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Beyond resources: Formal models of complexity effects and age differences in working memory

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We explore several alternative formal models of working memory capacity limits and of the effect of ageing on these capacity limits. Three models test variations of resource accounts, one assumes a fixed number of free slots in working memory, one is based on decay and processing speed, one attributes capacity limits to interference, and one to crosstalk between associations of content and context representations. The models are evaluated by fitting them to time–accuracy functions of 16 young and 17 old adults working on a numerical memory-updating task under varied memory-load conditions. With increasing complexity (i.e., memory load), both asymptotic accuracy and the rate of approach to the asymptote decreased. Old adults reached lower asymptotes with the more complex tasks, and had generally slower rates. The interference model and the decay model fit the individual time–accuracy functions reasonably well, whereas the other models failed to account for the data. Within the interference model, age effects could be attributed to the older adults' higher susceptibility to interference. Within the decay model, old adults differed from young adults by a higher degree of variability in the activation of working memory contents.

A well-documented finding in cognitive ageing research is that old adults perform considerably worse than young adults in tasks that require high amounts of working memory capacity (e.g., Babcock, 1994; Mayr & Kliegl, 1993; Salthouse, 1994). Research on individual differences as well as on cognitive development and ageing has shown that working memory

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capacity is a crucial limiting factor for human performance on a broad range of reasoning tasks (e.g., Case, 1985; Kyllonen & Christal, 1990; Salthouse, 1991). To understand the growth and decline of reasoning ability over the life span, therefore, it seems particularly important to understand the factors that limit working memory capacity in the first place. The purpose of this paper is to explore a number of hypotheses about the nature of capacity limits in working memory. We will propose a formal framework for modelling performance in working memory tasks, and pit a number of mathematical models incorporating different assumptions about the nature of capacity limits against each other within this framework. These models will be tested with data from young and old adults on a representative working memory task. Our goal is to narrow down a set of simple, plausible models of capacity limits in working memory to one or two promising candidates, and to identify the parameters of the viable models that carry age differences.

THE NATURE OF CAPACITY LIMITS IN WORKING MEMORY

We will discuss five potential sources of capacity limits in working memory: (1) limited cognitive resources, (2) a fixed capacity to hold a certain number of information elements simultaneously available, sometimes referred to as a "magical number", (3) a speed account based on the race between decay of memory traces and rehearsal, (4) similarity-based interference, and (5) crosstalk between elements in a memory set.

Limited resources

One common account of working memory capacity limits is that the cognitive system has limited resources for simultaneous storage and processing. Resource theories assume that resources are general (although they may be confined to broad domains like verbal or spatial contents); resources can be allocated to tasks and processes flexibly; and the amount of resources a person can spend at any moment is roughly constant during short periods of time. Two well elaborated models addressing capacity limits in cognition, ACT-R (Anderson, Reder, & Lebiere, 1996) and CAPS (Just & Carpenter, 1992), are based on the idea of limited resources. Resource theories have been criticised for being too vague and unconstrained (e.g., Meyer & Kieras, 1997; Navon, 1984). The theoretical precision of resource theories can be improved by fleshing them out as formal models, as was done with ACT-R and CAPS. Our own attempts to model working memory performance borrow many basic assumptions from these two approaches.

Magical numbers

The idea of a "magical number" of information elements or chunks that can be held in short-term memory was first discussed by Miller (1956) in his famous paper on the "magical number seven". Recently, the idea of a maximum number of chunks to be held in working memory was revived by Halford, Wilson, and Phillips (1998) and by Cowan (in press), who argued for a "magical number" around four. Apparently larger capacities of short-term or working memory in some tasks arise, so they argue, from chunking or rehearsal strategies or long-term memory contributions that increase recall performance over and above the basic capacity. To measure the "magical number", one therefore must use a task that rules out additional help from strategies, long-term memory, and other sources as much as possible.

Decay and rehearsal

Research on verbal short-term memory has produced serious doubts about a constant number of chunks that can be immediately recalled independent of material. One important finding was the word-length effect, a linear relationship between pronunciation time for a class of words and memory span for the same words (Baddeley, Thomson, & Buchanan, 1975). It led researchers to the conclusion that the limiting factor for immediate serial recall of verbal material is not a "magical number" of chunks, but a certain maximum articulation time—what Schweickert and Boruff (1986) called the "magic spell". One way to understand this finding is to assume a constant decay rate for memory traces, which can be refreshed by rehearsal with a speed that roughly corresponds the time to articulate the words. If traces decay below retrieval threshold within a certain time, the maximum span will equal the number of words that can be articulated in this time. The capacity limit results from a race between decay and rehearsal.

This model was first applied to the phonological loop, a short-term retention system for verbal material (Baddeley, 1986). It can be extended, however, to working memory in general. Many working memory tasks require the retention of information while the same or different information is manipulated. If we assume that memory traces decay by a constant rate, then the probability that a given information element is still available when it is needed for a processing step depends on the speed of earlier processing steps during which it had to be remembered. Working memory performance then is a function of the race between decay and processing speed. This may explain why working memory and processing speed measures share a large part of their age-related variance (Salthouse, 1996).

Similarity-based interference and crosstalk

Interference and crosstalk are two strongly related concepts, which are rarely distinguished in the literature; we distinguish them here because they lead to different formalisations of capacity limits. Both concepts rest on the assumption that working memory for some material is impaired by the presence of other, similar, material. We define interference as mutual degradation of memory traces that are held in working memory simultaneously. For example, the representation of a new word might overwrite all features of an old word that are shared among the two (Nairne, 1990), or features belonging to different words might mix up to new, spurious representations (Tehan & Humphreys, 1998).

We define crosstalk as the confusion between two elements that are held simultaneously in working memory. Like interference, crosstalk is a function of similarity between memory elements. Different from interference, which has an effect on the memory traces themselves, crosstalk arises at the selection of one out of several elements in working memory. Crosstalk is the basic mechanism that limits memory span in recent models of serial recall that are based on Hebbian associations between list items and contextual cues (Brown, Preece, & Hulme, 2000; Burgess & Hitch, 1999; Henson, 1998). At retrieval, a context representation coding a given ordinal list position cues the corresponding item at this position. Due to overlap between neighbouring ordinal positions, however, neighbouring list items are also cued, and occasionally a wrong item is activated highest and is selected for output. Note that through this mechanism the representation of the correct item is not degraded, so that there is a high probability that it will be recalled on another position (cf. Henson, Norris, Page, & Baddeley, 1996).

Old age and inhibition

Each of these hypothetical sources of capacity limits is compatible with the inhibition account of working memory deficits in old age as proposed by Hasher and Zacks (1988; Hasher, Zacks, & May, 1999). The general idea is that old adults have less efficient inhibitory processes that eliminate no-longer relevant contents from working memory and prevent irrelevant material from entering working memory. This leaves old adults with more irrelevant information in working memory. Irrelevant material can take away resources or free slots from the relevant material. Irrelevant material can overwrite relevant working memory contents or become confused with them. Irrelevant information can also distract people from rehearsing the relevant material and thereby lead to more forgetting. Therefore, we regard the inhibition-deficit hypothesis not as a further genuine source of capacity limits, but as a hypothesis about why capacity limits, whatever their cause may be, are exaggerated in old age.

A FRAMEWORK FOR MODELLING WORKING MEMORY CAPACITY

Our strategy is to compare different assumptions about the source of capacity limits by building them into a common formal framework. This section will develop such a framework that should be applicable to many, if not all working memory tasks.

We assume that the function of working memory is to hold a number of distinct information elements (e.g., numbers, words, objects, spatial positions) available for ongoing processes. This means that elements in working memory can be retrieved efficiently and selectively as inputs for cognitive operations. This function can be fulfilled by a system that links episodic representations of content elements (i.e., tokens of numbers, words, etc.) to context representations (i.e., temporal contexts, list positions, spatial positions, syntactic roles in parse trees, etc.). The links between content and context representations must be built and dissolved quickly, because usually there is not much time to encode new information into working memory or to update its contents. According to this framework, working memory is more than just a subset of highly activated representations in long-term memory, as was proposed in some models (Anderson, 1983; Cantor & Engle, 1993). Working memory contents must be both activated and flexibly linked to contexts.

We further assume that errors in working memory tasks arise mainly (as an idealisation in the models: exclusively) at retrieval. That is, we assume that the elementary processing steps by which information is manipulated are error free. This assumption is justified for working memory tasks that require only trivial processes like, for example, single-digit addition and subtraction and other tasks where participants usually perform close to ceiling when the memory load is minimal. Conway and Engle (1996) have shown that the difficulty of the processes involved in a working memory task does not play a role for its validity as a measure of working memory. Süß, Oberauer, Wittmann, Wilhelm, and Schulze (2000) provide evidence that working memory tasks with trivial elementary operations are good predictors of reasoning ability. Working memory tasks are difficult, and they tap capacity limits, because of their complexity and not because of the difficulty of the elementary cognitive processes they require. The complexity of a working memory task can be defined as the number of independent elements that must be kept available simultaneously (i.e., the memory load).

The probability of retrieving a single element i from working memory is modelled as a function of this element's activation level at the time of retrieval, A_i. An element in working memory is successfully retrieved as input for a cognitive operation if its activation value surpasses a threshold τ. In its deterministic form, the performance function that transforms activation into retrieval accuracy is a step function. We assume, however, that the activation level of an element, and therefore its availability, is affected by Gaussian noise. The probability of successful retrieval, therefore, follows the cumulative probability of a normal distribution with mean A_i and standard deviation σ, which can be approximated by the logistic function (cf. Anderson & Matessa, 1997):

$$p = \frac{1}{1 + \exp(-(A_i - \tau)/s)} \tag{1}$$

with $s = \text{sqrt}(3)\sigma/\pi$. The logistic function is shown in Figure 1a. Most of the models discussed in this paper will use the logistic function to relate activation to retrieval accuracy. Only the crosstalk model will use a variant of this function to capture the competition between target and distractor elements during retrieval.

Processes in working memory take time, and the most important dependent variable in cognitive psychology besides accuracy is latency. A model of working memory capacity should specify the duration of information processing steps. For the family of models explored here, we

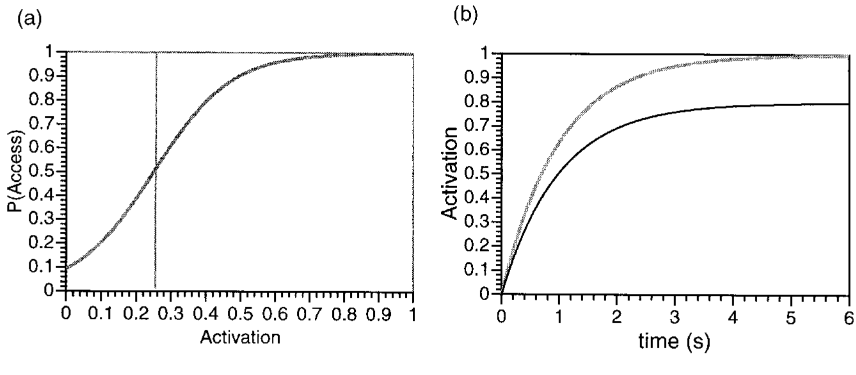

Figure 1. (a) Logistic performance function relating an element's availability to the probability of successful access. The threshold parameter is set to 0.25 and σ to 0.2. (b) Exponential functions for activation accumulation with an asymptote of 1 (dotted line) and with an asymptote of 0.8 (solid line), the rate parameter is set to 1.

assume that information is manipulated by cognitive operations that generate a new element in working memory and gradually increase its activation. The increase of activation is assumed to follow a negatively accelerated exponential function with the general form:

$$A_i = \alpha_i (1 - \exp(-t/r_i)), \quad (2)$$

where t is the time since the new element was created, r_i is the rate of activation for the new element, and α_i is the asymptote of activation for the new element i (see Figure 1b). The assumption of processing by gradually activating new elements is incorporated in several models, among them CAPS (Just & Carpenter, 1992) and the cascade model (McClelland, 1979). For one variant of a resource model, we will deviate from this equation to introduce a latency function directly borrowed from ACT-R (Anderson & Lebiere, 1998).

Differences between individuals and groups are assumed to arise from differences in parameter values. In modelling working memory performance for young and old adults, we hope to identify a subset of parameters on which age differences are pronounced. Provided that a viable model can be identified, this will help us to characterise the source of age-related cognitive deficits in complex cognition. Our working hypothesis is that the same parameter that drives the decline in performance with increasing memory load (i.e., the complexity effect) also carries the largest part of the age-related variance. This hypothesis directly implies the Age × Complexity interaction found with many cognitive tasks (e.g., Salthouse, 1992): The complexity effect will be stronger for old adults.

To summarise, we propose to build formal models of working memory capacity from three building blocks:

(1) A processing model for the specific task for which performance is modelled, which specifies the number of independent memory elements required at each time during task solution and the sequence of processing steps required for a solution.
(2) A complexity function that expresses the activation of each content element A_i as a function of task complexity (i.e., the number of content elements that are held in memory at the same time).
(3) Performance functions that express accuracy of retrieval for an element i and latency of processing element i as a function of this element's current activation level A_i.

Taken together, these three building blocks should suffice to make exact predictions for task solution accuracies and latencies of a person working on a task if the person's parameter values are known: The process model determines how many representation elements and processing steps are needed for task solution. The complexity function then determines the activation level of the elements that need to be retrieved at any step. The expected performance scores (accuracy and speed) can be computed by applying the performance functions to this information.

An unknown number of free parameters is hidden in the task-specific process model: Researchers have considerable freedom in specifying how a task is done. In particular, the information required for task solution and the transformations that must be performed on it can be segmented into elementary units in many different ways, yielding quite different complexity values for a task. Does a proposition, for example, count as a single element in working memory, or should we count the number of concepts linked by it? We propose, therefore, to develop a capacity model with as simple tasks as possible in order to limit the space of plausible processing models. We will present our process model together with the first resource model later, after introducing the memory-updating task in the next section.

THE EXPERIMENT

Method

Participants. Eighteen young adults (eight men and ten women; mean age 19.1 years, SD: 0.68) and eighteen old adults (nine women and nine men; mean age 68.8, SD: 3.55) were recruited from the Potsdam participant pool. The young group consisted of high school students, the old participants had responded to newspaper advertisements or were friends or relatives of other participants. The two groups were roughly equivalent in years of formal schooling (young: 11.67 years, SD: .69, old: 10.59 years, SD: 1.62) and a vocabulary test (young: 22.1, SD: 3.92, old: 23.3, SD: 4.55). Young adults performed better on the digit symbol test than old adults (young: 63.1, SD: 9.4, old: 45.4, SD: 8.0). Groups did not differ in their ratings of subjective health as ''good''. Thus, the two groups were comparable to typical samples of young and healthy old adults in the literature with respect to standard indicators of cognitive status. Participants were paid 15 DM (i.e., about $8) for each one-hour session.

Seventeen old and sixteen young adults from the first part of the experiment could be recruited for a second part. We present only data from the 33 participants who completed the whole experiment.

Materials and procedure. We chose a numerical memory-updating task introduced by Salthouse, Babcock, and Shaw (1991) to generate a data set for testing our models. Each trial began with simultaneous presentation of *n* digits, where *n* represents the working memory load. Each digit was presented in a separate rectangular frame; the frames were arranged on a virtual circle on the screen. After the initial numbers disappeared, arithmetic operations (e.g., "+ 2" or "–5") appeared in individual frames, one at a time. Participants had to apply the operation to the number in the respective frame, thereby updating it in their memory. Eight operations were presented in a regular sequence, always starting with the same frame and moving clockwise through the circular arrangement of frames. After eight arithmetic operations, all frames were probed by question marks in a random order, and participants were required to type the final results of the probed frames on the computer keyboard. An example task is illustrated in Figure 2.

This task has several advantages. First, it was shown to have high loadings on a working memory factor in a comprehensive individual-differences study (Oberauer, Süß, Schulze, Wilhelm, & Wittmann, 2000). Second, it uses only very simple elementary operations (single-digit addition and subtraction). Third, the memory load, as well as the number

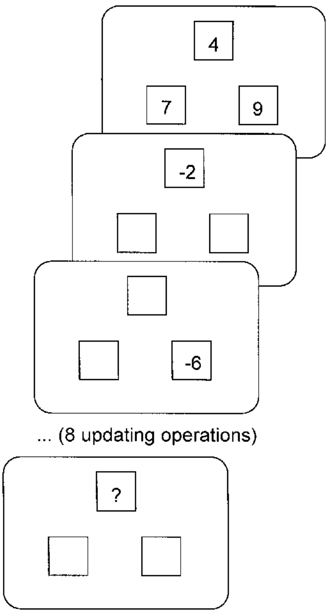

Figure 2. Example trials for memory updating with a memory demand of three digits.

of successive operations, can be varied flexibly over a large range. Fourth, the task is not amenable to obvious strategies to surpass a hypothetical capacity limit; e.g., chunking the elements is of little use because they must be updated individually. Finally, the experimenter has control over the available processing time for each updating step by manipulating the presentation time for individual arithmetic operations. We used an adaptive algorithm (Kaernbach, 1991) to vary presentation times for the updating operations over the whole range from chance to nearly asymptotic performance within each memory load condition. This allowed us to determine time-accuracy functions for each participant and each memory load condition.

Participants were informed that final results, as well as all intermediate values, always were numbers between 1 and 9. A time limit of 3000 ms (young) or 5000 ms (old) was set for each response; responses surpassing this limit elicited the feedback message "too slow" instead of "correct" or "false". These responses were nevertheless registered and treated as valid data because the time limit served only to prevent extensive computations after the last operation had been presented.[1] We also instructed participants that only trials with correct responses on all probes counted as passed to discourage the strategy of ignoring some frames from the beginning. Percentage of correct responses was used as score for each trial.

The experiment had two parts. In the first part, old and young adults worked on the memory-updating task with memory loads of one, two, three, and four. In the second part, we extended the range of memory loads, testing the same participants with loads of four, five, and six digits. The load factor was varied between blocks of 13 trials, and counterbalanced within each part of the experiment. For each memory load condition, 234 trials were presented.[2]

Results

A convenient way to summarise the results is to present parameter estimates from descriptive time–accuracy functions. Based on experience

[1]Reaction times for keying in the first results were 1232 ms (SD = 1025) for young adults and 1868 ms (SD = 1717) for old adults. This leaves little time for additional computations after the end of the presentation time. If response times were used for computations, this should be the case more often with short than with very long presentation times. The reaction times for the shortest and the longest presentation times, however, differed by only 272 ms for young adults and not at all for old adults.

[2]Details about the adaptive algorithm and the models described only briefly here can be inspected in a technical report at our webpage: http://www.psych.uni-potsdam.de/people/oberauer/working-e.html

with similar data (Kliegl, Mayr, & Krampe, 1994; Mayr, Kliegl, & Krampe, 1996; Verhaeghen, Kliegl, & Mayr, 1997), we used negatively accelerated exponential functions of the form

$$p = d + (c - d)(1 - \exp(-(t - a)/b)), \tag{3}$$

where d is a parameter for chance performance, c represents asymptotic performance, b is the rate of approaching asymptote, and a the point in time (t) where accuracy (p) rises above chance. For the present purpose, we fixed d to 1/9, because participants knew that each result must be a number between 1 and 9, leaving three free parameters for each participant and condition. Parameter estimation was done with the CLNR module of SPSS with a Maximum Likelihood loss function called G^2, which can be interpreted like a Chi^2 measure of deviation. Eight functions were fit for each participant simultaneously, five for the memory load conditions in the first part of the experiment, and three for the conditions in the second part.[3]

The descriptive functions yielded an excellent fit with G^2 values for individual data ranging from 28.13 to 97.78. Overall G^2 was 1702.8. Subtracting the free parameters for 33 subjects from the total of 3173 data points yields 2381 degrees of freedom, so that this value is far from significant.

Two summary indicators of performance were extracted from the time-accuracy functions. First, parameter c from equation 3 reflects the asymptotic accuracy reached when processing time is not externally limited. Second, we computed criterion-referenced presentation times (CPTs) relative to the asymptotes. CPTs can be derived from equation 3 by setting p to the desired relative criterion k (e.g., 80% of asymptote) and solving for t:

$$CPT = a + b\left[\ln\left(\frac{c - d}{c}\right) - \ln(1 - k)\right] \tag{4}$$

Relative CPTs represent the time a participant needs to reach a given proportion of her or his asymptote in a condition. Thus, CPTs reflect processing speed conditional on asymptotic accuracy. Figure 3 shows mean asymptotic accuracies for young and old adults (a) and CPTs for 80% of the asymptotes (b).

[3]The memory demand one condition was realised in two slightly different ways, which did not differ significantly in any respect and therefore were aggregated for all further analyses.

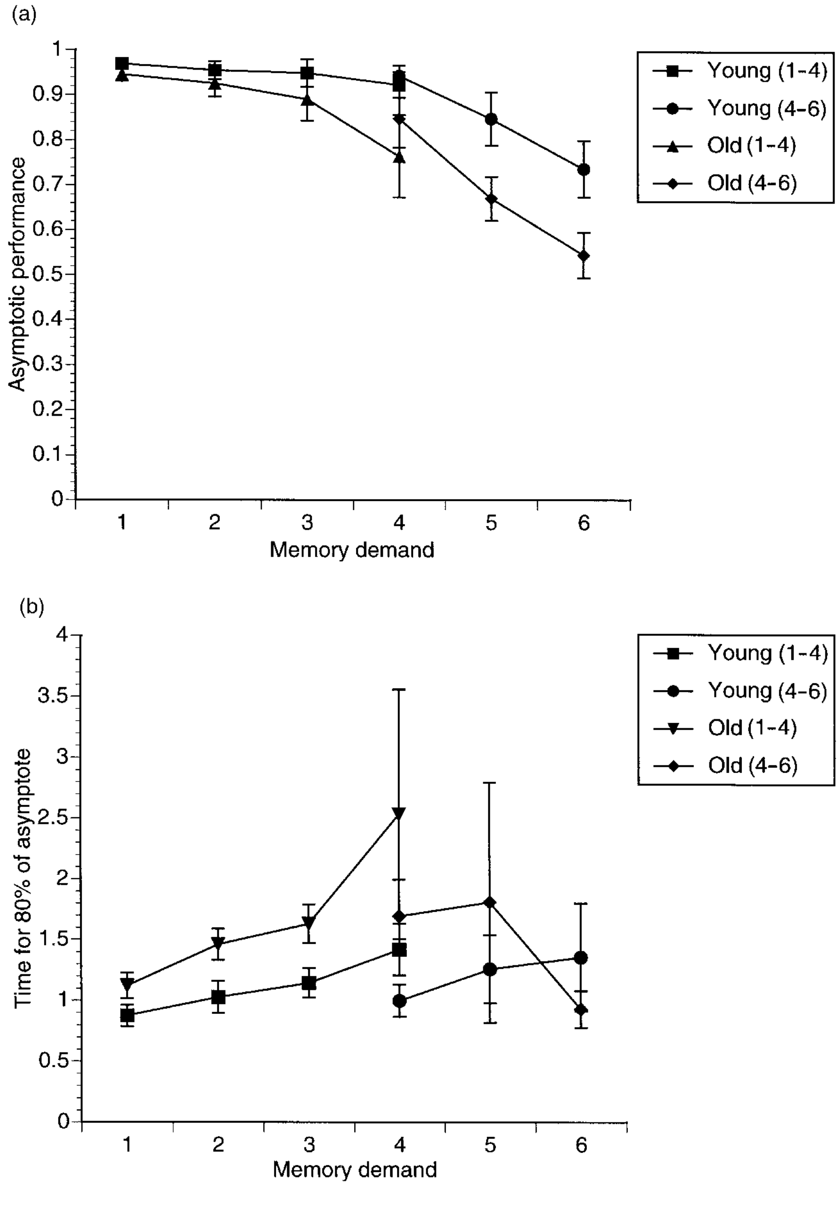

Figure 3. Parameters from exponential time–accuracy functions for young and old adults. (a) asymptotic accuracy. (b) relative criterion-referenced presentation time for 80% of the asymptote. Error bars represent two standard errors.

The data yielded four basic facts that a model should capture.

(1) Asymptotic performance declined with increasing memory load, $F(7, 217) = 77.2$, $MSe = 0.01$. The effect was clearly nonlinear with a highly significant quadratic trend, $F(1, 31) = 39.19$, $MSe = 0.01$, indicating a positively accelerated decline of the performance asymptote with increasing memory load.
(2) The decline in asymptotic accuracy was more pronounced in old adults, leading to an interaction of age and memory load, $F(2, 217) = 7.85$, $MSe = 0.01$.
(3) Processing time, as reflected by the CPTs, increased with memory load, $F(7, 217) = 18.76$, $MSe = 0.59$.
(4) Old adults were slower than young adults ($F = 11.28$, $MSe = 1.12$), and age interacted with memory load ($F = 2.72$, $MSe = 0.59$). In general, age differences increased with higher memory load, as can be expected when old adults are slowed by a constant proportion relative to young adults (Cerella, 1985).

There is a notable exception to the fourth observation for memory load condition 6, where old adults apparently needed less time than young adults to reach 80% of their asymptote. This anomaly in the data pattern was most likely due to strategic influences. If one decides to concentrate on only part of the memory set from the beginning, for example focus on three out of six elements, then a subset of operations can also be ignored. The time for these operations can in effect be used to process the remaining operations. As a result, the actual processing time for each attempted operation is much more than the presentation time controlled by the programme. This leads to an underestimation of processing time needed to reach a relative criterion. In a post-experimental debriefing session, a majority of the old adults confirmed that they used this strategy in the most demanding condition, despite being instructed not to do so, because they felt unable to do the task in any other way.

There was a clear effect of practice from the first to the second part of the experiment, evident in the improvement on memory load level 4. Both asymptotic accuracy ($F = 5.73$, $MSe = 0.01$) and log-transformed CPT values ($F = 10.41$, $MSe = 0.13$) were significantly better in the second part. Practice effects did not interact with age.

THE MODELS

We will first discuss a resource model for the memory-updating task. This model will also serve to explain our processing model for the memory-updating task and how the assumptions of each working memory model are linked to the processing model. Next we will briefly discuss two alternative resource models, and show that a magical number model makes predictions equivalent to one of these resource models. We will then test a model based on a race between decay and rehearsal, and finally turn to models incorporating interference and crosstalk, respectively.

Resource models

A resource sharing model. The most straightforward way to flesh out the notion of limited resources is to postulate a constant quantity of activation that is shared among the elements held in working memory at any time. This leads to a simple complexity function:

$$A_i = W/n \tag{5}$$

where W is the available activation and n is the memory load. Each initial number receives activation according to equation 5 before it is first updated. The task begins with an attempt to retrieve the number in the frame where the first arithmetic operation appears. The success of this attempt can be computed by the logistic function given in equation 1. If retrieval succeeds, the arithmetic operation is applied and the result is gradually activated according to the negative exponential (equation 2) until the presentation time for the operation is over. Since the new element must share the total activation resource with all other elements in working memory plus the arithmetic operand presented on the screen, its asymptote will be A_i as computed by equation 5, but with $n =$ memory load $+ 1$. The rate of activation is a function of the source activation, that is the activation of the elements that serve as input for the cognitive operation, and the connection weights linking the source elements to the resulting element. This is an assumption borrowed directly from CAPS (Just & Carpenter, 1992), but also incorporated in many other models based on spread of activation in semantic or connectionist networks. In the memory-updating task, the source activation comes from the two addends, one retrieved from memory and one presented on the screen:

$$r_i = w_{ji} A_j + w_{ki} A_k \tag{6}$$

Here, w_{ji} is the connection weight from source item j to target item i and w_{ki} is the weight connecting source k to target i. For simplicity, we assume that all addends have equal association weights with the result they generate. This allows us to reduce the individual association weights to a common parameter w. This parameter captures the speed with which activation is transmitted to the new element i, and therefore can be interpreted as a processing speed parameter for a person working on a specific task like addition or subtraction. The parameter w can vary with the type of operation, thereby reflecting mean latency differences between various operations, and with persons or groups of persons, thereby reflecting individual differences in processing speed.

At the first updating step, both addends will have an activation value close to A_i as computed by equation 6. At later steps, the activation of the element retrieved from memory can be considerably lower, because new elements gain activation only gradually according to equation 2, and with short presentation times, the results of earlier computations will not have been activated to asymptote. As a consequence, they will be less likely to be retrieved later, and if they are retrieved, they contribute less source activation to the next updating step in which they serve as an addend.

The models discussed here treat an updating step as a single operation, although it can certainly be broken down into distinct components like activation of the operand, retrieval of the required arithmetic fact, replacement of the old element by the new one, gradual activation of the new element, and maybe rehearsal of all the elements in working memory. The present data, however, do not allow us to distinguish these components, so we summarise them all in the accumulation of activation for a new element. Further research should try to disentangle the contributions of distinct processing components to the overall time demand for an updating step.

Because activation of the memory elements changes over the eight updating steps, the model must be computed iteratively. The model for a single trial consists of eight successive operation cycles, followed by n cycles with the attempt to recall the final values in each frame. For each cycle, the probability of retrieving the element and an activation value for the new element is computed. At the end of all the cycles, the probability of recalling each final element correctly is computed as

$$P_i = 1/9 + 8/9 \prod_c p_{ic} \qquad (7)$$

where p_{ic} is the success probability for retrieving element i in cycle c. The multiplication runs over all cycles where i was updated plus the final recall (e.g., four plus one cycles for each element at memory load level two); 1/9 is added for guessing probability.

The effect of practice between the first and the second part of the experiment was captured by a learning parameter h. We assumed that practice affects primarily the speed with which new elements can be activated because practice with the memory-updating task strengthens the weights between source and target elements used in arithmetic. Thus, the w parameters in equation 6 are multiplied with h in the three conditions from the second part of the experiment. The learning parameter was restricted to be larger than one to reflect positive gains from practice.

Finally, we introduced a strategic parameter specifically for the memory demand of six elements. We assumed that some participants (mostly from the old group) ignored a subset k of the six elements from the beginning, thereby effectively reducing n to $6–k$ and increasing their mean processing time per operation to t times $6/(6–k)$.

To summarise, the first model has six free parameters: The total activation resource W, the speed parameter w, the standard deviation of activation σ, the access threshold τ, the learning parameter h, and the strategy parameter k. Most of the assumptions and parameters outlined in this section are common to all (or at least most) of the models discussed here, only the complexity function expressed in equation 5 is a distinctive feature of the first resource model.

We fit this model to the data from 33 participants, leaving all six parameters free to vary among individuals. This implies that the model has $33 \times 6 = 198$ free parameters overall. They were subtracted from the total number of observations, yielding 2975 degrees of freedom (ranging from 81 to 96 for individual participants). The best fit we were able to produce with model 1 by trying various starting values yielded G^2 values from 49.99 to 250.85 for individual participants, the total G^2 was 4891. This indicates a highly significant deviation from the data.

For comparability, the predicted accuracy values computed by the model were submitted to the same treatment as the observed ones. This means that we estimated exponential time–accuracy functions for each participant and condition according to equation 3 and extracted asymptotic accuracy and the CPTs for 80% of the asymptote as performance indicators. Inspection of these predictions showed that the model captured the asymptotes quite well, but did poorly on the CPTs (space restrictions do not allow us to show the predictions here—see footnote 2). Since model 1 obviously does not fit the present data, we will not present further analyses of parameter estimates.

Resource models inspired by ACT-R and CAPS. There are several ways a resource model could be specified within our general framework. In addition to the one presented earlier, we tried two other variants, one inspired by ACT-R (Anderson et al., 1996) and one motivated by CAPS (Just & Carpenter, 1992). In ACT-R, processing time is not modelled as the gradual increase of activation for a new element. Instead, new elements receive their activation instantaneously, and a time demand for processing arises at retrieval. The time to retrieve an element is a function of this element's activation. We designed a model that incorporates the relevant equations from ACT-R. Since many assumptions of our framework common to all the models were also inspired by ACT-R, we believe that this variant of a resource model comes very close to the way the memory-updating task would be specified in ACT-R. This model had an overall G^2 of 3995.4 (range 60.72 to 163.83), which is better than the original resource model, but again deviates significantly from the data. Panels A and B of Figure 4 show the predictions.

The model inspired by CAPS differs from the previous models by its resource allocation policy. In the previous two resource models, the available activation is always distributed completely among the elements in working memory. An alternative allocation scheme is to provide each element with the activation it demands as long as there are sufficient resources, and cut down on activation proportionally when the sum of all demands surpasses the available resources. This scheme is incorporated in CAPS (Just & Carpenter, 1992) and can be formalised by a modified complexity function:

$$A_i = d_i \qquad \text{if} \sum_{j=1}^{n} d_j \leqslant W \tag{8}$$

$$A_i = d_i \frac{W}{n} \qquad \text{if} \sum_{j=1}^{n} d_j > W$$

With this modification, the resource model yielded an overall G^2 of 3193.7 (range 40.6–216.9), which is much better than the previous two models, but still indicates a significant deviation from the data with 2975 degrees of freedom ($p = .003$).

Why did the resource models fail? To sum up, all three resource models did not fit the data well. Why did these models fail? Consider the complexity function of the first and second model (equation 5), which is plotted in Figure 5 for a typical high capacity person ($W = 1$) and a typical low capacity person ($W = 0.7$). With increasing memory load, there is a steep drop in the activation allocated to a single element at the beginning of the complexity scale, which becomes much shallower at the higher end. Moreover, the differences between high and low capacity persons diminish with increasing complexity. The empirical asymptotic accuracies, however, remained stable over the first part of the complexity scale and decreased at higher complexity with positive acceleration. And the accuracy of young and old adults diverged with increasing complexity.

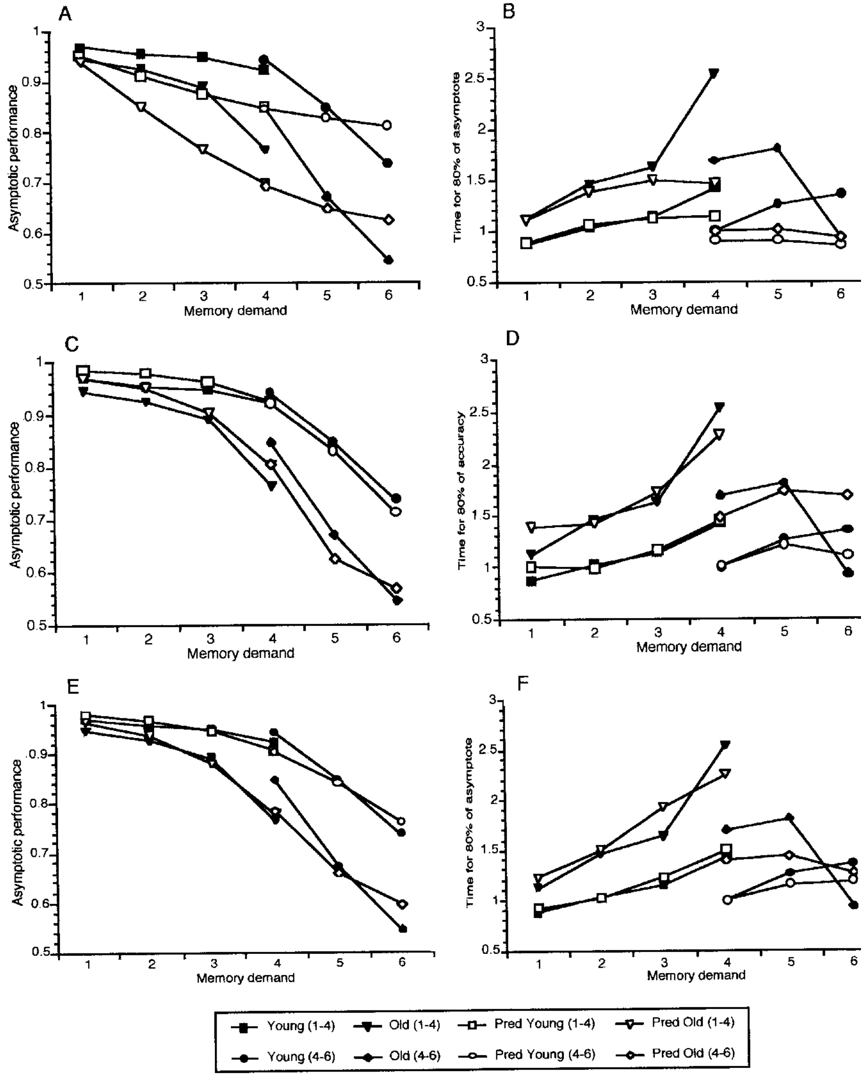

Figure 4. Data and model predictions for parameters of time–accuracy functions for the three models. A: Asymptotic accuracies for the second resource model (with equations from ACT-R). B: Relative criterion-referenced presentation times for 80% of asymptote, second resource model. C: Asymptotic accuracies for the decay model. D: Relative criterion referenced presentation times for the decay model. E: Asymptotic accuracies for the interference model. F: Relative criterion referenced presentation times for the interference model.

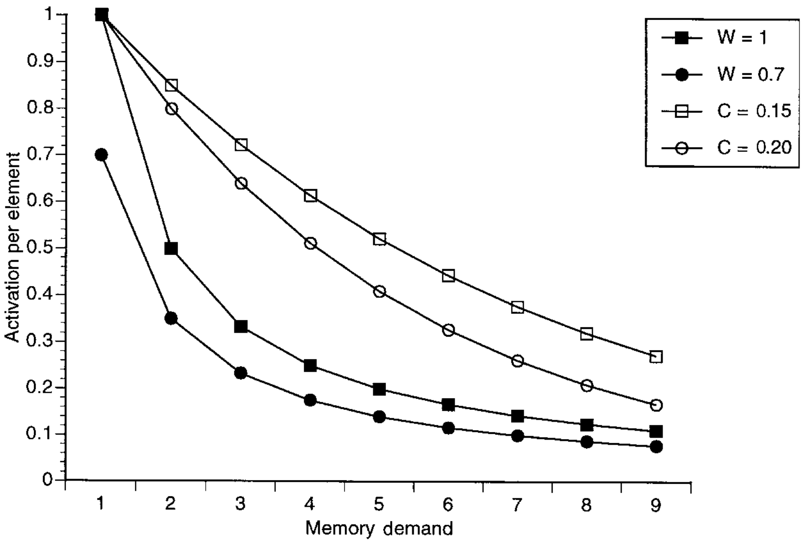

Figure 5. Mean activation of a single item as a function of complexity. Complexity functions are plotted for one high-capacity and one low-capacity individual. Solid squares and circles represent activation functions for resource sharing (with a resource pool W); open squares and circles are activation functions for the interference model (with an interference parameter C).

Likewise, the CPTs increased in an approximately linear way (disturbed by the effects of practice and strategy) and show no sign of convergence of young and old with increasing complexity. A model with a complexity function that behaves opposite to the data will obviously have difficulty reproducing these data. The logistic performance function (equation 1) helps to compensate the inconvenient form of the complexity function, but not enough to reach a good fit. This becomes manifest, for example, in the predictions for asymptotic accuracies derived from the second resource model (Figure 4, panel A), which decline in a negatively accelerated fashion, contrary to the data (Figure 3).

A "magical number" model

Models that assume a capacity for a fixed number of elements can be formalised by the same complexity function as was introduced for the earlier CAPS-oriented model (equation 8). Let us assume that each element that manages to enter working memory receives an activation level of one, and each element that does not find a slot receives zero activation. As long as the memory demand is less than or equal to the "magical number", all elements receive the full activation with a probability of one. If memory demand surpasses the "magical number", each element receives an activation of 1 with probability W/n, where W is the "magical number". Over many trials, the statistical expected value of activation for each element will then equal W/n. Hence, the complexity function of a "magical number" model can be expressed as equation 8. It turns out that a "magical number" model will make the same predictions that would be made by a resource model incorporating the complexity function of CAPS. As a consequence, the "magical number" model will also fail to give a satisfactory account of the data.

A decay-based model

Another plausible idea used to explain the limits of short term or working memory is time-based decay (e.g., Anderson & Matessa, 1997; Byrne, 1998). In this subsection, we discuss a model variant that incorporates the idea that working memory capacity is limited by the interplay of decay and reactivation.

The rationale of the decay model is as follows: The asymptote for the gradual activation of working memory elements is always one, independent of memory load. Each element in working memory decays according to a logarithmic decay rate (cf. Anderson & Matessa, 1997). The rate of decay δ is a free parameter:

$$A_t = A_0 - \delta \ln(t) \tag{9}$$

Decay can be counteracted by reactivation, e.g., through rehearsal. Rehearsal is modelled by equation 2, but with a specific rate parameter for rehearsal. All processes, including reactivation of working memory elements, are performed serially and therefore must share the available processing time. When confronted with a task that requires both manipulation and retention of information, the cognitive system must decide on what proportion of the total processing time is allocated to the manipulation task. This proportion is expressed by the parameter T. The time available for the arithmetic operation in the memory-updating task therefore is T times the presentation time t, and the time available for the reactivation of each of the remaining elements in working memory equals $(t-T)/(n-1)$, assuming that the rehearsal time is distributed evenly among the elements in memory. Thus, with increasing memory demand n the amount of reactivation for each element decreases, and this explains the decrease of asymptotic accuracy and the increase of time demand with memory load. The decay model has eight free parameters for each person, two more than model 1. We had to introduce three new parameters— T, δ, and the rate parameter for rehearsal—in return for the one saved (the resource parameter W).

Our decay model fit the data remarkably well. Overall G^2 was 2741.9 (range 49.3–140.8), which was not significant with 2909 degrees of freedom. Only two out of 33 individual data sets showed a deviation from the model significant at the 5% level. Figure 4 (panels C and D) shows that the predictions traced the asymptotic accuracies and criterion-referenced presentation times with only minor deviations (except for the drop in time demands at memory demand six for old adults, which was underestimated despite of the extra parameter k introduced for it).

Since the decay model gives a satisfactory account for the data, we can use it to investigate age differences in its parameters. The mean parameters of both age groups are summarised in Table 1. Significant age differences emerged for the standard deviation of activation and for the strategy parameter. Old adults' activation of working memory elements seems to be noisier, and they decided more frequently than young adults to drop some elements from the beginning when their capacity was overloaded. There was a nonsignificant trend for slower processing in old adults, but the estimated rehearsal rates were essentially the same for both age groups.

An interference model

Our interference model starts from the assumption that each element is represented in working memory by a set of features. The activation of an element i is the sum of the activation of its features. Any two elements i and j share a proportion C_{ij} of features. When two elements are held in working memory simultaneously, the features they have in common are

TABLE 1
Parameter estimates for decay model, young and old adults

Parameter	*Young*	*Old*	t*(diff)*	p*(diff)*
r (rehearsal rate)	3.06 (2.70)	3.0 (2.83)	0.05	.96
T (time split)	0.86 (0.15)	0.88 (0.15)	0.40	.69
δ (decay rate)	0.05 (0.01)	0.06 (0.01)	1.86	.07
w (speed)	1.22 (0.39)	0.99 (0.44)	1.57	.13
σ (stdev)	0.19 (0.03)	0.23 (0.07)	2.42	.02
τ (threshold)	0.26 (0.15)	0.23 (0.15)	0.65	.52
h (learning)	1.31 (0.16)	1.34 (0.19)	0.44	.66
k (strategy)	0.65 (0.68)	1.67 (1.33)	2.83	<.01

lost for these representations. One reson why this might happen is because features recruited by two different content elements that are linked to different context representations cannot be bound unambiguously to a specific context. Another reason could be that features included in a vector representing one element are overwritten when a new element including the same feature enters working memory.

Let us assume that an element receives a total activation of one if all its features become fully activated. The activation of an element in the context of other elements can then be expressed as the proportion of the element's features that are not lost through interference. When C_{ij} is the proportion of features that two elements i and j have in common, the proportion of their features that is still active when i and j interfere with each other is $1-C_{ij}$. For more than two elements in working memory, we assume that the sets of overlapping elements are independent of each other. Thus, the proportion of active features of element i can be expressed as

$$A_i = \prod_{j=1}^{n-1} (1 - C_{ij}) \qquad (10)$$

with n as the number of elements in working memory. When the degree of overlap among all elements is the same, as can be assumed for a homogeneous set of elements spaced evenly in their respective coordinate system (i.e., no grouping), this reduces to

$$A_i = (1 - C)^{(n-1)} \qquad (11)$$

with C as a common interference parameter for a given class of elements (e.g., digits). This provides the complexity function for the interference model. When applied to the memory-updating task, n equals the memory demand plus one, because the arithmetic operation adds one more digit to the set of elements in working memory that interfere with each other. Except for the new complexity function, the interference model is exactly like the first resource model developed earlier.

The interference model had an excellent fit with G^2 values ranging from 40.59 to 130.76 for individual participants. Only one out of 33 individual models was rejected with an alpha level of .05. The overall G^2 was 2524.87 with 2975 degrees of freedom, which is not significant. The predicted asymptotic accuracies and CPT values are plotted in panels E and F of Figure 4. The predictions are generally close to the data, except for the CPT values at higher memory demand levels for old adults. Like the decay model, the interference model underestimates the size of the drop in CPT between memory demands five and six. The data points where the model deviates from the observations, however, have large interindividual variability (see Figure 3), and since the model was fit to individual data, the group aggregates might not reflect the degree of fit on an individual level.

Table 2 presents the means and standard deviations of the six parameters for the two age groups. Separate comparisons revealed significant age differences only in the interference parameter *C*. This is compatible with the notion that young and old adults differ in their working memory capacity, defined as the capacity to resist interference in working memory. Presumably as a consequence of their reduced capacity, old adults showed a tendency to focus more frequently than young adults on only a subset of elements in the most complex condition. Age differences in several other parameters were marginally significant, so we cannot rule out the hypothesis that additional factors besides working memory differ between young and old adults.

Figure 5 shows the complexity functions of the interference model for a typical young adult ($C = 0.15$) and a typical old adult ($C = 0.2$). In comparison to the complexity functions of the resource models, these functions exhibit a less dramatic negative acceleration, which makes it easier for the interference model to fit the positively accelerated drop of asymptotic performance with increasing memory load. Perhaps more important, the two curves diverge with increasing memory load, so that the interference model can explain the Age × Complexity interaction much better than the resource models.

A crosstalk model

The crosstalk model differs from all other models in that memory load has no effect at all on the activation level of elements in working memory. Memory load effects arise only from the increased chance of

TABLE 2
Parameter estimates for interference model, young and old adults

Parameter	*Young*	*Old*	t*(diff)*	p*(diff)*
C (interference)	0.14 (0.03)	0.17 (0.05)	2.69	.01
w (speed)	1.67 (0.31)	1.46 (0.43)	1.57	.13
σ (stdev)	0.19 (0.03)	0.21 (0.05)	1.29	.21
τ (threshold)	0.22 (0.12)	0.20 (0.14)	0.37	.72
h (learning)	1.51 (0.25)	1.69 (0.33)	1.78	.08
k (strategy)	0.12 (0.21)	0.32 (0.41)	1.79	.08

selecting the wrong element from the memory set at retrieval. The general assumption is that the system selects the element with the highest activation at the moment of retrieval. The activation of the content elements comes from the context cues to which they are associated. A given context cue (e.g., a position in a list or a frame on the screen) will usually activate the target element most, but it will also spread activation to competing elements that are also associated to it (e.g., Burgess & Hitch, 1999). Crosstalk is one way to arrive at erroneous retrievals from long-term memory in ACT-R (Anderson & Lebiere, 1998). We incorporated the idea of crosstalk into our modelling framework by modifying the logistic performance function (equation 1) in such a way that it reflects the joint probability of an item i being activated above threshold *and* being activated higher than all other items in working memory. There is no limit to the activation resource, and no interference, so the effect of memory load is attributed entirely to increasing competition at retrieval.

The crosstalk model did not fit the data adequately. Overall G^2 was 3751.2 (range 45.2–231.8), a highly significant deviation from the data (df = 2975). The pattern of residuals suggests that the crosstalk model has similar problems as most of the resource models: It predicts a decelerated decline in performance for both asymptotic accuracy and speed, whereas the actual decline is accelerated for the asymptotes and approximately linear for the CPT's (ignoring the deviant point at memory demand 6).

DISCUSSION

We tested seven formal models of capacity limits in working memory with the same comprehensive data set. Only two models—one based on decay, one based on interference as the source of capacity limits—fit the data adequately. Several other models based on limited resources, a "magical number" limit, or crosstalk between context-content associations failed to reproduce the time–accuracy functions.

Implications for theories of capacity limits

The models we tested were designed to represent the most important hypotheses about the nature of capacity limits in the literature. We formalised these hypotheses within a common framework in order to make the models as comparable as possible. We also tried to keep the models simple (i.e., limiting the number of free parameters), while giving them the best chance possible to fit the data.

The failure of models tested here does not disprove conclusively the hypotheses on which they are based. It is possible that another model incorporating the idea of a limited resource pool, the assumption of a "magical number", or the crosstalk hypothesis will be able to reproduce the present data adequately. We suspect, however, that such a model will not be easily found. Where one of the models failed, we could identify the reason for its failure as one rooted in the underlying assumptions, not in some arbitrary feature of our formalisation.

As things stand, we regard the interference model as the best account of our data. The decay-based model also had an adequate fit, but it used two more free parameters, so that we prefer the interference model for reasons of simplicity.

Implications for Cognitive Ageing

Our data with the memory-updating task showed a pattern typical for the effect of ageing on working memory: Old adults performed worse on the task, in particular with higher memory load levels. Unfortunately, ordinal interactions like these are difficult to interpret, because a nonlinear monotonic scale transformation of the dependent variable (e.g., percentage correct) can make them disappear (Loftus, 1978; Kliegl et al., 1994). Formal models like those explored here can help to overcome this difficulty, because they make explicit assumptions about the transformations that translate a hypothetical variable (e.g., activation) into an observable outcome (e.g., percentage correct). For most of our models, we assume that a logistic function relates the activation value of an element into an observable performance score. Within a given model, we can therefore infer the hypothetical activation levels from the observable performance. To the degree that a model passes a rigorous test, we can be confident that the parameter estimates reflect theoretically meaningful constructs. A good model can then be used to measure hypothetical variables like activation, decay rate, or degree of interference. We can then ask, among other things, which of these variables is sensitive to an effect of ageing, and thereby attempt to pin down the source of ageing-related cognitive deficits.

The two models that accounted satisfactorily for the present data trace the source of the age difference to different parameters. In the decay model, it was mainly the Gaussian noise assumed for the activation levels of individual elements in working memory that distinguished the age groups. Although this model attributes the capacity limits of working memory to a speed factor (i.e., the speed of processing the computations and/or the speed of rehearsal, relative to the decay of information in memory), none of the two speed parameters reliably distinguished old and young adults. Thus, there is little evidence in our data for the speed theory of working memory decline in old age, as advanced by Salthouse

(1996). The results of the decay model are better compatible with the idea that ageing is associated with increased noise in the cognitive system (Allen, 1991; Allen, Kaufman, Smith, & Propper, 1998; Welford, 1958). Increased variability in the activation of working memory elements could also arise from non-optimal rehearsal strategies (e.g., rehearsing some items too often and others not often enough), which might point to a deficit in the control of attention as one aspect of executive functions (Engle, Kane, & Tuholski, 1999).

The results from the interference model suggest that old adults are more susceptible to interference than young adults. Consistent with this, Li (1999) reported that old adults suffer more from dual-task interference when an arithmetic task was combined with the memorisation of digits than when it was combined with memorisation of words. Presumably, the numbers involved in the arithmetic tasks have more feature overlap with the digit memory lists than with the words, resulting in a higher degree of interference which particularly impairs old adults.

The conclusion from the interference model seems to be at odds with results from a meta-analysis by Jenkins, Myerson, Hale, and Fry (1999). They compared simple memory spans with spans when a secondary task is added, and found that old and young adults did not differ in the amount of interference from the secondary task. Jenkins et al. (1999) noted, however, that the two age groups had different baselines (i.e., different mean simple spans). When subgroups of young and old adults with nearly equivalent simple spans were compared, the old subgroups showed larger interference effects than the young subgroups. A look at panel E of Figure 4 shows how the interference model proposed here can account for these data: Asymptotic accuracy declines over increasing complexity with positive acceleration. This implies that adding a constant amount of interfering material has a smaller absolute effect on performance when it is added at a lower complexity level than when it is added at a higher baseline of complexity. Thus, although old adults' performance drops steeper with increasing complexity, this is compensated by the fact that their baseline (i.e., simple spans) lies lower on the complexity scale. As a result, the drop in performance due to the same amount of additional interfering information is about equal for young and old adults.

One potential reason for the increased susceptibility to interference of old adults could be a reduced ability to inhibit irrelevant information (Hasher et al., 1999). Updating of working memory contents requires, among other things, to forget the old values when they are replaced. If old adults are less successful in getting rid of the old values, the remaining representations of old elements in working memory add to the total interference. In particular, each item suffers interference from n–1 present items plus *n* old elements, the latter weighted by the degree to which the old elements are still associated with the *n* frames.

Conclusions

A decline in working memory performance is a characteristic phenomenon of cognitive ageing. In this paper, we explored a number of potential factors that could be responsible for the limit of working memory capacity, and that could be affected by ageing. We think that our formalisation of a number of simple accounts of working memory capacity helps to chart the search space for an explanation of capacity limits in general, and of age-related declines in complex cognition in particular. Within this search space, we were able to identify two candidates that fit the time–accuracy data from one working-memory task particularly well, one based on decay and the other on interference. Decay and interference are the two main sources of forgetting in general theories of memory. It seems that we need no additional constructs, like limited resource pools or a "magical number" of free slots, to explain the limited capacity of working memory. Starting from the present results, we can now test specific predictions of the viable models in order to pin down more precisely the nature of one of the most important limiting factors in old adults' cognition.

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REFERENCES

Allen, P.A. (1991). On age differences in processing variability and scanning speed. *Journal of Gerontology: Psychological Sciences*, *46*, 191–201.

Allen, P.A., Kaufman, M., Smith, A.F., & Propper, R.E. (1998). A molar entropy model of age differences in spatial memory. *Psychology and Aging*, *13*, 501–518.

Anderson, J.R. (1983). *The architecture of cognition*. Cambridge, MA: Harvard University Press.

Anderson, J.R., & Lebiere, C. (1998). *The atomic components of thought*. Mahwah, NJ: Lawrence Erlbaum Associates Inc.

Anderson, J.R., & Matessa, M. (1997). A production system theory of serial memory. *Psychological Review*, 104, 728–748.

Anderson, J.R., Reder, L.M., & Lebiere, C. (1996). Working memory: Activation limits on retrieval. *Cognitive Psychology*, *30*, 221–256.

Babcock, R. (1994). Analysis of adult age differences on the Raven's Advanced Progressive Matrices Test. *Psychology and Aging*, *9*, 303–314.

Baddeley, A.D. (1986). *Working memory*. Oxford, UK: Clarendon Press.

Baddeley, A.D., Thomson, N., & Buchanan, M. (1975). Word length and the structure of short term memory. *Journal of Verbal Learning and Verbal Behavior*, *14*, 575–589.

Brown, G.D.A., Preece, T., & Hulme, C. (2000). Oscillator-based memory for serial order. *Psychological Review*, *107*, 127–181.

Burgess, N., & Hitch, G.J. (1999). Memory for serial order: A network model of the phonological loop and its timing. *Psychological Review*, *106*, 551–581.

Byrne, M.D. (1998). Taking a computational approach to aging: The SPAN theory of working memory. *Psychology and Aging*, *13*, 309–322.

Cantor, J., & Engle, R.W. (1993). Working-memory capacity as long-term memory activation: An individual-differences approach. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *19*, 1101–1114.

Case, R. (1985). *Intellectual development: Birth to adulthood*. Orlando, FL: American Press.

Cerella, J. (1985). Information processing rates in the elderly. *Psychological Bulletin*, *107*, 260–273.

Conway, A.R.A., & Engle, R. (1996). Individual differences in working memory capacity: More evidence for a general capacity theory. *Memory*, *4*, 577–590.

Cowan, N. (in press). The magical number 4 in short-term memory: A reconsideration of mental storage capacity. *Behavioral and Brain Sciences*.

Engle, R.W., Kane, M.J., & Tuholski, S.W. (1999). Individual differences in working memory capacity and what they tell us about controlled attention, general fluid intelligence, and functions of the prefrontal cortex. In A. Miyake & P. Shah (Eds.), *Models of working memory* (pp. 102–134). Cambridge, UK: Cambridge University Press.

Halford, G., Wilson, W.H., & Phillips, S. (1998). Processing capacity defined by relational complexity: Implications for comparative, developmental, and cognitive psychology. *Behavioral and Brain Sciences*, *21*, 803–864.

Hasher, L., & Zacks, R.T. (1988). Working memory, comprehension, and aging: A review and a new view. In G.H. Bower (Ed.), *The psychology of learning and motivation* (Vol. 22, pp. 193–225). New York: Academic Press.

Hasher, L., Zacks, R.T., & May, C.P. (1999). Inhibitory control, circadian arousal, and age. In D. Gopher & A. Koriat (Eds.), *Attention and performance XVII* (pp. 653–675). Cambridge, MA: MIT Press.

Henson, R.N.A. (1998). Short-term memory for serial order: The start–end model. *Cognitive Psychology*, *36*, 73–137.

Henson, R.N.A., Norris, D.G., Page, M.P.A., & Baddeley, A.D. (1996). Unchained memory: Error patterns rule out chaining models of immediate serial recall. *Quarterly Journal of Experimental Psychology*, *49A*, 80–115.

Jenkins, L., Myerson, J., Hale, S., & Fry, A. (1999). Individual and developmental differences in working memory across the life span. *Psychonomic Bulletin and Review*, *6*, 28–40.

Just, M.A., & Carpenter, P.A. (1992). A capacity theory of comprehension: Individual differences in working memory. *Psychological Review*, *99*, 122–149.

Kaernbach, C. (1991). Simple adaptive testing with the weighted up–down method. *Perception and Psychophysics*, *49*, 227–229.

Kliegl, R., Mayr, U., & Krampe, R.T. (1994). Time–accuracy functions for determining process and person differences: An application to cognitive aging. *Cognitive Psychology*, *26*, 134–164.

Kyllonen, P.C., & Christal, R.E. (1990). Reasoning ability is (little more than) working-memory capacity?! *Intelligence*, *14*, 389–433.

Li, K.Z.H. (1999). Selection from working memory: On the relationship between processing and storage components. *Aging, Neuropsychology, and Cognition*, *6*, 99–116.

Loftus, G.R. (1978). On interpretation of interactions. *Memory and Cognition*, *6*, 312–319.

Mayr, U., & Kliegl, R. (1993). Sequential and coordinative complexity: Age-based processing limitations in figural transformations. *Journal of Experimental Psychology: Learning, Memory and Cognition*, *19*, 1297–1320.

Mayr, U., Kliegl, R., & Krampe, R.T. (1996). Sequential and coordinative processing dynamics in figural transformation across the life span. *Cognition, 59*, 61–90.

McCelland, J.L. (1979). On the relations of mental processes: An examination of systems of process in cascade. *Psychological Review*, *86*, 287–330.

Meyer, D.E., & Kieras, D.E. (1997). A computational theory of executive cognitive processes and multiple-task performance: Part 2. Accounts of psychological refractory-period phenomena. *Psychological Review*, *104*, 749–791.

Miller, G.A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review*, *63*, 81–97.

Nairne, J.S. (1990). A feature model of immediate memory. *Memory and Cognition*, *18*, 251–269.

Navon, D. (1984). Resources—a theoretical soupstone? *Psychological Review*, *91*, 216–234.

Oberauer, K., Süß, H.-M., Schulze, R., Wilhelm, O., & Wittmann, W.M. (2000). Working memory capacity—facets of a cognitive ability construct. *Personality and Individual Differences*, *29*, 1017–1045.

Salthouse, T.A. (1991). Mediation of adult age differences in cognition by reductions in working memory and speed of processing. *Psychological Science*, *2*, 179–183.

Salthouse, T.A. (1992). Why do adult age differences increase with task complexity? *Developmental Psychology*, *28*, 905–918.

Salthouse, T.A. (1994). The aging of working memory. *Neuropsychology*, *8*, 535–543.

Salthouse, T.A. (1996). The processing speed theory of adult age differences in cognition. *Psychological Review*, *103*, 403–428.

Salthouse, T.A., Babcock, R.L., & Shaw, R.J. (1991). Effects of adult age on structural and operational capacities in working memory. *Psychology and Aging*, *6*, 118–127.

Schweickert, R., & Boruff, B. (1986). Short-term memory capacity: Magic number or magic spell? *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *12*, 419–425.

Süß, H.-M., Oberauer, K., Wittmann, W.W., Wilhelm, O., & Schulze, R. (2000). Working memory and intelligence. *Manuscript submitted for publication*.

Tehan, G., & Humphreys, M.S. (1998). Creating proactive interference in immediate recall: Building a DOG from a DART, a MOP, and FIG. *Memory and Cognition*, *26*, 477–489.

Verhaeghen, P., Kliegl, R., & Mayr, U. (1997). Sequential and coordinative complexity in time-accuracy functions for mental arithmatic. *Psychology & Aging*, *12*, 555–564.

Welford, A.T. (1958). *Aging and human skill*. London: Oxford University Press.