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Working Memory Capacity in a Go/No-Go Task: Age Differences in Interference, Processing Speed, and Attentional Control

AQ: au Odir Antonio Rodríguez-Villagra and Katrin Göthe
University of Potsdam

Klaus Oberauer
University of Zurich

Reinhold Kliegl
University of Potsdam

We tested the limits of working-memory capacity (WMC) of young adults, old adults, and children with a memory-updating task. The task consisted of mentally shifting spatial positions within a grid according to arrows, their color signaling either only go (control) or go/no-go conditions. The interference model (IM) of Oberauer and Kliegl (2006) was simultaneously fitted to the data of all groups. In addition to the 3 main model parameters (feature overlap, noise, and processing rate), we estimated the time for switching between go and no-go steps as a new model parameter. In this study, we examined the IM parameters across the life span. The IM parameter estimates show that (a) conditions were not different in interference by feature overlap and interference by confusion; (b) switching costs time; (c) young adults and children were less susceptible than old adults to interference due to feature overlap; (d) noise was highest for children, followed by old and young adults; (e) old adults differed from children and young adults in lower processing rate; and (f) children and old adults had a larger switch cost between go steps and no-go steps. Thus, the results of this study indicated that across age, the IM parameters contribute distinctively for explaining the limits of WMC.

Keywords: working memory capacity, interference model, inhibition, children, old adults and young adults

According to Oberauer, Süß, Wilhelm, and Sander (2008), working-memory capacity (WMC) "reflects the ability to keep several chunks of information simultaneously available for direct access" (p. 50). This capacity plays a crucial role in human cognition. Individuals with high WMC tend to perform better than individuals with low WMC in a range of cognitive tasks. Specifically, there is evidence for the predictive power of WMC for intelligence tests, language comprehension, and reasoning ability (Chen & Li, 2007; Oberauer et al., 2008; Palladino, Cornoldi, De Beni, & Pazzaglia, 2001). Therefore, a better understanding of the sources and mechanisms of limitation in WMC will inform psychologists about processes involved in a variety of cognitive tasks. AQ: 1

Regarding sources of limitation in WMC, some theories have suggested that cognitive processes such as inhibition, executive attention and control, processing speed, and differences in capacity of storage are responsible for individual differences in working memory (for a review on this topic, see Conway, Jarrold, Kane, Miyake, & Towse, 2007). Other theories have focused on the mechanisms responsible for forgetting in working memory. Some contemporary models of working memory and short-term memory assign a central role to the passage of time alone as a cause of decay of memory traces (Barrouillet, Bernardin, & Camos, 2004), whereas other models have postulated interference as the main cause of forgetting (Oberauer & Kliegl, 2006; Oberauer & Lewandowsky, 2008).

The interference model (IM) developed by Oberauer and Kliegl (2001, 2006) successfully fitted data from different versions of a working-memory updating task. The IM has two parameters reflecting two types of interference: the degree of feature overlap between representations in working memory, which governs interference by feature overwriting, and the noise parameter, which governs interference by confusion of items. A third parameter reflects the average speed of information processing. Oberauer and Kliegl (2006) examined interference among items within and across the verbal and spatial domains and the effect of phonological similarity. Their results showed that interference by feature overwriting is larger among items within the same domain than it is among items in different domains and that feature overwriting

Odir Antonio Rodríguez-Villagra and Katrin Göthe, Department of Psychology, University of Potsdam, Potsdam, Germany; Klaus Oberauer, Department of Psychology, University of Zurich, Zurich, Switzerland; AQ: 6 Reinhold Kliegl, Department of Psychology, University of Potsdam.

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Correspondence concerning this article should be addressed to Odir Antonio Rodríguez-Villagra, Department of Psychology, University of Potsdam, Karl-Liebknecht-Str. 24/25, 14476 Potsdam, Germany. E-mail: odir.rodriguez.villagra@uni-potsdam.de

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among items in working-memory updating tasks increases when items are phonologically more similar to each other.

Additionally, the IM provided a satisfactory quantitative fit for data of different age groups. An earlier version of the IM (Oberauer & Kliegl, 2001) successfully fitted data from young and old adults and showed that old adults, compared with younger adults, exhibited an increased susceptibility to interference. Furthermore, in a recent study, the IM was used to compare typically developing children to children with different learning difficulties (Göthe, Esser, Gendt, & Kliegl, 2012).

These successful applications of the IM have shown that interference by feature overwriting and interference by confusion are mechanisms that may help explain the causes of forgetting in WMC. Mechanisms and processes such as inhibition (Healey, Campbell, & Hasher, 2008), attentional control (Szmalec, Verbruggen, Vandierendonck, & Kemps, 2011; Vallesi, Hasher, & Stuss, 2010), processing speed (Chen & Li, 2007; Salthouse, 1996), and different kinds of interference (Szmalec et al., 2011) have been related to individual and age differences in WMC. The IM framework allows for the simultaneous examination of these proposals—of course, only relative to their conceptualization in this model. In the present study, we address the question of whether these alternative explanations are redundant with each other or whether they refer to separate, coexisting sources of age differences. In addition, we investigate whether different variables are responsible for differences between young adults and children on the one hand and the differences between young and old adults on the other hand.

The purpose of the present work was twofold. First, we aimed to extend the IM to a new version of the memory-updating paradigm. Our new task version enabled us to test the contribution of attention control in working memory by including *go* and *no-go* steps in the updating phase. The effect of this manipulation is captured in an additional IM parameter. We argue that inhibition or task-switching processes are the mechanisms underlying the control of attention. Thus, this manipulation allowed us to examine the dynamics between the two types of interference assumed by the IM and attention control in WMC. Second, we wanted to investigate the development of WMC across the life span. Studies and theories have attributed age and developmental differences to (a) storage capacity (Bayliss, Jarrold, Baddeley, Gunn, & Leigh, 2005; Cowan, 2001), (b) processing speed (Salthouse, 1996), and (c) attention control (Chiappe, Hasher, & Siegel, 2000; Elliot, 2002; Kane, Conway, Hambrick, & Engle, 2008; Redick, Heitz, & Engle, 2007). To test life span differences with respect to these limiting factors of WMC in an integrated approach, we tested children, young adults, and old adults. The remainder of the introduction is organized as follows: First we introduce the new version of the updating task used in our study. After that we briefly describe the IM, and then we detail the goals of the present study.

Go/No-Go Spatial Updating Task

The task involves two different conditions: the control condition and the new go/no-go condition. A trial of the control condition started with the presentation of the spatial position of one, two, or three stimuli placed in a 3×4 grid. The number of stimuli to be remembered formed the level of memory demand. The subjects were required to encode the initial position of each stimulus. After the encoding phase, a blue arrow together with a picture of one stimulus was presented, signaling the first updating step. An updating step involved the subject mentally shifting the stimulus, moving it one place from its current position in the direction indicated by the blue arrow, and remembering its new position. After five or six updating steps, the final position of each stimulus was queried. The subjects responded by clicking with the mouse into the field where they expected a particular stimulus to be. Finally, a feedback screen was presented displaying all stimuli together with a happy or a sad face for correct and false answers, respectively.

The new go/no-go condition was the same as the control condition, except for a white arrow that could be presented on updating steps. If a white arrow appeared on any of these updating steps, the subjects were requested to not update the stimuli. Thus, one trial in this condition could have one to three no-updating steps (see Figure 1 for schematic representation of one trial). The random selection of no-go updating steps prevented subjects from predicting a no-go step. Hence, the difference between the control condition and the go/no-go condition was the fact that in the go/no-go condition, subjects had to selectively ignore the arrows on no-go steps. That manipulation reduced the number of actually completed updating steps per trial in the go/no-go condition. F1

Against the background of our experimental conditions, we now present a brief description of the IM that closely follows the one provided by Oberauer and Kliegl (2006). Readers interested in further IM details are referred to the original article. The Appendix of this article shows how the IM parameters are estimated.

IM

Figure 2 (a modification of Figure 5 in Oberauer & Kliegl, 2006) shows a schematic illustration of the architectural assumptions of the IM. The IM is sketched as a network of four layers: the context layer, the feature layer, the focus layer, and the results layer. The example illustrates a state in which the spatial locations of two stimuli (called *objects* hereinafter) in the grid have to be stored in working memory. An assumption of the IM is that the contents of working memory are represented as a set of active feature units in the feature layer and in the context layer. The items to be retrieved are represented in the feature layer, and the cues that can be used to retrieve them are represented in the context layer. In the spatial memory-updating task, the objects serve as retrieval cues for their current locations. Therefore, the spatial locations are represented in the feature layer, and the objects are represented in the context layer. The features of each object are bound to the features of its current location. The model supposes that the synchronized firing of neurons could be a mechanism to bind features of the same object to each other and to their spatial location (Raffone & Wolters, 2001). In the example of Figure 2, synchronization is illustrated by filling feature and context units with the same pattern. Two objects are stored. The target location, that is, the spatial location one needs to retrieve for updating of the given object, is associated with the hatched feature units, and the competitor location (i.e., the other object's location) is marked by the checkered feature units. F2

The IM assumes that any two representations in working memory share a proportion, *C,* of their features (i.e., feature overlap), with more similar representations sharing more features. In the

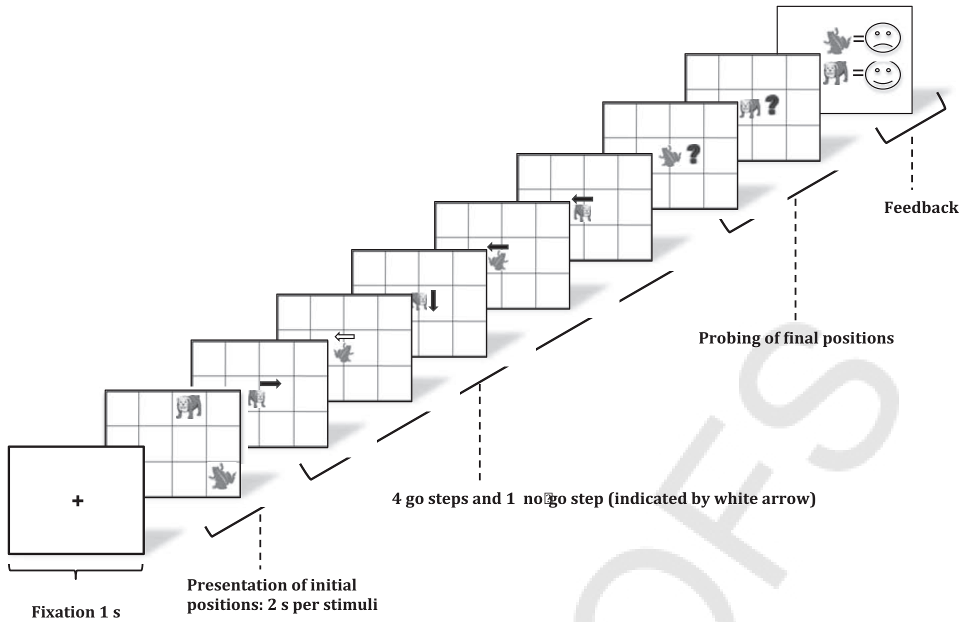

Figure 1. Task example of a trial involving a memory demand of two objects in the go/no-go condition.

example, the two spatial locations share two feature units denoted with 1 and 2. If a shared feature fires in synchrony with one phase, thereby being included in the same representation, then this feature cannot fire at the same time in synchrony with another phase. Consequently, the other representation loses the feature unit. This interference mechanism is called *feature overwriting* (Nairne, 1990). The example shows that each spatial location lost one feature because of overwriting. The target location lost Feature Unit 1 and the competitor location lost Feature Unit 2. In the example, the target location transfers only four fifths of its maximum activation strength, because it had lost Feature Unit 1. As a consequence of the feature overwriting of the two locations in our example, the focus unit of the competitor also receives one fifth of its maximum activation. This is because of the fact that Feature Unit 2, on which the locations overlap, fires in the hatched phase and transfers its activation to the focus unit of the competitor. In the focus layer, the location with the highest activation is selected for further processing. In the example, the relative activation levels of target and competitor in Figure 2 (i.e., 4/5 and 1/5, respectively) would lead to correct selection of the features of the target location, which would consequently be used it as input to the shifting operation. The result of the operation (i.e., the new location of the given object) is subsequently transferred to the result layer. However, activation in the focus layer is noisy. The activation levels must therefore be interpreted as expected values of random variables. The standard deviation of the activation in the focus layer (i.e., the σ parameter) is assumed to reflect interference by confusion.

The time it takes that activation spreads from the context layer (i.e., presentation of the cue) to the result layer (i.e., selection and updating of the stimulus) is captured by the processing rate, *r*. The IM takes into account that updating an object that has been updated on the immediately preceding step is faster than updating another item in working memory (Garavan, 1998; Oberauer, 2003). This so-called object-switch cost can be explained by assuming that, after an updating step, the result is projected back into the focus layer, so that the to-be-updated location is already strongly activated in the focus layer when the next updating step commences. To account for this assumption in the formalization, the IM distinguishes two rate parameters, r_1 and r. The rate parameter r_1 reflects the speed of updating in the condition when memory demand is equal to 1, that is, when no object switch is necessary. The rate parameter *r* reflects the speed of updating in conditions when memory demand is more than 1, that is, when an object switch is necessary between every updating step and the next.

The go/no-go condition has two different types of updating steps: one that was followed by another updating step (as in the go condition) and one that is followed by a no-go step. In the latter case, this no-go time can be used to complete the preceding go step. We therefore doubled in the model the time for an updating step followed by a no-go step, compared with an updating step that is followed by another updating step. We included a further parameter *sc* that reflects the time cost of switching between go and no-go steps. This was done because the switch between a go and a no-go step could demand time.

In summary, the basic implementation of the IM has four free parameters. The *C* parameter captures the mean degree of feature overlap among representations in the feature layer (in the present case, among representations of spatial locations). The noise parameter, σ, reflects the noise in the system and determines the extent of interference by confusion between locations at retrieval. The two rate parameters, r_1 and *r*, reflect the speed of updating one object's location that is or is not already activated in the focus layer, respectively. For our experiment, we specified an IM with an additional *sc* parameter, which reflects the time cost of switching between a go and a no-go step.

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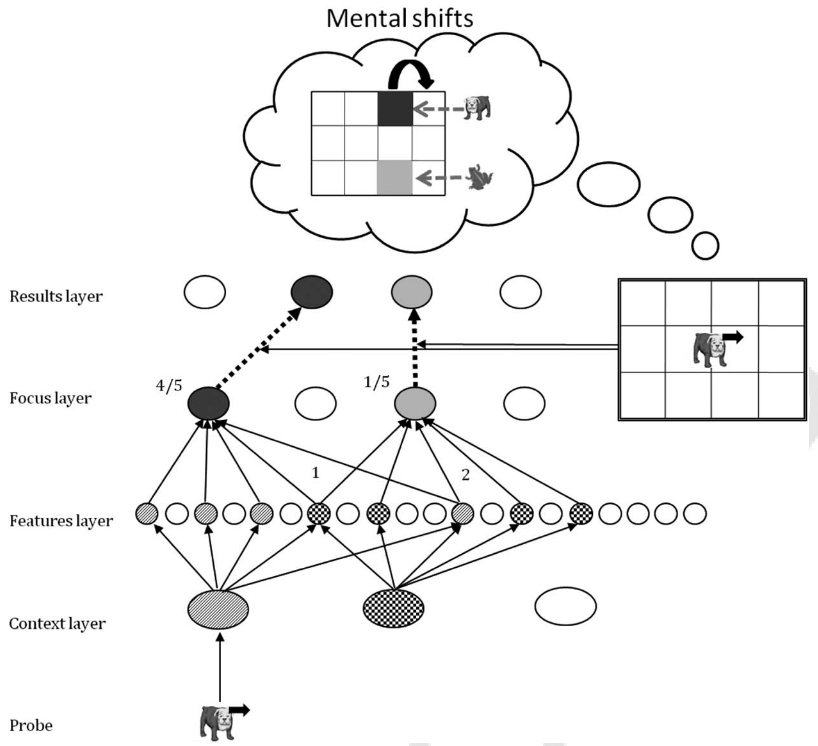

Figure 2. Schematic illustration of the architectural assumptions of the interference model. Adapted from "A Formal Model of Capacity Limits in Working Memory," by K. Oberauer and R. Kliegl, 2006, *Journal of Memory and Language, 55,* p. 608. Copyright 2006 by Elsevier.

Present Study

In the present study, we investigated several sets of hypotheses related to the postulated limiting factors of WMC: (a) storage (feature overlap, *C*; noise, σ); (b) processing speed (rate, *r*); and (c) attentional control (switching, *sc*) and, furthermore, looked at (d) life span differences with respect to these limiting factors. First, we expected that limits of working-memory updating due to increasing memory demand can be traced to two sources of interference associated with the IM parameters: a higher proportion of feature overwriting and a higher amount of interference by confusion (Göthe et al., 2012; Oberauer & Kliegl, 2001, 2006, 2010).

The second hypothesis related to speed of processing captured by the *r* parameter in the IM. Oberauer and Kliegl (2006) already tested two exploratory models (see Table 1, Models 1a and 5a, in Oberauer & Kliegl, 2006) with different rate parameters when memory demand was equal to 1, memory demand was equal to 2, and memory demand was more than 2, thereby further differentiating parameter *r* (for memory demands > 1). In the present study, we wanted to test again if the IM required more than one rate parameter for memory demands larger than 1. One reason why rate might continuously decrease with increasing memory demand is that competing responses inhibit each other, as proposed by Usher and McClelland (2001). Strong competition among working memory representations could slow down the retrieval of any one of them through inhibition, consequently reducing the rate of updating.

The third part investigated attentional control via the introduction of the go/no-go condition. For this condition, we at first adjusted time parameters that the presentation time of a no-go step can be used to complete the preceding updating step. This extension of processing time should lead to better overall performance in the go/no-go condition. To the degree that this model accurately reproduces the differences between the go/no-go and control conditions, this assumption gains support from the data.

In this condition, however, we also tested if an IM with a *sc* parameter reflecting the time of switching from a go step to a no-go step offers a better account for the data (i.e., improve the goodness of the model) compared with a model without that parameter. We consider two interpretations of the *sc* parameter in terms of different aspects of attentional control. One interpretation of the *sc* parameter, therefore, is that it reflects the time cost of inhibiting the updating during a no-go step. An alternative interpretation is that *sc* reflects the time to switch from the *update* task set to the *do not update* task set. We cannot empirically distinguish these interpretations of the *sc* parameter but, in both cases, attentional control is involved.

Furthermore, we explored whether switch cost increases with memory demand. The reason could be that the stimulus accompanying the arrow serves as an automatic cue to the location of the depicted object in the grid. If this leads to retrieval of a location that differs from the location to be updated on the preceding go step, it would disrupt the continuation of the preceding updating operation during the presentation time of the no-go step. This can happen only when memory demand is larger than one. Therefore, an increase in switching time as a consequence of larger memory

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demand would be sufficient to explain the time cost reflected in the *sc* parameter.

The fourth set of hypotheses is related to life span differences—that is, developmental and aging effects—in working-memory updating. Feature overlap was already found to increase with age (Oberauer & Kliegl, 2001). However, a developmental decrease—that is, a lesser susceptibility to interference through feature overwriting for younger adults compared with children—still needs to be tested. In a recent study, Göthe et al. (2012) compared children at the age of 8 years with children at the age of 11 years and were not able to attribute higher storage capacities for the latter group to lower feature overlap. With a much broader age range (i.e., comparing children with young adults), we expect to find developmental effects on feature overwriting. We predict the same for interference due to noise (i.e., the confusion of whole stimuli): Children and older adults are expected to show more noise than young adults.

Generally, speed of processing was found to decrease with age (Salthouse, 1996). Applying the IM to data of a numerical memory-updating task of young and old adults, Oberauer and Kliegl (2001) could not exactly attribute age differences to the noise or the rate parameter due to a high correlation between the parameters. We wanted to check whether dissociation is possible.

We expect that both children and older adults exhibiting a higher switch cost than do young adults. Bjorklund and Harnishfeger (1990) proposed that young children have inefficient inhibition in working memory. As they grow older, children are assumed to improve in selective attention and the ability to keep out of working memory irrelevant information. Inhibitory control deficiencies in old age are assumed by the inhibitory control theory of Hasher, Zacks, and May (1999). This theory postulates inhibition efficiency as the main source of individual and group differences (Hasher, Zacks, & May, 1999).

To summarize, the goals of the present study were (a) to provide new evidence for the proposition that limits of working memory are a consequence of interference by feature overwriting and interference by confusion; (b) to further test if the rate parameter increases with memory demand; (c) to examine an implementation of the IM postulating that the time during no-go steps is used to complete the preceding go step and to test if the inclusion of the *sc* parameter reflecting attentional control offers a better account for the data; and (d) to investigate which IM parameters change across the life span, especially when simultaneously testing the different accounts claiming to explain WMC limitations and whether different developmental trajectories can be found.

Method

Subjects

A total of 62 persons participated in the experiment. Children were recruited from a school in Potsdam, young adults were students from the University of Potsdam, and older adults were
T1 recruited from the Potsdam participant pool. Table 1 summarizes biographical, self-report, and test data as a function of age group. All subjects responded to a self-report with four questions (on a scale from 1 = *very good* to 5 = *very bad*) concerning life satisfaction, physical health, mental health, and mental performance. The last two issues were replaced for children to report school performance, which implies that children completed a self-report with three questions. All groups reported values on all questions above scale average (i.e., 3); children tended to rate themselves as more satisfied and healthier than young adults did and older adults tended to rate themselves as less satisfied and healthy than young adults did.

Table 1
Sample Description for the Three Groups

Effect	Children	Young adults	Older adults
n	22	18	22
Female/male	8/14	12/6	13/9
Age	10 (0.39)	23 (2.01)	73 (2.62)
Years of education	4	14.81 (1.28)	12.80 (2.78)
Life satisfaction	1.75 (0.78)	1.89 (0.65)	2.05 (0.65)
Physical health	1.7 (0.80)	2.21 (0.78)	2.36 (0.76)
Mental/school performance	2.4 (0.82)	2.36 (0.89)	2.38 (0.60)
Mental health		2 (0.57)	2.05 (0.87)
Vocabulary test		31.63 (2.00)	33.27 (1.52)
Digit–symbol test		65.11 (8.88)	47.27 (9.32)

Note. Entries refer to the mean values with standard deviations in parentheses except for *n* and the female/male ratio.

In addition, young and older adults performed a multiple-choice vocabulary test and the digit–symbol test from the German version of the Wechsler intelligence test. Older adults reached slightly higher scores on the vocabulary test but younger adults achieved higher scores on the digit–symbol test. Thus, the two groups were comparable to typical samples of young and older adults with respect to their cognitive status (e.g., Chen & Li, 2007).

Material

The task was programmed with E-Prime 2.0 (Schneider, Eschman, & Zuccolotto, 2002). We used nine different monochrome pictures representing animals or objects (see Figure 1 for an example). The selection of the stimuli made sure that their word names were of similar length with maximum phonological dissimilarity to minimize effects of the verbal representation of each picture (i.e., the German words for these pictures were *Frosch, Hund, Eis, Topf, Huhn, Ei, Mond, Kuh,* and *Hai*).

Design

The experiment crossed three factors: age (young adults, children, and old adults), updating conditions (control and go/no-go conditions), and memory demand (one, two, and three objects). It comprised three sessions of 1 hr each. Subjects performed one session per day with a 5-min break. In one session, they performed 12 blocks: two blocks per memory demand for each updating condition. Presentation orders of each updating condition and of each memory demand were counterbalanced across subjects. In total, subjects completed 216 trials in each updating condition.

Each block contained 12 trials each with a different presentation time for the updating steps. The 12 presentation times ranged from 563 ms to 3,474 ms with a constant 18% increase between successive times. The 12 presentation times of each block were categorized into fast, medium, and slow categories, with four times in each. Order of presentation-time categories was fixed within each block, repeating a sequence of medium—slow—fast. Within each category, presentation times were chosen randomly without replacement. The selection of these presentation times is an important aspect of our design because it would help to estimate how much time the different age groups need to achieve their particular asymptotic level of accuracy. Time–accuracy functions are a procedure that address this concern. Furthermore, an advantage of this procedure is that it avoids the speed–accuracy trade-off and issues of ceiling and floor effects, therefore enabling a comparison across age groups that is not compromised by these problems.

Trial Procedure

At the beginning of each trial, a screen displayed the memory demand of the upcoming trial together with the names of the stimuli that had to be shifted within the grid. The trial started with a 1,000-ms fixation cross in the screen center. This display was followed by presentation of one, two, or three stimuli placed in a 3 × 4 grid. Subjects had to encode their locations during an encoding phase, which lasted 2 s per stimulus (i.e., the encoding time of a trial with memory demand 3 was 6 s). An updating step was indicated by the presentation of the probe in the center of the screen; the probe consisted of the simultaneous presentation of a blue arrow and a picture of one of the encoded stimuli, with the arrow placed above, below, to the left of, to the right of, or in a diagonal position to the stimulus. Arrows could point to eight possible directions (e.g., top, below, left, right or diagonal). The subjects were instructed to mentally shift an object's position one step in the grid from its current position according to the direction of the arrow and remember its new position. Each trial consisted of five or six updating steps, and all objects had to be updated at least once. After updating, subjects had to enter the final position of each stimulus by clicking with the computer mouse in the specific cell of the grid. After all responses were given, feedback was displayed by presenting each stimulus together with a happy face or a sad face for correct and incorrect responses, respectively.

The go/no-go condition was identical to the control condition except for the presentation of a blue or white arrow on updating steps. If a white arrow appeared, subjects were instructed not to shift the position of the respective animal. A trial could have one, two, or three no-go steps.

Statistical Methods

We implemented the IM in a nonlinear mixed-models (NLMMs) framework as follows. The accuracy on a given trial is a function of the following independent variables: presentation time of updating operations (12 levels), updating conditions (control condition and go/no-go condition), three memory demands (one, two, and three), and age groups (children, young adults, and old adults). The IM model, together with its parameter values, predicts accuracy as a function of presentation time, memory demand, and updating condition as specified by the model equations presented in the Appendix. The model parameters are, in turn, regarded as dependent variables of the remaining independent variable, age group. Thus, the IM embedded in an NLMM framework is a two-stage model. In the first stage, model parameters for each individual are predicted from age group and updating conditions by mixed-effects linear regression. In the second stage, accuracy for each level of presentation time, memory load, and updating condition is predicted for each individual by the (nonlinear) equations of the IM model.

In the context of NLMMs, fixed effects specify the influence of independent variables on IM parameters; these effects are estimated as the mean change in the dependent variable relative to the levels of a condition of the design (slopes) and intercepts. For C and σ parameters, we coded the fixed effects of age group and updating condition as successive differences contrasts (Venables & Ripley, 2002, p. 148). These contrasts captured differences between the means of successive levels and the intercept estimates the grand mean. Thus, the fixed effect of age factor reflects the difference between the second level (young adults) and the first level (children) as well as the difference between the third level (old adults) and the second level. The fixed effect of updating condition involves the difference between the go/no-go condition (second level) and the control condition (first level). Contrasts for sc parameter captured differences among age groups—coded as successive differences contrasts—and between memory demand equal to 1 and memory demands more than 1. Likewise, the slope of r was modeled by successive differences contrasts, using memory demand of 1 as the first level, and memory demand of 2 as the second level, and memory demand of 3 as the third level.

Additionally in the context of NLMMs, individual differences in the intercept or slope of each IM parameter can be estimated as random-effect parameters (i.e., variance component). If a random-effect parameter improves the model's fit, the random-effect parameter represents evidence for reliable interindividual differences in the associated fixed effect.

IM parameters were estimated as follow. First, we averaged the accuracies by subject, memory demand, updating conditions, and presentation time. Second, these data were used to estimate the IM parameters separately for each subject. Following the IM formulas, we estimated a set of coefficients that included the C, σ, r, and sc, for each subject. Third, the estimated coefficients were used as start values to estimate fixed effects and variance components of the NLMMs. For data processing and analysis, we used R, a language and environment for statistical computing (R Development Core Team, 2010). The specific R packages used were the nlme package (Pinheiro, Bates, DebRoy, Sarkar, & the R Development Core Team, 2010), the lattice package (Sarkar, 2008), the ggplot2 package (Wickham, 2009), and the reshape package (Wickham, 2007).

Our model-building strategy consisted of the implementation of a full model, which included fixed effects (i.e., intercepts and slopes) and random effects. Additionally, we tested if the model needed different rate parameters according to age and memory demand. Then we specified a model that included all fixed effects (slopes and intercepts) and the intercepts C, σ, r, and sc as random effects. Afterward, we tested the statistical importance of random effects in a model by selecting the smallest random effect as candidate to be eliminated. Finally, we tested whether correlations among random effects were needed. Then we examined by graphical outputs its statistical adequacy with respect to the underlying distributional assumptions of NLMMs.

For model selection, we used multiple criteria: the log-likelihood statistic returned by the nlme function in R, along with Akaike's information criterion (AIC) and Bayesian information criterion (BIC). We also computed a R^2_{adj} statistic (McElree &

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Dosher, 1989) as a descriptive index. The AIC and BIC allow the comparison between models of different complexity and are derived from the log likelihood. The model with lowest AIC and BIC is preferred.[1] We checked if the elimination of a fixed effect or a random effect left a better fit with respect to AIC, BIC and log-likelihood criteria. Additionally, we included the AIC and BIC differences (i.e., ΔAIC, ΔBIC), which help to disambiguate the model selection process. The ΔAIC and ΔBIC differences are computed by the same procedure. So here we give an example based on the ΔAIC that shows how to compute them. The procedure selects the model with the lowest AIC; that is a preliminary winning model. Then the differences between a preliminary winning model and the remaining models are computed. After obtaining these differences, the winning model adopts a value of 0 and the other models adopt the differences. According to Burnham and Anderson (2002, p. 70), values of ΔAIC between 0 and 2 indicate little support to discriminate between models, from 4 to 7 indicate less support for the model with higher AIC, and of more than 10 suggests no support for the model with the higher AIC. According to Wasserman (2000), ΔBIC may be interpreted in the same way.

Results

First, we performed an analysis of variance to offer a standard overview of results, with proportion of correct responses as a dependent variable and presentation times (ordered from 563 ms to 3,474 ms), updating conditions, memory demand, and age as independent variables. The independent variables were specified as successive differences contrasts, and the levels of each factor were ordered as was described in the Statistical Methods section. Age is a between-subjects factor, and the other independent variables are within-subject factors. Table 2 shows the sources of variance in this analysis, and Figure 3 shows the means and their respective standard errors. The age group effect reflected higher accuracy for young adults than for children and old adults. As expected, accuracy increased with presentation time and decreased with memory demand. Accuracy was higher in the go/no-go condition than in the control condition. The Age Group × Presentation Times interaction and the Age Group × Memory Demand interaction suggest that the groups were affected differently by presentation times and memory demands, respectively. Specifically, young adults were less affected by the presentation times and memory demand than were the other age groups. Accuracy of each age group was similarly affected by updating conditions, as reflected by the nonsignificant interaction between age groups and updating conditions. Additionally, the Updating Conditions × Memory Demand interaction and the Updating Conditions × Presentation Times interaction indicated that the difference between conditions was more pronounced in shorter presentation times and with higher memory demands, respectively (see Figure 3). Finally, the Memory Demand × Presentation Times interaction showed that the decline of accuracy with memory demand was more pronounced at shorter presentation times than at longer presentation times.

Following the model-building strategy presented in the last section (i.e., to start with a full saturated model), we regarded Model 1 as the model that fits the data best while agreeing with NLMM distributional assumptions. Table 3 presents the descriptive R^2_{adj} statistic and the model-selection criteria of Model 1 and more constrained versions of the IM. Model 1 included the fixed effects specified in the Statistical Methods section but estimated the rate parameters for each memory demand as the same for young adults and children (see in Table 2 the parameters of r with the subscript Ch.Y.MD $>$ 1 and Ch.Y.MD $>$ 2). The reason for this constraint in Model 1 was that children and young adults did not differ in the rate parameter and therefore it was not necessary to include independent rate parameters for children and young adults. Model 1 included variance components for means (intercepts) and correlation parameters of C, r, σ, and sc parameters. Correlation parameters involving the C-intercept parameter were fixed to zero because they included 0 in their confidence intervals. Additionally, we modeled age-related heteroscedasticity by allowing for variance differences between young adults and the two other age groups (Pinheiro & Bates, 2000).

Table 3 shows how the progressive elimination of some fixed effects diminishes the goodness of fit of a specific model compared with Model 1. For instance, in Model 2, the elimination of the rate parameters with the subscript Ch.Y.MD $>$ 2 and O.MD $>$ 2 reduced the fit of the model to the data, which is especially clear in the ΔAIC and ΔBIC (see the guidelines described in the Statistical Methods section). This misfit could be interpreted as strength of evidence in favor of Model 1, which includes different rate parameters for a memory demand larger than two objects in children and young adults (Ch.Y.MD $>$ 2) and in old adults (O.MD $>$ 2), whereas Model 2 assumed that these rate parameters were the same as for memory demand 2. In contrast, the AIC values of Model 3 compared with Model 2 indicate that the elimination of the C and σ parameters with the subscript GNG-Contr. did not change its goodness of fit. In terms of BIC values, Model 3 was favored over Model 2. Thus AIC and BIC values supported our expectations; namely, updating conditions do not differ in terms of C and σ parameters. Finally, the last four models presented in Table 2 showed that models including the sc parameter are preferred. First, the model selection criteria supported Model 6 over Model 7. Model 6 differed from Model 7 in that it included the sc parameter as fixed effect and random effect (standard deviation and correlations). Second, the model-selection criteria favored Model 8 over Model 9, and these models differed only in the fixed effect of the sc parameter. Thus, the fit favoring Model 8 relative to Model 9 is not explained by the inclusion of random effects, as could be argued on the basis of a comparison between Model 6 and Model 7.

[1] These indexes penalize for the number of free parameters and therefore they are a compromise between accuracy and parsimony. Nevertheless, AIC and BIC must be interpreted differently. The AIC index gives information about which model among a set of models reduces the uncertainty with respect to a true model explaining the data. The BIC index is superficially similar to the AIC index because it is also derived from log likelihood, but it provides a different penalty term. The BIC index differs from the AIC index when the number of data points is larger than eight, which has as a consequence a greater preference for simple models. In addition to this difference, the derivation of the BIC index was motivated by Bayesian theory. D. Anderson (2007) stated, “Almost any short summary as to what BIC is supposed to do is probably somewhat wrong or incomplete” (p. 160). Here we offer only a presentation of BIC to offer some rules about the use of the BIC index as criteria in model selection. Readers interested on a detailed overview are referred to Appendix E in D. Anderson (2007), which offers a brief description and useful references of the BIC index.

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Table 2
Analysis of Variance

Effect	F	df	p	η_G^2
Age group	20.33	2, 59	<.001	.23
Presentation times	175.47	11, 649	<.001	.19
Memory demand	466.01	2, 118	<.001	.36
Updating conditions	225.60	1, 59	<.001	.04
Age Group × Presentation Times	6.28	22, 649	<.001	.01
Age Group × Memory Demand	12.97	4, 118	<.001	.03
Age Group × Updating Conditions	0.79	2, 59	.454	.00
Updating Conditions × Memory Demand	8.46	2, 118	<.001	.00
Updating Conditions × Presentation Times	15.48	11, 649	<.001	.01
Memory Demand × Presentation Times	6.52	22, 1298	<.001	.01

Note. The symbol η_G^2 represents generalized eta squared statistics. The generalized eta squared statistic takes into account others sources of variance that are overlooked in partial eta squared, but its interpretation is the same. In addition, generalized eta squared allows the comparability of effects sizes across designs that vary in terms of blocking factors and covariates or in the inclusion of additional factors (for details, see Olejnik & Algina, 2003).

F4 Figure 4 displays the data together with the predictions derived from parameters of Model 1 as a function of presentation time, the updating conditions, memory demand, and age group. The predictions of Model 1 recover the data very well. T4 Table 4 summarizes the parameter values for Model 1. Furthermore, with the exception of the correlation parameter between *sc* and *r,* the remaining random effects (i.e., standard deviations and correlation parameters) were significantly different from zero (see T5 Table 5 for details).

One of our goals in this work was to examine the effect of updating conditions on IM parameters. As expected, Model 1 showed that the control and go/no-go conditions did not differ on *C* and σ parameters (see Table 4); the difference between these updating conditions is entirely captured by the *sc* parameter. Another purpose of this study was to test whether IM parameters vary across age groups. The contrast of young adults with children (subscript Y-Ch) was not significant; thus, there is no evidence that children and young adults differ in their susceptibility to interfer-

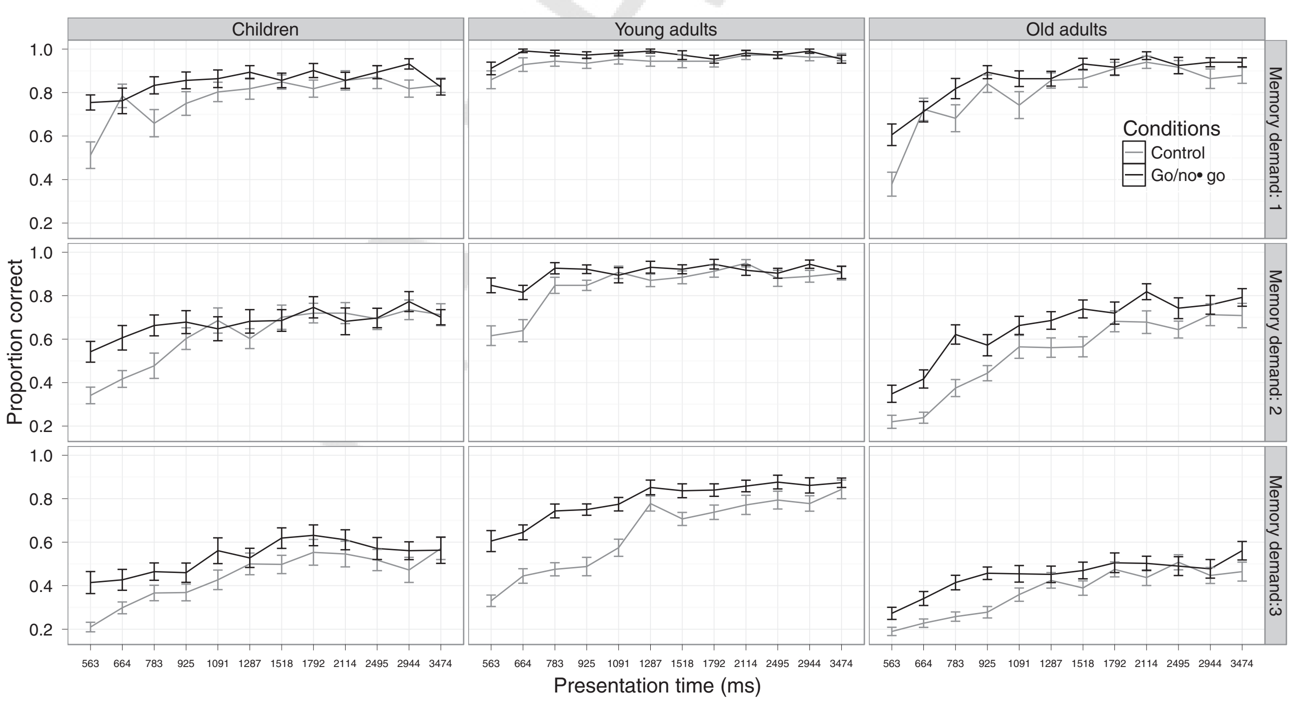

Figure 3. Mean proportion correct as a function of presentation time and updating conditions for the three memory demands (top panels show memory demand = 1, middle panels show memory demand = 2, and bottom panels show memory demand = 3) and age groups (children in the left panels, young adults in the middle panels, old adults in the right panels). Error bars represent ±1 standard error.

Table 3
Model Testing Sequence of the Interference Model With Fit Indices

Model	Fixed effects	Random effects	*df*	AIC	ΔAIC	BIC	ΔBIC	Log-lik	R^2_{adj}
1	$C_{\mathrm{Int.}}$, $C_{\mathrm{GNG\text{-}Contr.}}$, $C_{\mathrm{Y\text{-}Ch}}$, $C_{\mathrm{O\text{-}Y}}$, $\sigma_{\mathrm{Int.}}$, $\sigma_{\mathrm{GNG\text{-}Contr.}}$, $\sigma_{\mathrm{Y\text{-}Ch}}$, $\sigma_{\mathrm{O\text{-}Y}}$, $sc_{\mathrm{Int.}}$, $sc_{\mathrm{Y\text{-}Ch}}$, $sc_{\mathrm{O\text{-}Y}}$, $sc_{\mathrm{MD} > 1}$, $r_{\mathrm{Int.}}$, $r_{\mathrm{Ch.Y.MD} > 1}$, $r_{\mathrm{Ch.Y.MD} > 2}$, $r_{\mathrm{O.MD} > 1}$, $r_{\mathrm{O.MD} > 2}$, $r_{\mathrm{O\text{-}Y.Ch}}$	$C_{\mathrm{Int.}}$, $r_{\mathrm{Int.}}$, $\sigma_{\mathrm{Int.}}$, $sc_{\mathrm{Int.}}$, plus correlation parameters[a]	28	−5,522.171	0.000	−5,342.864	0.000	2,789.085	.80
2	$C_{\mathrm{Int.}}$, $C_{\mathrm{GNG\text{-}Contr.}}$, $C_{\mathrm{Y\text{-}Ch}}$, $C_{\mathrm{O\text{-}Y}}$, $\sigma_{\mathrm{Int.}}$, $\sigma_{\mathrm{GNG\text{-}Contr.}}$, $\sigma_{\mathrm{Y\text{-}Ch}}$, $\sigma_{\mathrm{O\text{-}Y}}$, $sc_{\mathrm{Int.}}$, $sc_{\mathrm{Y\text{-}Ch}}$, $sc_{\mathrm{O\text{-}Y}}$, $sc_{\mathrm{MD} > 1}$, $r_{\mathrm{Int.}}$, $r_{\mathrm{Ch.Y.MD} > 1}$, $r_{\mathrm{O.MD} > 1}$, $r_{\mathrm{O\text{-}Y.Ch}}$	The same	26	−5,430.945	91.225	−5,264.446	78.418	2,741.472	.80
3	$C_{\mathrm{Int.}}$, $C_{\mathrm{Y\text{-}Ch}}$, $C_{\mathrm{O\text{-}Y}}$, $\sigma_{\mathrm{Int.}}$, $\sigma_{\mathrm{Y\text{-}Ch}}$, $\sigma_{\mathrm{O\text{-}Y}}$, sc_{Int}, $sc_{\mathrm{Y\text{-}Ch}}$, $sc_{\mathrm{O\text{-}Y}}$, $sc_{\mathrm{MD} > 1}$, $r_{\mathrm{Int.}}$, $r_{\mathrm{Ch.Y.MD} > 1}$, $r_{\mathrm{O.MD} > 1}$, $r_{\mathrm{O\text{-}Y.Ch}}$	The same	24	−5,431.268	90.902	−5,277.577	65.287	2,739.634	.80
4	$C_{\mathrm{Int.}}$, $C_{\mathrm{Y\text{-}Ch}}$, $C_{\mathrm{O\text{-}Y}}$, $\sigma_{\mathrm{Int.}}$, $\sigma_{\mathrm{Y\text{-}Ch}}$, $\sigma_{\mathrm{O\text{-}Y}}$, $sc_{\mathrm{Int.}}$, $sc_{\mathrm{Y\text{-}Ch}}$, $sc_{\mathrm{O\text{-}Y}}$, $r_{\mathrm{Int.}}$, $r_{\mathrm{Ch.Y.MD} > 1}$, $r_{\mathrm{O.MD} > 1}$, $r_{\mathrm{O\text{-}Y.Ch}}$	The same	23	−5,360.731	161.439	−5,213.444	129.420	2,703.365	.79
5	$C_{\mathrm{Int.}}$, $C_{\mathrm{Y\text{-}Ch}}$, $C_{\mathrm{O\text{-}Y}}$, $\sigma_{\mathrm{Int.}}$, $\sigma_{\mathrm{Y\text{-}Ch}}$, $\sigma_{\mathrm{O\text{-}Y}}$, $sc_{\mathrm{Int.}}$, $sc_{\mathrm{Y\text{-}Ch}}$, $sc_{\mathrm{O\text{-}Y}}$, $r_{\mathrm{Int.}}$, $r_{\mathrm{O\text{-}Y.Ch}}$	The same	21	−5,327.760	194.410	−5,193.280	149.410	2,684.880	.79
6	$C_{\mathrm{Int.}}$, $\sigma_{\mathrm{Int.}}$, $sc_{\mathrm{Int.}}$, $r_{\mathrm{Int.}}$	The same	14	−5,277.207	244.963	−5,187.554	155.310	2,652.604	.79
7	$C_{\mathrm{Int.}}$, $\sigma_{\mathrm{Int.}}$, $r_{\mathrm{Int.}}$	$C_{\mathrm{Int.}}$, $\sigma_{\mathrm{Int.}}$, $r_{\mathrm{Int.}}$ [b]	10	−5,147.124	375.046	−5,083.086	259.777	2,583.562	.78
8	$C_{\mathrm{Int.}}$, $r_{\mathrm{Int.}}$, $\sigma_{\mathrm{Int.}}$, sc_{Int}	$C_{\mathrm{Int.}}$ [b]	6	−3,459.673	2,062.497	−3,421.250	1,921.614	1,735.837	.66
9	$C_{\mathrm{Int.}}$, $r_{\mathrm{Int.}}$, $\sigma_{\mathrm{Int.}}$	$C_{\mathrm{Int.}}$ [b]	5	−3,416.887	2,105.284	−3,384.868	1,957.966	1,713.443	.66

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion; ΔAIC = differences between winning model and the remaining models; ΔBIC = differences between winning model and remaining models; Log-lik = log-likelihood statistic; GNG = go/no-go condition; Contr. = control condition; Y = young adults; O = old adults; Ch = children; Int. = intercept (grand mean); O-Ch.Y = contrasts between old adults and children and young adults as one group; O.Ch-Y = contrasts between old adults and children (as one group) and young adults; Ch-O = contrasts between children and old adults; *MD* > 1 = different rate parameter when memory demand is greater than 1; MD > 2 = different rate parameter when memory demand is greater than 2; GNG.MD > *1*: contrasts between memory demand of 1 versus memory demand larger than 1, a contrast specific for the go/no-go condition.
[a] Model 1 includes as variance components: standard deviations of intercepts, correlation parameters (correlation parameters of the $C_{Int,}$ were constrained to 0), a different variance between young adults and the other age groups. [b] Model 7 includes as variance components standard deviation of $C_{\mathrm{Int.}}$, $\sigma_{\mathrm{Int.}}$, $r_{\mathrm{Int.}}$, a correlation parameter between, $\sigma_{\mathrm{Int.}}$ and $r_{\mathrm{Int.}}$, and a different variance between young adults and the other age groups. Models 8 and 9 include the standard deviation of $C_{\mathrm{Int.}}$ and a different variance between young adults and the other age groups.

ence through feature overwriting. Children, however, had a higher noise parameter σ compared with young adults, as indicated in the pairwise contrasts of young adults with children (subscript Y-Ch). The *C* parameter was smaller for young adults than old adults, as reflected in the significant slope parameter for the pairwise contrast of old adults with young adults (subscript O-Y). With regard to noise, there was no significant difference between old adults and young adults (subscript O-Y). Thus, compared with young adults, children, but not old adults, appeared to be more susceptible to interference by confusion. Furthermore, in Table 4, the *r* parameter with the subscript O-Ch.Y indicated that old adults were slow in processing the updating steps compared with children and young adults. The rate parameters for young adults and children did not differ significantly. The *sc* parameters with the subscripts Y-Ch and O-Y showed that children and old adults needed more time than young adults for switching from go to no-go steps.

We also tested whether an additional *r* parameter is needed for memory demand that is greater than 2. The *r* parameters with the subscripts Ch.Y.MD > 1 and Ch.Y.MD > 2 indicated that for young adults and children, a distinction between rates for memory demands of 2 and 3 improved model fit. In contrast, old adults had a lower estimated rate, and they did not need a different rate for memory demand larger than 2. Thus, the data support different rate parameters for each memory demand in children and young adults but not in old adults.

Finally, the effect of memory demand on the *sc* parameter with subscript MD greater than 1 was in the opposite direction of our expectations. That is, the *sc* parameter decreased for memory demands larger than 1.

Discussion

In the present study, we tested two forgetting-related mechanisms and sources of variation in WMC in three groups varying widely in age (i.e., children, young adults, and old adults). To this end, we fitted the IM to data of a working-memory updating task with a control condition and a go/no-go condition. In the following, we summarize and discuss general results and life span differences with respect to storage, speed of processing, and attentional control.

Storage

The IM recovered the data well, and this provides support for the model's main assumptions: A higher memory demand increases the probability that representations lose a proportion of features units through interference by overwriting, and items are confused at recall due to noise (Oberauer & Kliegl, 2001, 2006, 2010; Göthe et al., 2012).

Children were more susceptible to interference by confusion, as indicated by their σ parameter being larger than that of young

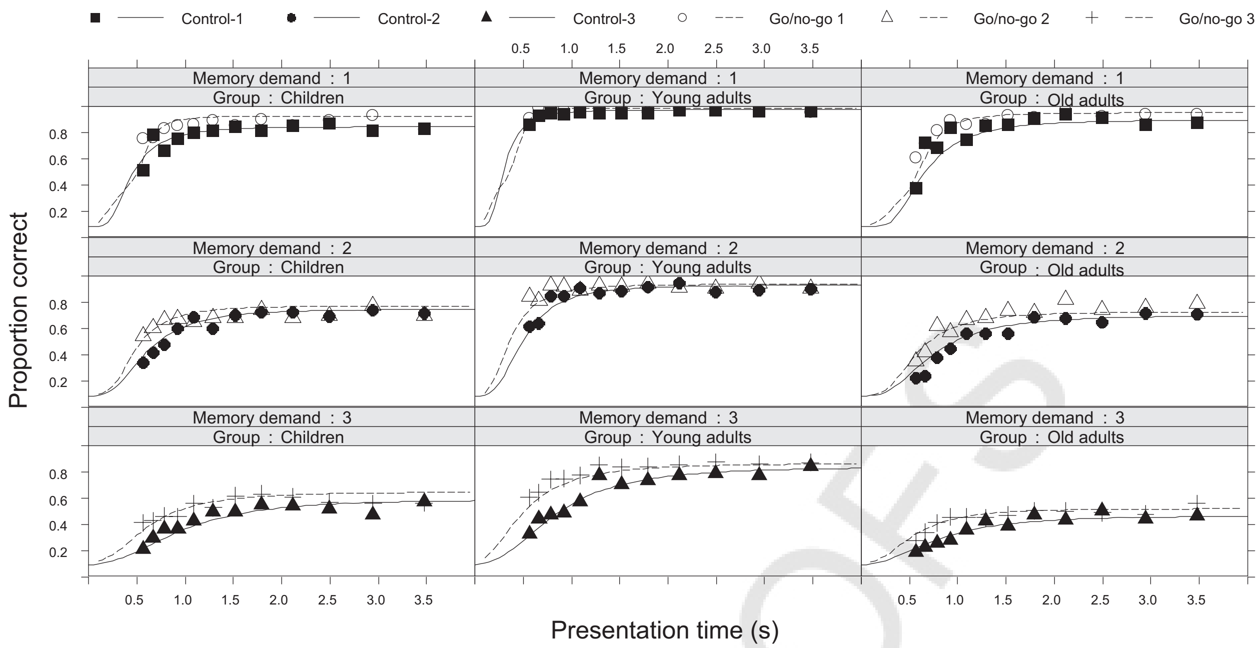

Figure 4. Time–accuracy functions aggregated by memory demand, updating condition, and age group. Dots represent data. Lines indicate the predictions derived from interference model.

adults. This parameter reflects problems accessing the appropriate representation in working memory, leaving more competition for the activation in the focus layer. At the same time, there was no difference between children and young adults in the degree of interference by overwriting, as reflected in parameter *C*. These results are in accordance with an earlier developmental study by Göthe et al. (2012), who also found that 11-year-old children had less noise (for a spatial and a verbal memory updating task) compared with 8-year-old children, although there was no difference in the overwriting parameter between these two groups.

Table 4
Parameters Estimates of Model 1

Effect	Parameter	Value	Approximate 95% confidence intervals	*SE*	*T*	*p*
Intercept of *C*	$C_{\text{Int.}}$	0.417	[0.391, 0.442]	0.012	32.49	<.001
Slope of *C* (updating conditions)	$C_{\text{GNG-Contr.}}$	−0.005	[−0.025, 0.014]	0.010	−0.53	0.589
Slope of *C* (age)	$C_{\text{Y-Ch}}$	−0.029	[−0.082, 0.024]	0.027	−1.06	0.285
Slope of *C* (age)	$C_{\text{O-Y}}$	0.162	[0.010, 0.222]	0.030	5.26	<.001
Intercept of σ	$\sigma_{\text{Int.}}$	0.184	[0.174, 0.195]	0.005	34.40	<.001
Slope of σ (updating conditions)	$\sigma_{\text{GNG-Contr.}}$	0.001	[−0.003, 0.006]	0.002	0.69	0.489
Slope of σ (age)	$\sigma_{\text{Y-Ch}}$	−0.038	[−0.058, −0.019]	0.009	−3.91	<.001
Slope of σ (age)	$\sigma_{\text{O-Y}}$	0.016	[−0.007, 0.041]	0.012	1.32	0.184
Intercept of *sc*	$sc_{\text{Int.}}$	0.530	[0.437, 0.623]	0.047	11.16	<.001
Slope of *sc* (age)	$sc_{\text{Y-Ch}}$	−0.192	[−0.379, −0.005]	0.095	−2.00	<.05
Slope of *sc* (age)	$sc_{\text{O-Y}}$	0.253	[0.069, 0.437]	0.093	2.69	<.01
Slope of *sc* (MD > 1)	$sc_{\text{MD} > 1}$	−0.617	[−0.746, −0.488]	0.066	−9.34	<.001
Intercept of *r*	$r_{\text{Int.}}$	1.674	[1.556, 1.784]	0.056	29.77	<.001
Slope of *r* (MD > 1 × Age)	$r_{\text{Ch.Y.MD} > 1}$	−0.569	[−0.762, −0.377]	0.098	−5.78	<.001
Slope of *r* (MD > 2 × Age)	$r_{\text{Ch.Y.MD} > 2}$	−0.546	[−0.648, −0.443]	0.052	−10.44	<.001
Slope of *r* (MD > 1 × Age)	$r_{\text{O.MD} > 1}$	−0.340	[−0.457, −0.224]	0.059	−5.72	<.001
Slope of *r* (MD > 2 × Age)	$r_{\text{O.MD} > 2}$	0.034	[−0.091, 0.159]	0.064	0.53	0.592
Slope of *r* (age)	$r_{\text{O-Y.Ch}}$	−0.438	[−0.650, −0.227]	0.108	−4.05	<.01

Note. Contr. = control condition; GNG = go/no-go condition; Y = young adults; O = old adults; Ch = children; Int. = intercept (grand mean); Y-Ch = contrasts (i.e., differences) between young adults and children; O-Y = contrasts (i.e., differences) between old adults and young adults; MD > 1 = contrasts (i.e., differences) between memory demand (MD) 1 versus MD larger than 1; Ch.Y.MD > 1 = different rate parameter for MD > 1 (the same rate parameter for young adults and children); O.MD > 1 = different rate parameter for MD > 1 (old adults); Ch.Y.MD > 2 = different rate parameter for MD > 2 (the same rate parameter for young adults and children); O.MD > 2 = different rate parameter for MD > 2 (old adults); O-Y.Ch = contrast between old adults on one side, and young adults and children on the other side.

Table 5
Random Effects Matrix of Model 1

Parameter	Random effect	$\sigma_{\text{intercept}}$ (correlation)	$r_{\text{intercept}}$ (correlation)
$C_{\text{intercept}}$	0.071 [0.057, 0.089]		
$\sigma_{\text{intercept}}$	0.038 [0.031, 0.047]		
$r_{\text{intercept}}$	0.321 [0.244, 0.422]	0.706 [0.447, 0.885]	
$sc_{\text{intercept}}$	0.181 [0.121, 0.269]	0.531 [0.191, 0.757]	0.238 [0.264, 0.639]
Residual error	0.10		

Note. Approximate 95% confidence intervals are given in brackets.

In contrast, older adults were more susceptible than young adults to interference by feature overwriting. Interference by feature overwriting was the greatest effect differentiating between old adults and young adults (see Table 4). This replicates previous results comparing young and old adults using the IM (Oberauer & Kliegl, 2001). Interference by overwriting is assumed to arise from a loss of bindings between features and the object they belong to (Oberauer & Kliegl, 2006). Therefore, age difference in C could reflect weaker bindings between features and objects in older adults, consistent with prior evidence showing that older adults suffer from a specific binding deficit in working memory (Oberauer, 2005) and long-term memory (Naveh-Benjamin, Hussain, Guez, & Bar-on, 2003).

Whereas Oberauer and Kliegl (2001) also found an increase in the susceptibility to interference due to noise in older adults, our study could not replicate this. However, in both studies, there was a strong correlation of the noise and rate parameters (for which we found an aging effect); this correlation makes it difficult to unambiguously assign the aging effect to one of these parameters.

Our results are in agreement with previous reports postulating storage as an important source of differences between old adults and young adults (Babcock & Salthouse, 1990; Oberauer, Wendland, & Kliegl, 2003) and differences between children and young adults (Bayliss et al., 2005). The present modeling approach goes beyond prior studies by describing the storage deficit in the context of a formal model, attributing it to two sources, feature overwriting and confusion among items. Our present results and those of two previous studies (Göthe et al., 2012; Oberauer & Kliegl, 2001) revealed that the storage deficits of children arise primarily from confusion between items, whereas those of old adults arise primarily from an increased susceptibility to feature overwriting. This possibly points to different developmental trajectories of the two interference mechanisms postulated by the IM. However, this interpretation is only preliminary, and new studies should be conducted to trace this issue further.

Speed of Processing

With respect to speed of processing, our aim was to examine whether the increment from two to three updating objects further decreased the rate, thereby testing whether the competition among working memory representations slows down the speed of updating through the inhibition of their retrieval (Usher & McClelland, 2001). Evidence for this conjecture was only obtained for children and young adults, not for older adults.

Generally, there was no difference between children and younger adults in the speed of processing. However, older adults had a significantly slower rate than young adults. This is in agreement with the age differences in the digit symbol test (see Table 1), which to a large extent reflects mental speed. As mentioned earlier, there was a strong correlation between processing rate and amount of noise in our study and that of Oberauer and Kliegl (2001). Hence, developmental and aging effects in these parameters cannot be unambiguously attributed to one of these parameters.

Taken together, differences in processing rate between young and old adults are in agreement with a well-established perspective of cognitive aging. The present results support the proposal of processing speed as one source of age differences when the available amount of time for doing a task is restricted (Salthouse, 1996). At the same time, our results show that age differences in processing speed are not sufficient to explain all age-related differences in working memory, because the age groups differed in other parameters as well (Kliegl, Mayr, & Krampe, 1994; Mayr, Kliegl, & Krampe, 1996).

Attentional Control

The results also supported the new assumption that subjects could use part of the time during no-go steps to complete the preceding go step. A parsimonious interpretation of the data suggests that the two updating conditions differ in the time available to carry out the updating steps; that is, subjects use the strategy of completing go steps during the presentation time of no-go steps. However, during no-go steps, a proportion of time reflects switching between go steps and no-go steps. This switching cost was captured in the *sc* parameter. The inclusion of this new parameter improved the goodness of fit of performance in the working-memory updating task.

We argued that the *sc* parameter reflects attentional control. Nevertheless, a detailed characterization of this switch cost is still needed. One possibility is that *sc* parameter reflects an inhibition cost; namely, the time for stopping the tendency to carry out the updating operation. Another possibility is that it reflects a task-switching cost, which is the time to remove the *update* task set and replace it with the *do not update* task set stimulus. Furthermore, **AQ: 3** the decrease of the *sc* parameter as a consequence of larger memory demand was contrary to our expectations, and we cannot give a suitable explanation for this finding. Thus, the processes underlying the *sc* parameter remain unclear. Further research should address this phenomenon in detail.

That said, the switching parameter behaved as expected for the developmental effects. Children and older adults had larger switching times than young adults. As a consequence, young adults had

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more time to complete the previous go step during a no-go step. Therefore, the higher accuracy of young adults in the go/no-go condition is in part due to the fact that young adults had more time for completing the preceding go step.

The developmental differences in the sc parameter are consistent with earlier results. For example, some studies showed that inhibition processes are less efficient in children and old adults (Bjorklund & Harnishfeger, 1990; Hasher, Zacks, & May, 1999), consistent with the interpretation of the *sc* parameter as reflecting the time for inhibition of updating. The interpretation of *sc* in terms of task switching is consistent with studies showing that children and old adults have larger general switch costs (also called mixing costs) in task-switching paradigms (for a review, see Karbach & Kray, 2009).

Studies using formal approaches usually suffer from one limitation: small sample sizes. The main reason for this limitation is that it is necessary to collect a very rich data set from each subject to obtain reliable estimates of the parameters; therefore, a larger number of trials is needed. Future studies should increase the sample size for testing whether the pattern of the parameters found in the present study can be replicated.

Summary

The parameters of a formal working memory model were tested to simultaneously examine storage capacity (determined by feature overwriting and retrieval noise), processing speed (rate), and attentional control (switching) as possible limiting effects of working memory capacity across life span. Our comparison of children, young adults, and old adults revealed that the three sources of working-memory limitation were not redundant. Rather, all of them significantly contributed to life span differences. Many findings support earlier results showing that older adults and children had larger switching times than young adults and that older adults are reduced in processing speed compared to young adults. However, results with respect to the two parameters modeling storage limitations may point to differential life span trajectories. Whereas children were found to be susceptible to confusion between items at retrieval, old adults were specifically impaired in maintaining bindings between features, rendering their representations more vulnerable to feature overwriting.

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(*Appendix follows*)

Appendix

Interference Model

The proportion of not overwritten features for one location directly translates into the asymptotic activation level of the target location, A_i:

$$A_i = (1 - C/2)^{n-1}, \tag{A1}$$

where n is number of objects in working memory (i.e., memory demand). The activation of location i depends on the time available for retrieving it. The activation of location i at time t is described by a negatively accelerated function (McClelland, 1979):

$$a_i(t) = Ai(1 - \exp(-tr)). \tag{A2}$$

Here, a_i (t) represents the activation of location i at time t, t is the time since the beginning of the retrieval process, and r is the processing rate. To compute the activation of a target location after a given time t, we insert Equations A1 and A2 into Equation A3:

$$a_i(t) = (1 - C/2)^{n-1}(1 - \exp(-tr)). \tag{A3}$$

As a consequence of the feature overwriting of $n - 1$ locations, the competitor also receives a part of its maximum activation. In general, the level of activation of remaining competitor locations is defined as

$$a_j(t) = (C/2)(1 - C/2)^{n-2}\,(1 - \exp(-tr)). \tag{A4}$$

However, activation is noisy. The activation levels $a_i(t)$ and $a_j(t)$ must therefore be interpreted as expected values of random variables. The probability that the target location i is actually the one with the highest activation is given by the Boltzmann equation (J. R. Anderson & Lebiere, 1998, p. 90). Therefore, the IM expresses the probability of selecting the target location i among n locations by that equation:

$$p_i = \frac{\exp(a_j/T)}{\sum_{j=1}^{n} \exp(a_j/T)}, \tag{A5}$$

where p_i represents the selection probability of the target location i, with activation a_i (omitting the time index for simplicity), in the presence of all n locations (with activation levels a_j) that are concurrently occupied by objects bound to them in working memory. Parameter T is the noise in the system, which relates to the standard deviation of activation by T = sqrt(6)*σ/π, where σ is a free parameter reflecting activation noise. In addition, the model takes into account the possibility that locations not currently occupied by objects are erroneously retrieved due to noise. All grid locations that are not among the n locations currently bound to objects are assumed to have an expected activation value of zero. The 3 × 4 grid contains 12 possible locations. Therefore, the number of unoccupied locations is given by $12 - n$. Thus, we expanded Equation A5 to

$$p_i = \frac{\exp(a_i/T)}{\exp(a_i/T) + (n-1)\exp(a_j/T) + (12-n)\exp(0/T)}. \tag{A6}$$

In the case of complete forgetting, subjects are forced to select one of the 12 cells in the 3 × 4 grid. Hence, the chance to guess the correct location is 1/12. Thus, accuracy of recalling each is computed as

$$P_i = 1/12 + (1 - 1/12)p_i^m p_i^{'}. \tag{A7}$$

Here, P_i is the probability to recall the correct location of object i at the end of the trial; m expresses the number of updating operations applied to object i, p_i is the probability of success in a single updating step, and $p_i^{'}$ represents the probability to succeed in the final retrieval, which is computed in the same way as p_i but with processing time t set to infinity, because there was no time limit for retrieval.

For the go/no-go condition, the probability to recall the location of object i at the end of the trial was computed slightly differently. We doubled in the model the time t for an updating step followed by a no-go step, compared with an updating step that is followed by another updating step. The activation resulting from an updating step that was followed by a no-go updating step was therefore given as

$$a_{i(go-/no-go)}(t) = Ai(1 - \exp(-(2t - sc)r)). \tag{A3a}$$

The parameter sc in this equation to reflect the time cost of switching between go and no-go steps. In the go/no-go condition, the activation for an updating step that was followed by another updating step was modeled as for the go condition given by Equation A3. Both activations were transferred to Equation A7. The probability to recall the location of object i at the end of the trial for the go/no-go condition therefore is given by

$$P_i = 1/12 + (1 - 1/12)p_{i1}^{m1} p_{i2}^{m2} p_i^{'}, \tag{A7a}$$

with p_{i1}^{m1} representing the success probability of an updating step that is followed by another updating step and *m1* representing the average number of go steps followed by other go steps. The second probability, p_{i2}^{m2}, represents the success probability of an updating step that is followed by a no-go step, with *m2* representing the average number of go steps followed by no-go steps.

Additionally, the IM takes into account that updating an object that has been updated on the immediately preceding step is faster than updating another item in working memory (Garavan, 1998; Oberauer, 2002, 2003). To account for this assumption in the formalization, the IM distinguishes two rate parameters, r_1 and r. The rate parameter r_1 reflects the speed of updating in the condition with memory demand of 1, that is, when no object switch is necessary. The rate parameter r reflects the speed of updating in conditions with memory demand more than 1, that is, when an object switch is necessary between every updating step and the next.

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