complex, reaction time increases, and whether this increase in reaction time in more difficult tasks would interact with slowing due to aging. Applying a stepwise multiple linear regression to an extended set of data indicated that a combined effect of age and task type explained the Brinley plots best. In other words, the plots suggested that two different functions were necessary to characterize performance rather than a single linear function. Specifically, the mean reaction time of older adults over 60 years of age slowed by a factor of 1.66 for the tasks that required higher cognitive functions and by a factor of 1.25 for the tasks that required sensory functions. On the other hand, older adults below 60 years of age slowed by a factor of 1.18 and 1.14 for sensory and higher cognitive tasks, respectively. After analyzing a set of additional data, Cerella (1985) concluded that an invariant slowing factor can explain the age-related slowing in Brinley plots, and that slowing in higher cognitive tasks was more severe than in simple sensory motor tasks.

Among higher cognitive functions, Sliwinski and Hall (1998) further showed that the age related slowing in memory scanning was, in fact, less than the slowing in mental rotation and visual search tasks. They reached this conclusion again using Brinley plots, but instead of analyzing the reaction time data with ordinary least squares (OLS) methods, they used hierarchical linear models (HLM). The rationale for using HLM is that the mean reaction time data obtained from each task and each experiment from young and older adults have a nested structure, such that for a mean reaction time data point, there is an experiment effect, an age effect, and an overall task effect. Thus, OLS regressions might fail to capture those effects and result in a misleading slope parameter values (and thus exposing the difficulty in interpreting original Brinley plots). In their meta-analysis, Sliwinski and Hall (1998) used HLM with Brinley plots and showed different slope values for different higher cognitive tasks, suggesting that aging causes different rates of slowing in different higher cognitive tasks.

This debate about the number of factors that slow in aging is still not resolved (e.g., Cerella, 1985; Myerson, Wagstaff, & Hale, 1994; Perfect, 1994; Salthouse, 1996; Sliwinski & Hall, 1998). Speed of processing declines as people age. However, when the measure of interest is accuracy, there is converging evidence that older adults perform similar to young adults in some memory tasks and worse in others. Thus, slowing in processing speed alone might fail to explain the underlying mechanisms behind cognitive aging. In addition, although there is evidence supporting the hypothesis that worse performance observed in certain tasks could be explained by general slowing in older adults (Benjamin, 2010; Salthouse 1996), there is contrary evidence supporting selective deterioration in controlled processes (e.g., Hay & Jacoby, 1999; Jacoby, Debner, & Hay, 2001; Jennings & Jacoby, 1993; Kilic, Sayalı, & Öztekin, 2016; Öztekin, Güngör, & Badre, 2012).

Practical Advice

In terms of best practices for methodology, it is probably not appropriate to assume that age-related changes in memory are due to general cognitive slowing. Although it is well known that response times become slower with advancing age, it is also important to understand the changes in accuracy measures in memory literature. Brinley plots are sometimes misleading and provide an undue simplification of the complexity of cognitive aging. Therefore, we recommend a model based approach to evaluating memory, in which both accuracy and reaction time measures are analyzed jointly. Below, we will review the diffusion model, which is one of the most common methods for jointly analyzing accuracy and speed.

Jointly analyzing accuracy and response time

Ratcliff and colleagues showed that older adults are generally slower not only because of slowing in sensory-motor responses but also because they become more cautious in their responses (Ratcliff, Spieler, & McKoon, 2000; Ratcliff & Starns, 2005; Ratcliff, Thapar, & McKoon, 2004). This conclusion comes from applying the Ratcliff diffusion model (Ratcliff, 1978), which decomposes accuracy and response time into cognitive processes. The diffusion model was first developed as a memory retrieval model, in which accuracy and response time was analyzed jointly to measure recognition memory performance; however, it was later used in other 2-choice decision tasks where it continues to be of prime importance.

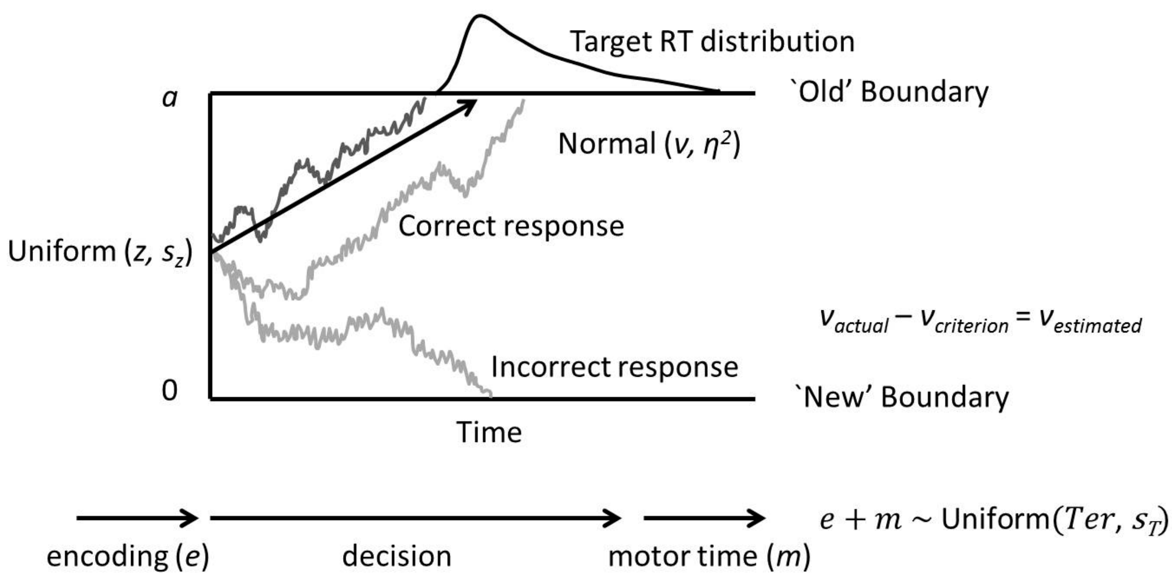

Figure 2: Illustration of the diffusion model shows the accumulation paths for correct and incorrect responses. In recognition memory, the upper boundary represents 'old' responses and the lower boundary represents 'new' responses. In this specific example, the accumulation of evidence for targets is illustrated.

The Diffusion Model

The diffusion model (DM; Ratcliff, 1978; Ratcliff & McKoon, 2008) can be considered a dynamic detection model, which uses accuracy and reaction time in an attempt to specify the underlying psychological parameters (e.g., memory and meta-cognitive decision processes). In the DM, a ‘yes/no’ recognition task is represented as two response boundaries ‘old (yes)’ and ‘new (no)’ (see Figure 2). Once the test item is presented, the memory evidence regarding the item will accumulate over time towards one of the response boundaries. This rate of accumulation, driven by the quality of evidence, is determined by the *drift rate* parameter (v), assumed to be normally distributed within trials with a mean of ξ and a standard deviation of s. The parameter s is a scaling parameter and usually fixed to the arbitrary value of 0.1 (Ratcliff, 1978; Ratcliff, Van Zandt, & McKoon, 1999; Vandekerckhove & Tuerlinckx, 2007). Furthermore, ξ is assumed to be normally distributed with a mean of v and a standard deviation of η. Therefore, v is the mean drift rate across trials, and η is the across trial standard deviation for the drift rate. At each time step, the memory evidence is sampled and compared to a criterion that is also known as the *drift criterion* (Ratcliff, 1978, 1985; Ratcliff & McKoon, 2008). If the sampled evidence exceeds that criterion, the evidence accumulates towards the ‘old’ boundary; otherwise the evidence accumulates towards the ‘new’ boundary. Thus, only the relative position of the drift criterion can be defined, and the drift criterion cannot be specified independent of the mean drift rates. Most often, the drift criterion is set to zero, and the targets are best characterized by positive drift rates whereas the foils are best characterized by negative drift rates, with the magnitude of the value indicating the strength of the signal. *Boundary separation* (a) is well known in characterizing the speed-accuracy trade-off (Ratcliff, 1985; Ratcliff et. al, 1999; Wagenmakers, Ratcliff, Gomez, & McKoon, 2008). When the response boundaries are narrow, meaning that a is small, the evidence reaches the boundaries faster but with more error. When the boundaries are wider, more evidence is required resulting in slower but more accurate responses. Another meta-cognitive parameter is the *starting point* (z), which takes a value between 0 and a and has a uniform distribution with a range of s_z. The parameter z represents the point between the two boundaries at which the accumulation of evidence starts and is typically involved for classic response bias manipulations such as test composition (Criss, 2010; Ratcliff & Smith, 2004). Finally, the non-decision component, which refers to the time required to encode the item and execute a motor response, is modeled in a uniform distribution with a mean of T_{er} and a range of s_T.

In order to study the effects of aging on reaction time, Ratcliff, Thapar, and McKoon (2001) fitted the diffusion model to simple signal detection data. In two experiments, Ratcliff et al. gave participants set of stimuli, and participants were asked to respond whether the number of asterisks presented on the screen come from a low or a high distribution (Experiment 1) and whether the difference between two dots are coming from a small or a large distribution (Experiment 2). In addition to a signal detection task, in Experiment 2, participants were given a speed-accuracy manipulation. For half of the blocks, participants were instructed to respond quickly, whereas for the remaining blocks, they were asked to respond as accurately as possible. The results of the two experiments showed an age-related slowing in two parameters of the model: the boundary separation parameter and the non-decision time parameter. Greater boundary separation for older adults suggests more cautious responses for older adults, meaning that older adults require more evidence to accumulate before they respond compared to young adults. That difference was also observed in the speed-accuracy manipulations of Experiment 2. The boundary separation was even wider for older adults in the accuracy condition compared to the speed condition. The slowing was also observed in the non-decision time parameter, which measures the time required for sensory-motor responses. The slowing in non-decision time was expected based on the earlier reaction time studies, indicating that overall slowing in older adults were mainly due to slowing of neural responses.

Ratcliff and colleagues observed similar findings in other cognitive tasks, such as brightness discrimination (Ratcliff, Thapar, & McKoon, 2003), letter discrimination (Thapar, Ratcliff & McKoon, 2003), and recognition memory (Ratcliff, Thapar, & McKoon, 2004). In the brightness discrimination task (Ratcliff, Thapar, & McKoon, 2003), in which participants were presented with arrays of black and white pixels with the proportion white pixels determining the brightness of the array, older adults were slower in non-decision time parameter. However, different from the previous study, these older adults set their response boundaries comparable to young adults under both the speed and the accuracy instructions. This suggests that the way information accumulates to the criterion could be controlled by experimental designs. In the letter discrimination task (Thapar, Ratcliff & McKoon, 2003), participants were presented with pairs of letters, one on the right side of the screen and another on the left side of the screen. Then, participants responded with a certain key depending on which side of the screen the letter appeared. Similar to the previous experiments, the speed-accuracy instructions were manipulated across blocks of trials. The fits to the diffusion model revealed that older adults had wider boundary separation than young adults, and that non-decision response time was also longer for older adults compared to young adults. Different from earlier findings, the drift rate parameter was lower for older adults, indicating that the information regarding letter identification task accumulated slower for older adults than for young adults. Finally, when the diffusion model was applied to recognition memory in older adults, similar findings were observed; that is, compared to young adults, older adults showed slower non-decision time as well as more conservative decision criteria especially when participants were given speed instructions. The interesting finding was that the drift rates did not differ significantly across age groups, which indicates that memory accuracy did not decline with advancing age. This illustrates an essential point; that is, the advantage of using a model-based approach is that it allows researchers to decompose the actual processes that are affected by advancing age. What might otherwise look like a deficit in recognition memory accuracy was instead revealed to be more cautious responding along with approximately equivalent memory accuracy. This type of analysis is not possible through analysis of raw data alone and instead depends on a model-based analysis.

Later studies further investigated the nature of the cautious behavior of older adults by measuring how older adults deviate from an optimal setting of response boundaries (Starns & Ratcliff, 2010). Starns and Ratcliff (2010) reanalyzed the data presented above with an emphasis on boundary optimality. When participants are instructed to respond as quickly as possible, the error rates increase; however, when they are instructed to respond as accurately as possible, responses get slower. Thus, there is a point that maximizes the proportion of correct responses with adequately fast responses. Starns and Ratcliff showed that the optimal speed-accuracy tradeoff was comparable across age groups but older adults were actually responding slower, and consequently, their actual behavior was less optimal compared to young adults. That was mainly due to older adults being more cautious to minimize errors. This cautious behavior of older adults remained even when they were given a task that explicitly required them to balance speed and accuracy (e.g., Starns & Ratcliff, 2012). The results from these studies showed that older adults were suboptimal in their boundary placement and over cautious not only in recognition memory tasks but generally in signal detection tasks. Critically, older and young adults did not differ in their ability to retrieve from memory, as indexed by the drift rate parameter.

Response deadline procedure

We can obtain converging evidence experimentally through modeling reaction time data in the form of response deadlines. Response-deadline procedures provide conjoint and unbiased measures of speed and accuracy (Dosher, 1981; Hintzman & Curran, 1994; Liu & Smith, 2009; Kılıç & Öztekin, 2014; McElree, 2006; McElree & Dosher, 1989; Öztekin, Güngör, & Badre, 2012; Reed, 1973; Wicklegren, 1977). Unlike reaction time experiments, this procedure yields independent assessment of accuracy and processing speed by providing the full time-course of retrieval. In response-deadline experiments, participants are cued with a signal presented at one of several time points following the test probe. Rather than allowing the participant to respond when they are ready, processing is interrupted and a response is requested at a variety of times after the onset of the stimulus. Typically, the lag between probe onset and response cue ranges from 60 to 3000 ms, and the lag condition is presented randomly across test trials. Participants are trained to respond within 300 ms after they receive the response signal. In this way, accuracy is plotted as a function of time that is required for retrieval.

Figure 3 presents an illustration of a retrieval function, which shows an increase in accuracy as a function of processing time. Retrieval functions typically start with a period of chance performance in which the retrieved information is insufficient to discriminate between the accurate and inaccurate responses, due to limited time to retrieve. Once the retrieved information exceeds the chance level, accuracy increases until the retrieved information reaches an asymptote. The data are usually fit by an exponential function that approaches a limit. Three parameters that describe these retrieval functions are (a) an asymptote, indicating the total available information that could be retrieved, (b) an intercept, reflecting the time point at which performance exceeds chance level, and (c) a rate at which information accrues over additional processing time until it reaches an asymptote. In short, the asymptotic accuracy measures the total available information, whereas the intercept and the rate parameters measure the retrieval speed.

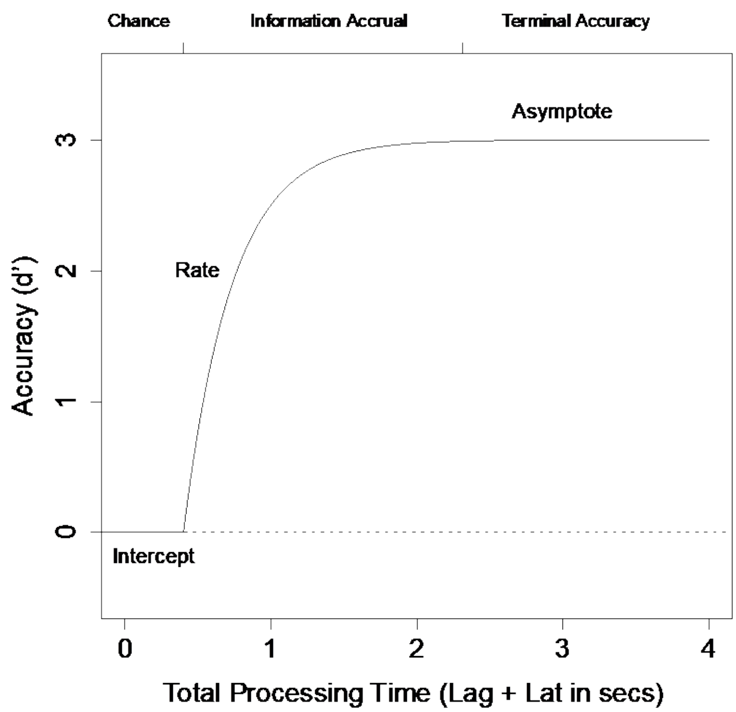

Figure 3. Illustration of a hypothetical speed-accuracy trade-off function which plots accuracy (*d'*) as a function of total processing time.

Öztekin, Güngör, and Badre (2012) employed the response deadline procedure in a recent negative probe task (Monsell, 1978) in order to test if aging causes an impairment in interference resolution. In the negative probe task, participants are presented with a list of items, typically letters or words, with a list length ranging from 3 to 6 items. Later, participants were presented with a positive probe drawn from the most recent list or a negative probe drawn from either a distant trial or from a more recent trial. The retrieval functions of the positive probes indicated an age-related difference only for the speed of retrieval. More specifically, older adults exceeded the chance level later in retrieval (had later intercepts), and the rate of information accrual was slower compared to young adults. However, asymptotic accuracy did not differ significantly across age groups. In other words, although older adults were slower in retrieval, the total amount of information they retrieved was comparable to that of young adults. That is, if older adults are given sufficient time, they can retrieve information from working memory to a comparable level as young adults. However, the retrieval functions of the negative probes indicate that older adults are in fact impaired in interference resolution. When participants are shown a recent negative probe, they incorrectly accept the test item as studied more frequently than a distant negative probe early in retrieval. Figure 4 plots the functions of differences in false alarm rates between recent negative and distant negative probes over the course of retrieval for young and older adults. These functions are based on the best fitting parameter values obtained from the data. They indicate an increase in false alarm rates for recent negative probes when compared to distant probes; however, later in retrieval, contextual information becomes available at a point in time which is measured by a second intercept parameter. Here, the second intercept reveals the time at which contextual information first becomes available, and in the figure, it corresponds to the point where the difference in false alarm rates reaches a peak. Once the contextual information becomes available, the false alarm rates of negative probes start to decrease. The retrieval functions of negative probes showed an age-related slowing at the time when the contextual information became available to older adults, and in addition to slowing, the difference between asymptotic false alarm rate for recent negative probes and distant negative probes was greater for older adults, suggesting that older adults were still incorrectly endorsing recent negative probes more than distant probes compared to young adults. Therefore, the results from Öztekin et al. (2012) study showed that older adults were slower in retrieving information from memory in general; however, the decline in asymptotic accuracy was only observed when they were required to retrieve contextual information from memory. In other words, employing a response deadline procedure allowed disentangling the cognitive processes in memory by providing independent measures of retrieval speed and accuracy.

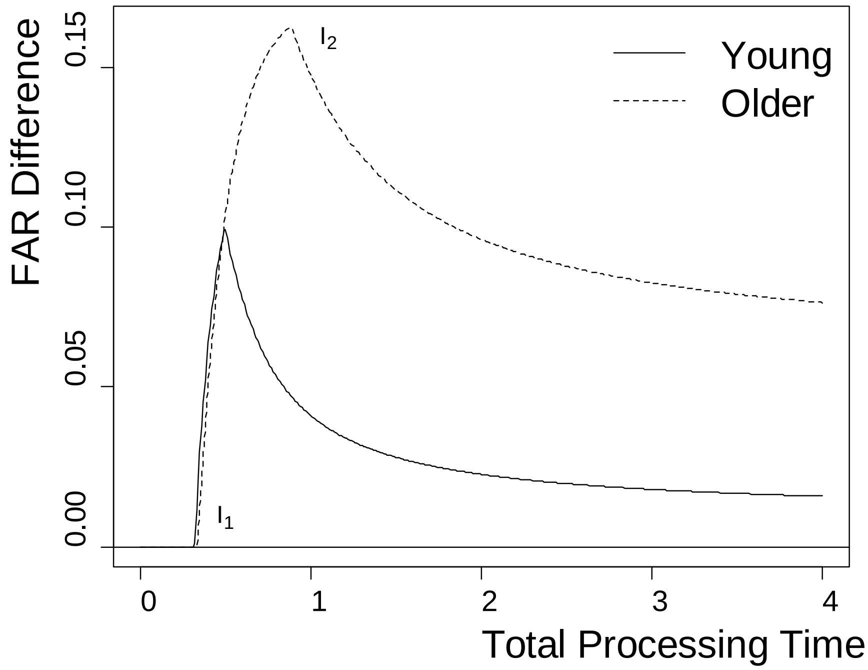

Figure 4: Illustration of false alarm rate differences between recent and distant negative probes plotted as a function of total processing time based on the dual process model that describes interference resolution in recent negative probe task (Öztekin et al., 2012). The first intercept parameter (I_1) represents the point in time when false alarm rate for recent negative probes exceed the false alarm rate for distant negative probes. The second intercept parameter (I_2) represents the point in time when contextual information first becomes available. Greater I_2 for older adults indicates that older adults access contextual information later in retrieval compared to young adults. The asymptotic difference between recent and distant negative probes were greater for older adults compared to young adults, suggesting that older adults cannot fully resolve interference caused by a recent prior occurrence of an item.

Taken together, the above results suggest that observing reaction time or accuracy alone might be misleading, and a model based approach or experimentally controlling for speed-accuracy tradeoffs could be more informative in understanding age-related cognitive changes.

Overall, these findings suggest that slowing in reaction time with advancing age may be due to different processes in the cognitive system, and more rigorous methods could be useful in examining which cognitive processes change with age. Most evidence suggests a different degree of cautiousness for older than young adults with some evidence for differences in memory retrieval under specific circumstances (e.g., discriminating fine contextual details).

Practical Advice

To reduces the computational burden of using the diffusion model, Wabersich and Vandekerckhove (2014) provided a simple R package, and Wagenmakers, van der Maas, Dolan, and Grasman (2007, 2008) provided the EZ diffusion model in both an excel file and an interactive website. These implementations simplify the model by eliminating some of the variability parameters. Furthermore, the EZ model eliminates starting point and non-decision time parameters. These simplifications make measurement properties of the model easier to implement and interpret, providing an avenue for non-experts to make use of this powerful tool for analyzing response times and accuracy. Beyond such practical advantages, the simplified implementations are shown to be capable of recovering parameter values from the generated data (Van Ravenzwaaij & Oberauer, 2009), and in some cases, the EZ model has greater power to detect an empirical effect than the full model (Van Ravenzwaaij, Donkin, & Vanderkerckhove, 2017).

Cognitive models that disentangle the impaired processes

Another useful method for studying cognitive aging is utilizing the approach of cognitive modeling. For example, Healy and Kahana (2015) presented a well-established model of episodic memory, which is based on the framework of context maintenance and retrieval model (Howard & Kahana, 2002; Lohnas, Polyn, & Kahana, 2015; Polyn, Norman, & Kahana, 2009; Sederberg, Howard, Kahana, 2008), and changed the related parameters of the model to mimic a lesion in the cognitive system. They proposed a four-component theory of cognitive aging, which includes processes, such as attention, retrieval of contextual representations, rejection of intrusions, and noisy competition in retrieval.

In order to test their four-component theory, Healy and Kahana simulated a set of benchmark effects observed in free recall with the proposed model. The first effect is that the qualitative pattern of the serial position curve is comparable across age groups. In both groups, the probability of recalling the last (recency effect) and the first (primacy effect) items is greater than the probability of recalling the items studied in the middle of the list. Although overall older adults recall fewer items from the study list than young adults, the pattern of the serial position curve remains intact. The second benchmark effect is that the probability of recalling a word first to initiate recall showed an identical pattern for both young and older adults. Particularly, the first word to be recalled is typically the most recently presented word, and the probability of initiating recall drops as a function of the serial position of the word. Thus, a model that explains a general decrease in accuracy across the serial position curve should also explain the null effect of age on the serial position of first recall. The third benchmark effect is the reduced contiguity effect observed in older adults. The contiguity effect refers to the finding that the next item recalled following a retrieved item is most likely to come from an adjacent position in the study list. For example, in a study list that is ordered: A B C D E, if C is recalled, then B and D are more likely to be recalled next compared to A and E. A decreased contiguity effect in older adults indicates an impairment in forming temporal associations with advancing age. As the forth benchmark effect, older adults tend to incorrectly recall words that were not presented in the study list more than young adults. These intrusions either come from prior study lists or could be words that were not even studied in the experiment (called extralist intrusions). The rate of these intrusions is similar across prior-list and extralist conditions for both young and older adults. Additionally, the prior list intrusions show a recency effect such that the words in the list that is presented immediately before the target study list intrudes more than the words that are presented farther from the target list. This recency effect on prior list intrusions is also comparable across age groups, indicating that recency effect is robust and is not affected much from normal aging.

To further test these benchmark effects, Healy and Kahana used a genetic algorithm[1] to obtain the best-fitting parameters of the model for each individual participant. Then, the best fitting parameters were compared across age groups. The results reveal the parameters that tap onto certain psychological constructs in an age-dependent fashion. For example, the age-related change in the parameter that control the primacy effect showed a primacy boost that allowed older adults to attend more to the beginning of the list but their attention parameter dropped much faster compared to young adults, and consequently recall performance decreased as they recalled words towards the middle of the list. Another parameter, which differed with age, was the rate of context drift during retrieval which was slower for older adults. In fact, the slowing of contextual drift resulted in a reduction in the temporal contiguity effect mainly because the retrieved item reactivated its associated context with lower strength. Thus, the retrieved context served as a weak cue for subsequent retrieval attempts, increasing recall of items distant from the just-recalled item. The third parameter that was affected by aging was the post retrieval threshold parameter, which controls the rate of intrusions. The lower values of this parameter indicate a willingness to accept unstudied items as list items, resulting in a higher intrusion rate. Finally, the parameters that control the competition among items showed an increase in older adults. The

[1] The genetic algorithm is a method to solve optimization problems. This method is inspired from evolutionary biology and uses terminology such as selection, fitness, and inheritance. For example, initially a group of parameters are randomly created. Then, fit value of each parameter set is calculated. The fittest individuals (e.g., top 20% of the parameters) later produce offsprings (a new parameter set), which later become the parent parameters (individuals) of the next generation. The same process applies over a couple of generations and finally the best fitting parameters are obtained.

changes in these parameters led to random noise that decreased performance. As a result, the words that were less likely to be recalled were recalled more often, whereas the words that were more likely to be recalled were recalled less often. Together, these changes in the model parameters explained the benchmark effects of aging in free recall, suggesting that aging caused impairments in four psychological constructs. Thus, a cognitive model based approach could further inform studies on cognitive aging by quantifying constructs that are not directly measurable.

Practical Advice

Computational models typically require some degree of computer programming. However with the increasing focus on open science, reproducibility, and transparency, many researchers have posted code online and taken a more careful approach to making code accessible. One approach to understanding age related changes is to lesion a part of the model system that is believed to be related to aging to predict the patterns of data expected from older and younger adults. Another approach is to fit the model to obtained data and compare parameter values across groups. This is an important step in validating the model and testing the predictions of the model.

Controlling individual differences

Earlier studies on cognitive aging showed that as people grow older, they also score lower on working memory tasks, such as span tasks, indicating weakening in control processes. The worsening of working memory functions as a result of normal aging is important because it indicates that declines in other functions might not be selective but rather an indirect consequence of poor working memory. Likewise, vision and motor control decline with age. If these declines are not properly evaluated, then what look like decreases in memory may in fact be the result of poor vision or inability to report memory output with the provided format (e.g., poor pencil grip or poor resolution with the mouse). Even if these individual differences do not directly affect measures of memory performance, they may contribute to the outcome in other ways. For example, Verhaeghen et al (1993) showed that the magnitude of age-related changes in performance is influenced by overall education such that lower education predicted greater age differences.

Practical Advice

In order to study aging in memory research, it is important to ensure that working memory measures, vision, motor, etc. are comparable across age groups. Otherwise, the age-related change observed in the task of interest to the researchers could be misleading. If it is not possible to control these measures, one can employ advanced statistical analysis or more advanced measurement models. For example, if working memory measures are obtained for each individual, these can be entered as a covariate factor in regression models, which would then allow researchers to separate the variance caused by differences in working memory. Similarly, participants can be grouped into different levels based on working memory measures, and a hierarchical linear model could be used to control for working memory differences statistically. Alternatively, advanced models, which disentangle different processes, such as the diffusion model, can be used to measure the timing of sensory-motor responses.

Limitations

One of the most basic distinctions in aging studies is whether the age-related change is measured within-groups or across groups (Schai & Caskie, 2005). Usually, age-related decline in human memory is measured using cross-sectional designs, in which two different age groups are tested using a given memory task, and later their performances on that task are compared. Following that, the group differences in the obtained results are interpreted as age differences when other variables, such as education level, are controlled. However, cross-sectional designs are susceptible to a variety of problems including cohort effects. Alternatively, age-related change over the course of life span can be measured using longitudinal designs, in which same individuals are tested at different times. Thus, longitudinal designs allow researchers to eliminate certain confounds including cohort differences between groups. Despite its immunity to cohort effects, longitudinal designs are less common in studying age-related decline in memory (cf., Salthouse, 2016). Perhaps, that is due to the impractical nature of basic memory research, which almost always requires individuals to participate experiments in laboratory settings. Thus, it would take enormous time and effort to ask individuals to participate in a study in their early 20s and have them come back to the laboratory in their late 70s. Because we focused on basic memory research in the current chapter, we limited our scope to research that used cross-sectional designs, problematic though they may be.

Memory has been divided into different systems based on neuroanatomical differences (e.g., Squire, 2005) and behavioral evidence (e.g., Tulving, 1972). Various theories have been developed in order to explain how normal aging causes problems in certain memory functions (see Park & Festini, 2017, for a review). Building on this systems view, we further limited the scope of our review to short-term memory and long-term memory, in which the rate of impairment increases from cue-available tasks (such as item-recognition) to cue-generation tasks (such as free recall; Verhaeghen, et al., 1993). Despite worsening of certain cognitive tasks with advancing age, others either remain intact or even improve as people get older. For example, verbal skills get better with advancing age, such that vocabulary scores of healthy older adults are higher in Wechsler Adult Intelligence Scale-Revised (WAIS-R) and Nelson-Denny Reading Test compared to their young counterparts (see Verhaeghen, 2003 for a meta-analysis). Similarly, in repetition priming studies, older adults perform equally well as young adults, which could be due to the fact that in these priming studies, the cue is available to the participant (Mitchell & Bruss, 2003). To conclude, we reviewed different methods for studying cognitive aging specific to short-term and long-term memory where age-related decline is observed most prominently.

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