Sources of Interference in Memory across Development

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Abstract

Episodic memory involves remembering not only what happened but also where and when the event happened. This multi-component nature introduces different sources of interference which stem from previous experience. However, it is unclear how the contributions of these sources change across development and what may cause the changes. To address these questions, we tested 4-5-year-olds ($N = 103$), 7-8-year-olds ($N = 82$), and adults ($N = 70$) using item/source recognition memory tasks with various manipulations (i.e., list-length, list-strength, word-frequency), and decomposed sources of interference using a computational model. We find that interference stemming from other items on the study-list rapidly decreases with development, whereas interference from pre-experimental contexts gradually decreases but remains the major source of interference. The model further quantifies these changes indicating that the ability to discriminate items undergoes rapid development, whereas the ability to discriminate contexts undergoes protracted development. These results elucidate fundamental aspects of memory development.

150/150 words

Statement of Relevance

Memory research has shown that memory interference stems from different aspects of our previous experience. However, even though children accumulate experience throughout development, and the potential for interference may increase, memory performance typically improves. What prevents interference from overwhelming memory as children acquire experience? We show that this change is linked to the ability to distinguish memory representations from each other, and that this ability develops at a faster rate than that of experience accumulation. We show that the ability to distinguish specific items from each other emerges early in development while the ability to distinguish different contexts undergoes more protracted development. Therefore, theoretically, this work substantially advances our understanding of different sources of interference in memory development, while also providing a method that decomposes the effects from experience and maturation, which can be used in cognitive development research more broadly.

141/150words

Sources of Interference in Memory across Development

Episodic memory involves remembering multiple components of an event such as what, where, and when an event happened (Tulving, 1972). For example, in a courtroom, the testimony becomes valid not when the eyewitness remembers the suspect's face, but when she remembers the face within the context of a certain place and time. However, our ability to form episodic memories is not perfect and is prone to interference stemming from previous experiences. Therefore, when the witness provides the testimony, inaccuracies (or forgetting) can be driven by other similar faces they have encountered during the event, or from other similar places, times, and faces that they have experienced before the event.

Identifying different sources of interference, and understanding their involvement in memory retrieval has been an important part of building theories of episodic memory (Anderson & Bower, 1972; Criss & Shiffrin, 2004; Dennis & Humphreys, 2001; Osth & Dennis, 2015). For example, suppose that you are trying to recognize whether you met your colleague Adam at the party yesterday (see Figure 1a). If you actually met him yesterday, there would be a corresponding trace in your memory, which will create a matching signal to the probe (i.e., *self-match*). However, other non-target memories will produce interference. First, you may be confused because you met other people at yesterday's party. These memories will match the to-be-recognized cue in terms of context (i.e., yesterday's party) but mismatch the item (i.e., Adam). This form of interference has been called *item-noise* (Gillund & Shiffrin, 1984; Shiffrin & Steyvers, 1997). Additionally, you may also be confused because you met Adam at other places in the past. These memories match the item cue (i.e., Adam) but mismatch the relevant context (i.e., yesterday's party). This form of interference has been called *context-noise* (Dennis & Humphreys, 2001). Finally, memories that do not match either the item or context also produce interference (Murdock & Kahana, 1993a, 1993b; Osth & Dennis, 2015). This form of interference is called *background-noise*.

a

b

where,

Self-match = $r \times \text{item-match} \times \text{context-match}$	$= r \times \text{Normal}(1, \sigma_i) \times \text{Normal}(1, \sigma_c)$
Item-noise = $(l-1) \times r \times \text{item-mismatch} \times \text{context-match}$	$= (l-1) \times r \times \text{Normal}(0, \sigma_i) \times \text{Normal}(1, \sigma_c)$
Context-noise = $n \times \text{item-match} \times \text{context-mismatch}$	$= n \times \text{Normal}(1, \sigma_i) \times \text{Normal}(0, \sigma_c)$
Background-noise = $m \times \text{item-mismatch} \times \text{context-mismatch}$	$= m \times \text{Normal}(0, \sigma_i) \times \text{Normal}(0, \sigma_c)$

Figure 1. Sources of interference and how they are decomposed by the computational model. **(a)** Different sources of interference in episodic memory. **(b)** An illustration of the different components included in the lure and target distribution of the model, and how the model parameterized these components. The bottom section describes the equations that are involved in calculating the distributions in the item recognition task. In the item recognition task, the model assumes that participants use a generalized source cue that matches the source component in the memory storage with a mean value of one and a variance of zero. Therefore, for the item recognition task that is described above, all terms have an implicit source-match component that is not expressed in the equations. (images: Freepik.com)

These sources of interference have been studied with different experimental manipulations. For example, item-noise has been measured by comparing memory tasks with different numbers of study

items by either adding more unique items (i.e., list-length manipulation; Gronlund & Elam, 1994) or repeating some of the items in the list to evaluate their impact on the non-repeated items (i.e., list-strength manipulation; Ratcliff et al., 1990). Context-noise has been examined by manipulating the pre-experimental frequency of items. For example, when using words as stimuli, low-frequency words and high-frequency words are compared with the assumption that less frequent words appear in fewer sentence or story contexts, and are thus expected to create less context-noise.

Computational models of memory have been used to quantitatively decompose different sources of interference. For example, Osth and Dennis (2015) used a computational model to show that the composition of interference varies across different studies depending on the pre-experimental familiarity of the stimulus. For instance, unfamiliar stimuli (i.e., fractal-patterns) generate more item-noise than familiar stimuli (i.e., words) since unfamiliar stimuli are harder to distinguish from each other than familiar ones. Moreover, the model showed that frequently encountered stimuli (e.g., high-frequency words) create more context-noise than those that are less frequently encountered (e.g., low-frequency words) since more frequent stimuli appear in more contexts and generate more interference during retrieval.

An important implication of these findings is that there are both *costs and benefits of experience on memory performance*. With more experience, more memory traces will be stored, and these traces may become sources of interference. On the other hand, with more experience the representation of the stimulus becomes more distinct and less confusing, which results in less interference.

In a similar way, the accumulation of experience may also affect memory performance across development. As a child grows both the number of memory traces and the robustness of representations will tend to increase. Therefore, as young children have less experience than adults, the costs and benefits of experience may be relatively small for young children compared to adults. Moreover, since memory performance typically improves during childhood, the benefit of experience may outweigh the cost at some point in development.

However, it is unclear how the costs and benefits of experience change across development, how different aspects of experience contribute, and what drives these changes. Previous studies show that (1) memory accuracy increases throughout early development (e.g., Ackerman, 1984; Bauer, 2007;

Cycowicz et al., 2001; Hayes et al., 2017; Mandler & Robinson, 1978) and (2) the ability to remember different components of an event (e.g., item, context) may have a different developmental trajectory (e.g., Lee et al., 2020; Ngo et al., 2019; Picard et al., 2012). For example, Picard et al. (2012) provided evidence that the ability to remember the content of the event (i.e., item) reaches adult-like performance much earlier (i.e., around 7yrs) than the ability to remember the context of the event, such as the time and space of the event. However, these studies have not fully considered the consequences of prior experience when testing memory performance, which makes it hard to evaluate the cost and benefit of experience in memory.

To answer these questions, in the current study, we examined how the sources of interference change and affect memory across development. We used item and source memory tasks - systematically manipulating different sources of interference in various ways (i.e., list-length, repetition of the items, and pre-experimental frequency/familiarity of the items), and compared the performance across three different age groups. Then, we investigated the mechanisms that drive these changes by using a computational model that can decompose different sources of interference in each age group and untangle the cost and benefits of experience affecting memory performance.

Method

Participants were tested using a memory task that was introduced as a 'secret word game'. In each game, participants were presented with two speakers (one male and one female) each telling them secret words one at a time, and were asked to remember the secret words (item recognition) and the speaker who said the word (source recognition). There were three different within-subject conditions, which were designed to capture different sources of interference used in previous adult studies (Kinnell & Dennis, 2011, 2012; Osth et al., 2014). Item-noise was measured by repeating half of the items (i.e., mixed strength condition) and by including additional unique items (i.e., long condition), with performance in these conditions compared to a baseline condition. Context-noise was measured by using stimuli (i.e., words) of different normative frequencies (Dennis & Humphreys, 2001) as frequency information provides a proxy for how often the word was experienced pre-experimentally. The results were analyzed using a computational model (Osth, Fox, et al., 2018; Osth & Dennis, 2015). The model decomposes the

total memory interference into different kinds of interference (i.e., item-noise, context-noise, and background-noise), and estimates the ability to discriminate different elements of an event (i.e., benefit of experience), while considering the amount of prior experience the participant received before being tested (i.e., cost of experience).

Participants. One hundred and three 4-5-year-olds ($M = 4.82$ yrs, $SD = .29$, 47 females), 82 7-8-year-olds ($M = 7.74$ yrs, $SD = 1.03$, 44 females), and 70 adults ($M = 19.16$ yrs, $SD = 1.03$, 46 females) participated in the experiment. The sample sizes for adults and 7-8-year-olds were determined by previous studies that used a similar design (Kinnell & Dennis, 2011; Osth et al., 2014). For 4-5-year-olds we aimed to collect approximately double the sample size of the adult sample as previous memory experiments suggested that the young children's data may be noisier than that of adults' (e.g., Yim et al., 2013).

Adults were undergraduate students attending the Ohio State University, who were participating for course credit, and children were recruited from local schools around Columbus, Ohio, USA. The research was approved by the Ohio State University Institutional Review Board. An additional 35 4-5-year-olds and one 7-8-year-old were excluded from the sample due to having d' below zero in more than two test conditions majorly due to not paying attention to the task.

Figure 2. Stimulus and experimental design. **(a)** An example of the video-clips used in the experiment, where a speaker presented each word one at a time. **(b)** Study phase of the recognition task. **(c)** Test phase of the recognition task, where an item recognition test was administered followed by a source recognition test contingent upon a ‘Yes’ response in the item recognition test. The figure depicts the procedure for adults where the cue word was presented auditorily by a pre-recorded voice. **(d)** Design of the three different conditions.

Materials. One-hundred and fifty words were selected from Wordbank (Frank et al., 2017), where all words had the Proportion of Children Producing higher than .5 at the age of 30-month. There were 80 low- and 80 high-frequency words, where for the low-frequency words the average count per million was 11.4 in CHILDES (MacWhinney, 2000), and 4.51 in the TASA corpus (Touchstone Applied Science Associates, Inc.; Landauer & Dumais, 1997), and for the high-frequency words the average count per million was 104.68 in CHILDES, and 127.75 in TASA. The mean age-of-acquisition (AOA) for the words was 4.59yrs ($SD = 1.31$ yrs; Kuperman, Stadthagen-Gonzalez, & Brysbaert, 2012). There were significant correlations between the frequencies derived from the CHILDES corpus and TASA corpus (Spearman’s

$\rho = .84, p < .0001$), between the CHILDES corpus and the AOA scores ($\rho = -.52, p < .0001$), and between the TASA corpus and the AOA scores ($\rho = -.45, p < .0001$). Eighteen video-clips were created for each word, where there were nine different female and male speakers pronouncing the word. Each speaker appeared on a unique background in order to aid participants to better discriminate between the different speakers (see Figure 2a).

Procedure. The experiment had four blocks, where each block had a study phase followed by a retention-interval and a test phase. In the study phase, participants were told that they would be playing a secret word game, where they would see two speakers each presenting secret words one at a time, and their task would be to remember the secret words and the speaker who said it. Each trial started with a fixation (+++) for 500ms, followed by a blank screen for 500ms, and a video clip showing a speaker saying a word for approximately 2700ms (see Figure 2b). In all blocks, one of the speakers was female and the other was male. The video-clips were presented on one side of the screen throughout the experiment depending on the speaker's sex (e.g., female speakers on the left side, male speaker on the right side), and the position was randomized across participants. During the retention interval, participants were presented with two groups of dots on each side of the screen and were told to choose the side that had more dots. After a 500ms fixation (+++) the adults were presented with the two groups of dots for 250ms followed by a random colour dot mask, which was presented until a response was made. For the children group, the dots were presented until a response was made without the mask. The number of dots varied between 10 and 40 while manipulating the ratio of the two numbers. On each trial, the ratio was randomly selected between the four ratio bins 1.2171-1.4089, 1.4089-1.6308, 1.6965-1.9638, 2.6260-3.0397 for the children group, and 1.0991-1.1915, 1.1915-1.2917, 1.3302-1.4421, 2.2906-2.4833 for the adult group, based on previous studies (Halberda & Feigenson, 2008). In the test phase, participants were auditorily presented with a cue word in a third person's voice (or by the experimenter for the children groups so that they do not miss the cue word) and were asked if the word was a secret word (see Figure 2c). If the participant responded that the word was a secret word, they were additionally asked who said the secret word.

The four blocks had three different conditions (Baseline, Mixed-strength, and Long), where the Mixed condition repeated twice in order to match the total number of target items in other conditions (see Figure 2d). These three different conditions have been extensively used in the adult literature (e.g., Dennis et al., 2008; Kinnell & Dennis, 2012; Osth et al., 2018). In the Baseline condition, eight different words were presented in the study phase, where half were delivered by a female speaker and the other half by a male speaker. Half of the words for each speaker were high-frequency words and the other half were low-frequency words. Ten trials were presented during the test phase, where eight were from the study phase (i.e., old items), and two were new words (i.e., lures). In the Mixed-strength condition, first, eight different words were presented in the study phase. Then half of them repeated two more times in a blocked fashion (i.e., strong items). The repeated words are named ‘strong’ items as they are strengthened with repetition, while the non-repeated words are named ‘weak’ items. During the test phase, the four weak items and four strong items which were presented during the study phase were randomly presented with two lures. In the Long condition, 16 words were presented in the study phase. During the test phase, the first half of the items (8) during the study-phase were presented with two lures first, then the second half of the items (8) were tested with another two lures. As in the Baseline condition, the words in the Mixed-strength and Long conditions were balanced by frequency and the speaker’s sex. The length of the retention interval was 60sec for the Mixed strength and Long conditions and 89.6sec for the Baseline condition. The additional 29.6sec in the Baseline condition corresponds to the additional eight trials that the Mixed strength and Long conditions have during the study phase, and was added to equate the total length of the retention-interval (Kinnell & Dennis, 2011).

Before the main experiment, there was a practice session where two words were presented during the study phase, where one was presented by a female speaker and another by a male speaker. Then during the test phase three words were presented, two from the study phase (old items), and a new word (lure item). For the children groups, participants repeated the identical practice session up to three times if they did not understand the task. All children understood the task within three practice sessions. The speakers and the words used in the practice session were not used in the main experiment.

Presentation of all stimuli was controlled using Matlab with Psychtoolbox-3 (Kleiner et al., 2007) equipped with a 22-inch monitor and individual headphones. Responses were collected using a computer mouse by clicking the corresponding image on the screen (or touching the touch-screen for the children groups). The combination of the word pairs and speakers, and the order of the conditions were randomized across participants.

Results

Behavioral data analysis

Behavioral data were analyzed using a signal detection theory (SDT) model to account for decision biases which are usually reported in studies involving young children. We specifically used a hierarchical Bayesian version of the model (Lee & Wagenmakers, 2014) in order to avoid edge effects (i.e., statistical biases that occur for correcting hit rates and false alarm rates of 1 or 0 when calculating d'). Moreover, the Bayesian analysis produces Bayes factors, which unlike p-values used in frequentist analysis, allows us to evaluate both the null-hypothesis and the alternative hypothesis. We used the interpretation of Bayes factors (BF_{10}) by Jeffreys (1961), where a BF_{10} value between 1 and 3 is considered weak evidence, between 3 and 10 is considered substantial evidence, and above 10 is considered strong evidence for the alternative hypothesis. On the other hand, a BF_{10} value between 1 and 1/3 is considered weak evidence, between 1/3 and 1/10 is considered substantial evidence, and below 1/10 is considered strong evidence for the null hypothesis. All models used for data analysis were implemented using STAN (Carpenter et al., 2017) with twelve chains, each with 60,000 iterations (20,000 warm-up). The convergence of the chains was checked visually and convergence statistic R -hat values were all below 1.01. The full details of the hierarchical Bayesian SDT model and the results are reported in SOM-R section A, which includes all mean values, Bayesian 95% High Density Intervals (HDI), Bayes factors for individual analysis, analyses on hit rates and false alarm rates separately. Here we present the main findings for conciseness. Data from this study can be found on our Open Science Framework page (<https://osf.io/2fg5w/>).

For the item recognition task, the overall accuracy increased across age groups shown by the group d' parameter (μ_d) of the SDT model (see Figure 3a; $BF_{10s} > 1800$). Item-noise was measured in

two ways. First, we compared the performance of weak items in the mixed-strength condition to the baseline condition (i.e., list-strength effect). If there is a significant amount of item-noise, weak items (i.e., items that were presented only once in the study list) will be affected by the interference caused by the strong items (i.e., items that were repeated three times in the study list). We also compared the performance of the items in the first-half of the list in the long condition to the baseline condition (i.e., list-length effect). Only the items in the first-half are used since they are comparable to the items in the baseline conditions in terms of retention interval, and if there is a significant amount of item-noise, the items in the first-half will be affected by the interference caused by the items in the second-half. Results showed a weak support for no list-length effects (see Fig. 3a; 4-5yrs: $BF_{10} = .47$; 7-8yrs: $BF_{10} = .46$; adults: $BF_{10} = .36$) and no list-strength effects (4-5yrs: $BF_{10} = .39$; 7-8yrs: $BF_{10} = .45$; adults: $BF_{10} = .44$).

If context-noise exists, performance will be better for low-frequency words than high-frequency words. This is because low-frequency words would have been encountered in fewer contexts than high-frequency words, and, therefore, create less interference¹. Results showed an advantage for low-frequency words (i.e., frequency effect) for the 7-year-olds and adults, and a tendency for 4-year-olds, which is replicating previous adult studies and providing evidence for context-noise (see Fig. 3b; 4-5yrs: $BF_{10} = 2.14$; 7-8yrs: $BF_{10} = 9.28$; adults: $BF_{10} = 13.77$).

¹ However, note that the magnitude of the frequency effect is not directly connected to the magnitude of the context noise. Since context noise is a multiplication between the variance of the context mismatch parameter and the actual frequency count, the frequency difference between the high and low frequency words is the main driver of the magnitude of the frequency effect when the context noise is greater than zero.

Item recognition

Figure 3. Behavioral results for item recognition and source recognition. **(a)** Sensitivity (d') estimated as a group-level hyper-parameter (μ_d) for item recognition by condition and age. **(b)** Sensitivity (d') estimated as a group-level hyper-parameter (μ_d) for item recognition by word frequency and age. **(c)** Sensitivity (d') estimated as a group-level hyper-parameter (μ_d) for source recognition across age and condition. **(d)** Sensitivity (d') estimated as a group-level hyper-parameter (μ_d) for source recognition across age and frequency. Note that white dots and the black line inside the violin plots represent the median and 95% credible intervals of the posterior distribution.

Source recognition performance was also analyzed using a hierarchical Bayesian signal detection theory model, where we only analyzed the trials with correct item recognition. Results showed an increase in performance across age groups (see Figure 3c; 4-5yrs-adults: $BF_{10} = 1.97E11$, 4-5yrs-7-8yrs: $BF_{10} = 1.47$, 7-8yrs-adults: $BF_{10} = 31.09$). We found only a numerical effect for frequency in all age groups (see Figure 3d; 4-5yrs: $BF_{10} = .34$; 7-5yrs: $BF_{10} = .43$; adults: $BF_{10} = 1.23$). There was also weak evidence for null list-length and list-strength effects (list-length: 4-5yrs: $BF_{10} = .34$; 7-8yrs: $BF_{10} = 3.47$; adults: $BF_{10} = .43$; list-strength: 4-5yrs: $BF_{10} = .50$; 7-8yrs: $BF_{10} = .45$; adults: $BF_{10} = .94$).

In sum, the results from the item recognition task showed a similar pattern compared to previous studies, where memory accuracy increases across development (Ghetti & Angelini, 2008; Hayes et al., 2017), and accuracy for low-frequency words were better than high-frequency words (Dennis & Humphreys, 2001; Glanzer et al., 1993; Glanzer & Bowles, 1976). Also, consistent with previous adult studies which used words as stimuli, there was no evidence for a strong list-length or list-strength effect (Kinnell & Dennis, 2011; Osth et al., 2014). Similarly, results from the source recognition task showed a

developmental increase in accuracy as in previous studies (e.g., Drummey & Newcombe, 2002) with a numerical advantage for low-frequency words and no list-strength effect.

Although the results from the behavioral data provide some evidence for the existence of different sources of interference, it is not easy to directly compare the contribution of these sources across different age groups. Therefore, we further analyzed the data using a computational model that can quantitatively decompose the amount of different sources of interference. The results from the computational model will allow us to compare the amount of interference across age groups more directly and estimate specific mechanistic changes that underlie these performance differences.

Computational modeling

We modified a computational model by Osth and Dennis (2015), which is implemented in a hierarchical Bayesian framework (Kruschke, 2014). The model has been successful in capturing a number of different episodic recognition phenomena and is also capable of decomposing the total interference into different sources quantitatively in a way behavioral data does not on its own (Fox et al., 2020; Osth, Fox, et al., 2018; Osth, Jansson, et al., 2018).

Two main components of the model are worth highlighting before describing the model in greater detail. One is the discriminability of different representations. In the current version, the model represents item, source, and context components as a three-way binding (e.g., Yim et al., 2018), and for each kind of representation there is a parameter responsible for how well the representations can be distinguished from each other. Higher discriminability between representations reduces interference and improves recognition. Another main component of the model is the number of memory traces experienced. Both the total number of memories and the number of memories corresponding to a particular word determine interference (e.g., Figure 1a) as the number of memories is increased, there is more interference. These two features, along with the interaction of other components (e.g., learning rate, decision bias, and etc.), allow for the estimation of the noise that affects recognition performance. Additionally, they allow us to estimate (1) the cost of experience in memory performance by considering the number of items that one has experienced prior to the experiment and (2) the benefit of experience by parameterizing the discriminability of items and contexts.

Here we describe the model on the conceptual level, while the mathematical details can be found in SOM-C. Following many other episodic memory models that explain recognition memory, the current model assumes that when a cue is presented at test, the cue is compared to all stored memories (i.e., global matching; Clark & Gronlund, 1996; Osth & Dennis, 2020). Then the summed similarity (i.e., memory strength) between the cue and all contents of memory is calculated. More specifically, the probe-memory similarity is calculated for each cue dimension (item, context, and source) and the product between them is calculated. As described in the Introduction, even if the cue was experienced in the past, the calculated similarity will be a sum of a matching signal (i.e., self-match) along with the different sources of noise from memories that do not match the presented cue (e.g., item-noise, context-noise, background-noise) to produce strength for targets. If the cue was not experienced, only noise is produced, resulting in the strength for lures. Strengths of targets and lures are combined with their expected strengths to produce a log-likelihood ratio that the cue is a target, as depicted in the top part of Figure 1b (Glanzer et al., 2009; Osth et al., 2017). When the log-likelihood ratio is above a criterion the model elicits a “Yes” response.

The crux of the model is that the signal and noise distributions are further parameterized into match and mismatch components (see Figure 1b bottom). For example, item-noise is calculated as the product of the item-mismatch and context-match parameters. Additionally, we multiplied the number of items that were presented in the study list (l) minus one in order to incorporate item noise stemming from all mismatching items in the study list. For the components that involve items in the study (self-match and item noise), a learning rate (r_{weak} or r_{strong} depending on the number of repetitions of the item in the study list) is multiplied and estimated by the model. Context-noise is the product of the item-match and context-mismatch parameters multiplied by the number of times one has encountered the matching item (i.e., word) in their lifetime (n). Finally, background noise is calculated by the product of item-mismatch and context-mismatch parameters multiplied by the number of words one has encountered in their lifetime (m).

The constants n and m are important as they provide information about one’s prior experience to the model and incorporate the cost of experience in memory. The two constants were derived from

natural language corpora and empirical studies providing better constraints to capture the developmental differences compared to previous versions of the model. We used the empirical estimation that each individual experienced 10,950,000 words each year (Hart & Risley, 1995), and therefore, each participant's m was derived by multiplying the individual's exact age by 10,950,000. The number of times a word was experienced in the past (n) was approximated for each individual as well. We derived per-million counts for each word using CHILDES for the children data (MacWhinney, 2000) and TASA for the adult data (Landauer & Dumais, 1997). Then raw frequency was calculated based on the estimated total number of words experienced (m) for each individual. Each age group was modelled separately and fit using differential evolution Markov chain Monte Carlo (Turner et al., 2013) with 21 chains of 10,000 samples (25,000 burn-in, 20 thin) each. The convergences of the chains were checked visually and all chains showed R-hat values below 1.01.

The match and mismatch components are the main parameters of the model, and each follows a normal distribution (see SOM-E for the description of all the parameters that were used in the model). To fix the scale of the model, we set the means of the distributions to 1.0 if they matched the cue and 0.0 if they mismatched, and estimate the variance of the mismatch parameters. Importantly, the variance of the mismatch parameters index the discriminability of the representations and will be interpreted as a proxy for the benefit of experience. A higher value of variance of the mismatch parameter indicates lower discriminability. Model code from this study can be found on our OSF page (<https://osf.io/2fg5w/>).

Figure 4. Model simulations where recognition performance in terms of hit rates and false alarm rates are shown as a function of item noise and context noise. (a) recognition performance when item noise

was changed in the model (solid lines are hit rates and dashed lines are false alarm rates). As item noise is a multiplication between the length of the study list and the variance of the item mismatch parameter, we changed each component separately. (b) recognition performance when context noise was changed in the model (solid lines are hit rates and dotted lines are false alarm rates). As context noise is a multiplication of the frequency of the item (i.e., word) and the variance of the context mismatch parameter, we changed each component separately. Please see Supplementary Online Materials section G for additional simulations, where decision bias is also changed in addition to item and context noise components.

For an illustrative example of how the item-noise and context-noise affect recognition performance in the model, we present model simulations in Figure 4. We fixed all other parameters but changed the components of the item-noise or the components of the context-noise. In Figure 4a, we changed the length of the study list and the variance of the item mismatch parameter, as item noise is the multiplication between these two elements. Hit rates (HR) are presented in solid lines and false alarm rates (FAR) are presented in dashed lines. The simulation shows that performance decreases as both the length of the study list and the variance of the item mismatch parameter increases, where the performance decrease is manifest in both a decrease in HR and an increase in FAR. In Figure 4b, we manipulated word frequency and the variance of the context mismatch parameter, as context-noise is the multiplication between these two elements. The simulation shows that performance decreases as both the frequency and variance of the context mismatch parameter increases. Also see SOM-R section G for additional simulations, which includes how the model behaves when the decision bias changes along with item- and context-noise.

Figure 5. Model fits across age groups and conditions. Overall, the blue violin plots represent model prediction (i.e., posterior predictive), whereas the black markers represent results from the experiment with error bars representing the standard error of the mean. **(a)** Model fit for the item recognition task. The first column shows hit rates for items presented once (circles), hit rates for items presented three times (stars; only in the MS condition), and false alarm rates (diamond) for the Baseline (BL), Mixed strength (MS), and Long (LG) conditions that are used to examine the list-length effect (LL) and list-strength effect (LS). The second column shows the same data as the first column, except that they are arranged in high and low frequencies. **(b)** Model fit for the source recognition task. The first column shows accuracy for items presented once (circles) and items presented three times (stars) in each condition. The second column shows the same data as the first column, except that they are arranged in high and low frequencies.

We used the model to estimate the different sources of interference across age and condition in the item recognition task (see Figure 5 for model fits). As can be seen in Figure 6, the overall amount of

interference decreases across age (see SOM-D for detail values). Most importantly, item-noise in all three conditions drastically drops between the ages of 4-5yrs and 7-8yrs, whereas context-noise continues to decrease between 7-8yrs and adulthood, and remains as the primary source of interference in adults. At the same time, the overall contribution of background noise is negligible throughout development.

Figure 6. Sources of interference (noise) estimated by the model across age groups in the item recognition task. Item noise is estimated for each condition (i.e., Baseline, Long, and Mixed strength) and context noise is estimated for high and low frequency. Error bars represent 95% High-Density Intervals.

Interference in the source recognition task shows a similar pattern as in item recognition, where item-noise rapidly decreases early in development and background noise is not a major source of interference (see Figure 7). However, unlike in item recognition, context-noise did not change across development. The constant context noise estimates across development could be explained by the fact that the source recognition task was only administered when the participants responded that they recognized the item in the item recognition task, which means that the participants already discriminated the experimental context from previous contexts. Therefore, the procedure may have filtered out the age difference of context noise.

The modeling results can appear puzzling, as the model is showing that 4-5yrs have higher item-noise, while the behavioral results show a null list-length and -strength effect. However, it is worth noting that the model is measuring item-noise through both the list-length effect (i.e., performance difference between the baseline condition and the long condition) and the list-strength effect (i.e., performance difference between the baseline condition and the mixed strength effect) in both memory tasks. Moreover, the model separates other factors that may affect recognition memory performance (e.g.,

context-noise) from the behavioral data when estimating item-noise. Therefore, the model is more sensitive in capturing item noise than merely comparing the behavioral results (e.g., d-prime) between different conditions. A way to examine the connection between the behavioral data and the model parameter is by looking into each participant's (1) list-length, list-strength effect, and (2) the proportion of item-noise estimated by the model. When conducting a correlation analysis between these two components, there was only a statistically significant correlation between the 4-year-old's proportion of item-noise and list-strength effect score (Spearman's $\rho = .755$, $p < .001$), whereas other relations did not show a statistically significant effect (4yrs: list-length, $\rho = .012$, $p = .91$; 7yrs: list-length, $\rho = -.075$, $p = .54$, list-strength, $\rho = .205$, $p = .07$; adults: list-length, $\rho = -.071$, $p = .56$, list-strength, $\rho = .087$, $p = .48$). The results imply that the high item-noise in the 4-year-olds are stemming from the list-strength effect (see SOM-R section H for details).

Figure 7. Sources of interference (noise) estimated by the model across age groups in the source recognition task. Item noise is estimated for each condition (i.e., Baseline, Long, and Mixed strength) and context noise is estimated for high and low frequency. Error bars represent 95% High-Density Intervals.

Overall, interference decreased with age. The decrease occurred despite the fact that the number of memory traces across development increased in the model (i.e., the n and m constants), which will contribute to increasing memory interference (i.e., cost of experience in memory). To understand the underlying mechanism of this change, we investigated the mismatch parameters that are responsible for the discrimination of different representations and can serve as a proxy for the benefit of experience in memory. Figure 8 shows the posterior distribution of the group means of two parameters -- variance of

the item mismatch (σ_{ii}) and context mismatch (σ_{su}) parameters (posterior distributions of the other model parameters are presented in SOM-F). We evaluated the difference between parameters by examining whether the two HDI_{95%} overlap, where a lower value of the mismatch parameters indicate a better discrimination (c.f., the parameters are log transformed for an easier visual comparison). First we see that the variance of the item mismatch parameter ($\log(\sigma_{ii})$) decreases with development (see Figure 8a; 4-5yrs: $M = -4.41$, HDI_{95%} = [-5.02, -3.81], 7-8yrs: $M = -9.27$, HDI_{95%} = [-10.48, -8.14], adults: $M = -12.36$, HDI_{95%} = [-14.09, -10.90]). The result indicates that items become more distinct (i.e., less confusable) with development, despite the fact that vocabulary size increases. The variance of the context mismatch ($\log(\sigma_{su})$) also decreases with development indicating that different contexts also become more distinct (i.e. less confusable) with development (see Fig. 8b; 4-5yrs: $M = -3.39$, HDI_{95%} = [-3.65, -3.13], 7-8yrs: $M = -3.93$, HDI_{95%} = [-4.05, -3.80], adults: $M = -4.66$, HDI_{95%} = [-4.84, -4.48]). Regarding the overall decrease in interference across development, the results imply that even though memory traces accumulate with age, the ability to distinguish different representations develops at a faster rate and overcomes the interference that these accumulated traces generate.

Figure 8. Item-mismatch and context-mismatch parameters across age groups. **(a)** Log variance of the item-mismatch parameter σ_{ii} . **(b)** Log variance of the context-mismatch parameter σ_{su} . Note that the parameters are log transformed for an easier visual comparison.

It is also notable that the developmental pattern of the context mismatch parameter differs from that of the item mismatch parameter. For the item-mismatch parameter, the value decreases more

rapidly early in development, while for the context mismatch parameter the decrease is more gradual and protracted across age. This asynchronous pattern, to an extent, underlies the drastic decrease in item noise between the age of 4-5yrs and 7-8yrs, while having a constantly decreasing context noise across development shown in Figures 5 and 6.

General Discussion

The current study examined how different sources of interference in memory change across development, and how prior experiences may contribute to these changes. We tested three different age groups using item/source recognition tasks with manipulations of list-length, list-strength, and word frequency, and decomposed different sources of interference using a computational model. Results showed that interference stemming from other items during study (i.e., item-noise) rapidly decreases between the ages of 4-5yrs and 7-8yrs, while interference stemming from other contexts outside of the experiment (i.e., context-noise) gradually decreases through to adulthood and remains as the major source of interference in recognition memory. The model accounts for this change through an early development in the ability to discriminate items and a more gradual development in the ability to discriminate between different contexts.

In accordance with the fact that memory performance typically increases through development, the results show that the benefit of experience overrides the cost. The rapid decrease in item-noise from 4-5yrs to 7-8yrs aligns well with previous literature suggesting that the representations of concepts are refined with learning and development (Keil, 1979; Mandler et al., 1991). As words are used as items in the current study, a better discrimination among different words can be explained by the extra exposure to language and formal education that the 7-8yrs start to receive (Hoff, 2014). The argument is additionally supported by the fact that the mean age-of-acquisition for the words used in the experiment was 4.59yr ($SD = 1.31$ yr; Kuperman et al., 2012), which is slightly lower than the average age of the 4-5-year-olds group (i.e., 4.82yrs).

On the other hand, context-noise, which is closely linked to the ability to discriminate between different contexts, decreases gradually over the course of development and remains as a major source of interference in adults. This accords with other studies that have found the ability to discriminate among

different contexts has a protracted development (Ghetti & Lee, 2011). However, previous studies mainly examined how well different contexts can be discriminated in the study without considering the effects of prior experience that the participants bring to the experiment (Drummey & Newcombe, 2002; Lloyd et al., 2009; Yim et al., 2013). By contrast, the current study distinguished these two components by approximating the effect of prior experience and then using a computational model to estimate the ability to discriminate between different contexts.

The increase in the ability to discriminate among different representations may be driven by at least two mechanisms. First, evidence shows that discrimination may be enhanced by refining the representations through learning (Keil, 1979), which we termed the benefit of experience. For example, previous studies show that children's memories are better than adults' when child-friendly items are used (Gross et al., 2016) or when they are tested in a domain in which they show expertise (Gobbo & Chi, 1986). However, it is also possible that the change can be driven by maturation. For example, pattern separation, or the ability to dissociate highly similar memory representations, has been linked to the maturation of the hippocampus (Keresztes et al., 2018), with the hippocampus developing through to adulthood (De Master et al., 2014). The two mechanisms are not mutually exclusive, and the division of labor between the two requires further investigation.

To capture how different sources of interference change across development, the current study utilized a computational model. Previous studies have been able to explain developmental changes with increases in discriminability (Hayes et al., 2017). However, studies are agnostic about the cognitive sources of development, such as whether changes are due to representations or retrieval mechanisms. Our model decomposed performance changes to measure how latent parameters (i.e., discriminability of different memory representations) developed, while considering the increase in prior experience with age. The results showing an asynchronous development of the item and context discrimination in recognition memory is an interesting finding and suggests that there are at least two representational changes involved in recognition memory development. Additionally, the current model explains memory development and the changes in representations that underlie development through a retrieval process

based on familiarity, which suggests that familiarity may be an important construct in understanding human memory (c.f., Geurten et al., 2020; Ghetti & Angelini, 2008; Hayes et al., 2017).

Finally, the current study provides a basis for interesting future investigations. First, although we proposed a computational model that assumes representational change across development, we did not describe *how* it changes. As our results show that the process of making representations more distinguishable from each other is a crucial component in memory development, incorporating a mechanistic account of how different representations get refined in the model will provide a more complete understanding of how memory develops (e.g., Saxe et al., 2019). Second, the current study used a cross-sectional design, where the developmental changes can not be directly measured, and only be inferred. We, therefore, are planning to confirm the current findings using a longitudinal design. Embedded in the longitudinal design, we also plan to measure other cognitive abilities (e.g., executive function, vocabulary knowledge) that may aid us to better understand the mechanisms involved in memory development. Future studies should also investigate other age groups to fully understand the developmental trajectory of human memory as our current study only examines three age groups. Finally, improvements can be made to the measurement of previous exposure of an item rather than using normative frequency (e.g., TASA/CHILDES). For example, using experience sampling methods an individualized corpus can be constructed, and individualized frequency will provide better measures of previous exposure for each participant. Moreover, the recency of the item can be controlled as it will also affect memory performance (c.f., Yim, O'Brien, Stone, Osth, & Dennis, 2020).

In conclusion, the current study presents evidence that different sources of interference change across development at a different rate, and that this difference stems from the fact that the ability to discriminate between different kinds of memory representations (i.e., item and context) develop asynchronously. While item-based interference (i.e., item-noise) decreases rapidly between the ages of 5 and 7, context-based interference (i.e., context-noise) decreases gradually and continues to affect memory in adults. These findings advance our understanding of memory development by identifying its sources. Moreover, the novel computational model provides a way to decompose the effects stemming

from experience and from maturation, which can be further applied in cognitive development research more broadly.

References

- Ackerman, B. P. (1984). Item-specific and relational encoding effects in children's recall and recognition memory for words. *Journal of Experimental Child Psychology*, 37(3), 426–450.
- Anderson, J. R., & Bower, G. H. (1972). Recognition and retrieval processes in free recall. *Psychological Review*, 79(2), 97–123.
- Bauer, P. J. (2007). *Remembering the times of our lives: Memory in infancy and beyond*. Laurence Erlbaum Associates.
- Carpenter, B., Gelman, A., Hoffman, M., Lee, D., Goodrich, B., Betancourt, M., Brubaker, M., Guo, J., Li, P., & Riddell, A. (2017). Stan: A Probabilistic Programming Language. *Journal of Statistical Software, Articles*, 76(1), 1–32.
- Clark, S. E., & Gronlund, S. D. (1996). Global matching models of recognition memory: How the models match the data. *Psychonomic Bulletin & Review*, 3(1), 37–60.
- Criss, A. H., & Shiffrin, R. M. (2004). Context Noise and Item Noise Jointly Determine Recognition Memory: A Comment on Dennis and Humphreys (2001). *Psychological Review*, 111(3), 800–807.
- Cycowicz, Y. M., Friedman, D., Snodgrass, J. G., & Duff, M. (2001). Recognition and source memory for pictures in children and adults. *Neuropsychologia*, 39(3), 255–267.
- De Master, D., Pathman, T., Lee, J. K., & Ghetti, S. (2014). Structural development of the hippocampus and episodic memory: Developmental differences along the anterior/posterior axis. *Cerebral Cortex*, 24(11), 3036–3045.
- Dennis, S. J., & Humphreys, M. S. (2001). A context noise model of episodic word recognition. *Psychological Review*, 108(2), 452–478.
- Dennis, S. J., Lee, M. D., & Kinnell, A. (2008). Bayesian analysis of recognition memory: The case of the list-length effect. *Journal of Memory and Language*, 59(3), 361–376.
- Drummey, A. B., & Newcombe, N. S. (2002). Developmental changes in source memory. *Developmental*

Science, 5(4), 502–513.

- Fox, J., Dennis, S., & Osth, A. F. (2020). Accounting for the build-up of proactive interference across lists in a list length paradigm reveals a dominance of item-noise in recognition memory. *Journal of Memory and Language*, 110, 104065. <https://doi.org/10.1016/j.jml.2019.104065>
- Frank, M. C., Braginsky, M., Yurovsky, D., & Marchman, V. A. (2017). Wordbank: An open repository for developmental vocabulary data. *Journal of Child Language*, 44(3), 677–694.
- Geurten, M., Willems, S., & Lloyd, M. (2020). Too Much Familiarity! The Developmental Path of the Fluency Heuristic in Children. *Child Development*, cdev.13449.
- Ghetti, S., & Angelini, L. (2008). The Development of Recollection and Familiarity in Childhood and Adolescence: Evidence from the Dual-Process Signal Detection Model. *Child Development*, 79(2), 339–358.
- Ghetti, S., & Lee, J. (2011). Children's episodic memory. *Wiley Interdisciplinary Reviews: Cognitive Science*, 2, 365–373.
- Gillund, G., & Shiffrin, R. M. (1984). A retrieval model for both recognition and recall. *Psychological Review*, 91(1), 1–67.
- Glanzer, M., Adams, J. K., Iverson, G. J., & Kim, K. (1993). The regularities of recognition memory. *Psychological Review*, 100(3), 546–567.
- Glanzer, M., & Bowles, N. (1976). Analysis of the word-frequency effect in recognition memory. *Journal of Experimental Psychology: Human Learning & Memory*, 2(1), 21–31.
- Glanzer, M., Hilford, A., & Maloney, L. T. (2009). Likelihood ratio decisions in memory: Three implied regularities. *Psychonomic Bulletin & Review*, 16(3), 431–455.
- Gobbo, C., & Chi, M. T. H. (1986). How knowledge is structured and used by expert and novice children. *Cognitive Development*, 1, 221–237.
- Gronlund, S. D., & Elam, L. E. (1994). List-length effect: Recognition accuracy and variance of underlying distributions. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 20(6), 1355–1369.
- Gross, J., Gardiner, B., & Hayne, H. (2016). Developmental reversals in recognition memory in children

and adults: Developmental Reversals in Recognition Memory. *Developmental Psychobiology*, 58(1), 52–59.

Halberda, J., & Feigenson, L. (2008). Developmental change in the acuity of the “Number Sense”: The Approximate Number System in 3-, 4-, 5-, and 6-year-olds and adults. *Developmental Psychology*, 44(5), 1457–1465.

Hart, B., & Risley, T. R. (1995). *Meaningful differences in the everyday experience of young American children*. Paul H Brookes Publishing.

Hayes, B. K., Dunn, J. C., Joubert, A., & Taylor, R. (2017). Comparing single- and dual-process models of memory development. *Developmental Science*, 20(6), e12469–e12469.

Hoff, E. (2014). *Language development* (Fifth edition). Wadsworth Cengage Learning.

Jeffreys, H. (1961). *Theory of Probability* (3rd ed.). Oxford University Press.

Keil, F. C. (1979). *Semantic and conceptual development: An ontological perspective*. Harvard University Press.

Keresztes, A., Ngo, C. T., Lindenberger, U., Werkle-Bergner, M., & Newcombe, N. S. (2018). Hippocampal Maturation Drives Memory from Generalization to Specificity. *Trends in Cognitive Sciences*, 22(8), 676–686.

Kinnell, A., & Dennis, S. (2011). The list length effect in recognition memory: An analysis of potential confounds. *Memory & Cognition*, 39(2), 348–363.

Kinnell, A., & Dennis, S. J. (2012). The role of stimulus type in list length effects in recognition memory. *Memory and Cognition*, 40(3), 311–325.

Kleiner, M., Brainard, D., & Pelli, D. (2007). What's new in psychtoolbox-3? *Perception*, 36, 14–14.

Kruschke, J. K. (2014). *Doing Bayesian Data Analysis: A Tutorial with R, JAGS, and Stan*. Academic Press.

Kuperman, V., Stadthagen-Gonzalez, H., & Brysbaert, M. (2012). Age-of-acquisition ratings for 30,000 English words. *Behavior Research Methods*, 44, 978–990.

Landauer, T. K., & Dumais, S. T. (1997). A solution to Plato's problem: The latent semantic analysis theory of acquisition, induction, and representation of knowledge. *Psychological Review*, 104(2),

- Lee, J. K., Fandakova, Y., Johnson, E. G., Cohen, N. J., Bunge, S. A., & Ghetti, S. (2020). Changes in anterior and posterior hippocampus differentially predict item-space, item-time, and item-item memory improvement. *Developmental Cognitive Neuroscience, 41*, 100741. <https://doi.org/10.1016/j.dcn.2019.100741>
- Lloyd, M. E., Doydum, A. O., & Newcombe, N. S. (2009). Memory binding in early childhood: Evidence for a retrieval deficit. *Child Development, 80*(5), 1321–1328.
- MacWhinney, B. (2000). *The CHILDES Project: Tools for analyzing talk*. (Third). Lawrence Erlbaum Associates.
- Mandler, J. M., Bauer, P. J., & McDonough, L. (1991). Separating the sheep from the goats: Differentiating global categories. *Cognitive Psychology, 23*(2), 263–298.
- Mandler, J. M., & Robinson, C. A. (1978). Developmental changes in picture recognition. *Journal of Experimental Child Psychology, 26*(1), 122–136.
- Murdock, B. B., & Kahana, M. J. (1993a). Analysis of the List-Strength Effect. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 19*(3), 689–697.
- Murdock, B. B., & Kahana, M. J. (1993b). List-strength and list-length effects: Reply to Shiffrin, Ratcliff, Murnane, and Nobel (1993). *Journal of Experimental Psychology: Learning, Memory, and Cognition, 19*(6), 1450–1453. <https://doi.org/10.1037/0278-7393.19.6.1450>
- Ngo, C. T., Lin, Y., Newcombe, N. S., & Olson, I. R. (2019). Building Up and Wearing Down Episodic Memory: Mnemonic Discrimination and Relational Binding. *Journal of Experimental Psychology: General, 148*(9), 1463–1479.
- Osth, A. F., & Dennis, S. J. (2015). Sources of interference in item and associative recognition memory. *Psychological Review, 122*(2), 260–311.
- Osth, A. F., & Dennis, S. J. (2020). *Global matching models of recognition memory*.
- Osth, A. F., Dennis, S. J., & Heathcote, A. (2017). Likelihood ratio sequential sampling models of recognition memory. *Cognitive Psychology, 92*, 101–126.
- Osth, A. F., Dennis, S. J., & Kinnell, A. (2014). Stimulus type and the list strength paradigm. *Quarterly*

Journal of Experimental Psychology, 67(9), 1826–1841.

- Osth, A. F., Fox, J., McKague, M., Heathcote, A., & Dennis, S. J. (2018). The list strength effect in source memory: Data and a global matching model. *Journal of Memory and Language*, 103(July), 91–113.
- Osth, A. F., Jansson, A., Dennis, S. J., & Heathcote, A. (2018). Modeling the dynamics of recognition memory testing with a combined model of retrieval and decision making. *Cognitive Psychology*.
- Picard, L., Cousin, S., Guillery-Girard, B., Eustache, F., & Piolino, P. (2012). How Do the Different Components of Episodic Memory Develop? Role of Executive Functions and Short-Term Feature-Binding Abilities. *Child Development*, 83(3), 1037–1050.
- Ratcliff, R., Clark, S. E., & Shiffrin, R. M. (1990). List-Strength Effect: I. Data and Discussion. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 16(2), 163–178.
- Shiffrin, R. M., & Steyvers, M. (1997). A model for recognition memory: REM-retrieving effectively from memory. *Psychonomic Bulletin & Review*, 4(2), 145–166. <https://doi.org/10.3758/BF03209391>
- Tulving, E. (1972). Episodic and semantic memory. In E. Tulving & W. Donaldson (Eds.), *Organization of memory* (pp. 381–403). Academic Press.
- Turner, B. M., Sederberg, P. B., Brown, S. D., & Steyvers, M. (2013). A Method for efficiently sampling from distributions with correlated dimensions. *Psychological Methods*, 18(3), 368–384.
- Yim, H., Dennis, S. J., & Sloutsky, V. M. (2013). The Development of Episodic Memory: Items, Contexts, and Relations. *Psychological Science*, 24(11), 2163–2172.
- Yim, H., O'Brien, C. R., Stone, B., Osth, A., & Dennis, S. J. (2020). Using Emails to Quantify the Impact of Prior Exposure on Word Recognition Memory. In Denison, S., Mack, M., Xu, Y., Armstrong, B. C. (Eds.) *Proceedings of the 42nd Annual Conference of the Cognitive Science Society*, (pp. 185-190). Austin, TX: Cognitive Science Society.
- Yim, H., Osth, A. F., Sloutsky, V. M., & Dennis, S. J. (2018). Evidence for the use of three-way binding structures in associative and source recognition. *Journal of Memory and Language*, 100(November 2017), 89–97.

Supplemental Online Materials-Reviewed

A. Behavioural Results

Group d-prime (μ_d) was analyzed using a hierarchical Bayesian signal detection model. The group parameters were derived by equation A1.

$$\begin{aligned}(\mu_d, \mu_c) &\sim \text{Gaussian}(0, .001) \\(\lambda_d, \lambda_c) &\sim \text{Gamma}(.001, .001) \\d'_i &\sim \text{Gaussian}(\mu_d, \lambda_d) \\c_i &\sim \text{Gaussian}(\mu_c, \lambda_c)\end{aligned}\tag{A1}$$

$i=1, \dots, N_s$

where d'_i and c_i are each participant's sensitivity and decision criterion respectively, μ_d , λ_d are mean and precision of the group sensitivity, and μ_c , λ_c are mean and precision of the group decision criterion. N_s is the total number of participants. For the source recognition task, male items were considered as old items whereas female items as new items for convenience. All Bayes factors used for comparison were calculated using the Savage-Dickey ratio (Wagenmakers et al., 2010) with the effect-size as a measure of difference and a Cauchy prior of scale 1.0.

A.1. Group d-prime estimates

(A.1.1) Age effect in the item recognition task -- 4-5yrs-adults: $BF_{10} > 1.43E307$, 4-5yrs-7-8yrs: $BF_{10} = 3.05E18$, 7-8yrs-adults: $BF_{10} = 1881$; 4-5yrs: $M = 1.52$, 95% Highest Density Interval ($HDI_{95\%}$) = [1.34, 1.71], 7-8yrs: $M = 2.32$, $HDI_{95\%} = [2.12, 2.54]$; adults: $M = 3.37$, $HDI_{95\%} = [3.01, 3.77]$.

(A.1.2) Item recognition list length and strength effects (see Fig. 3a) -- 4-5yrs: baseline (BL), $M = 1.56$, $HDI_{95\%} = [1.30, 1.83]$, mixed strength (MS), $M = 1.57$, $HDI_{95\%} = [1.36, 1.79]$, long (LG), $M = 1.64$, $HDI_{95\%} = [1.36, 1.95]$; 7-8yrs: BL, $M = 2.39$, $HDI_{95\%} = [2.04, 2.77]$, MS, $M = 2.27$, $HDI_{95\%} = [2.00, 2.56]$, LG, $M = 2.39$, $HDI_{95\%} = [2.03, 2.78]$; adults: BL, $M = 3.46$, $HDI_{95\%} = [2.89, 4.14]$, MS, $M = 3.47$, $HDI_{95\%} = [2.95, 4.09]$, LG, $M = 3.49$, $HDI_{95\%} = [2.87, 4.22]$.

(A.1.3) Item recognition frequency effect results (see Fig. 3b) -- 4-5yrs: low-freq. $M = 1.70$, $HDI_{95\%} = [1.46, 1.95]$, high-freq. $M = 1.36$, $HDI_{95\%} = [1.16, 1.58]$; 7-8yrs: low-freq. $M = 2.61$, $HDI_{95\%} = [2.34, 2.91]$, high-freq. $M = 2.05$, $HDI_{95\%} = [1.80, 2.31]$; adults: low-freq. $M = 4.43$, $HDI_{95\%} = [3.70, 5.38]$, high-freq. $M = 3.01$, $HDI_{95\%} = [2.60, 3.45]$.

(A.1.4) Age effect in the source recognition task -- 4-5yrs-adults: $BF_{10} = 1.97E11$, 4-5yrs-7-8yrs: $BF_{10} = 1.47$, 7-8yrs-adults: $BF_{10} = 31.09$; 4-5yrs: $M = 1.90$, $HDI_{95\%} = [1.70, 1.97]$, 7-8yrs: $M = 2.20$, $HDI_{95\%} = [1.98, 2.44]$; adults: $M = 2.78$, $HDI_{95\%} = [2.52, 3.07]$.

(A.1.5) Source recognition list-length and strength effects (see Fig. 3c) -- 4-5yrs: BL, $M = 1.95$, $HDI_{95\%} = [1.63, 2.31]$, MS, $M = 2.05$, $HDI_{95\%} = [1.73, 2.42]$, LG, $M = 1.78$, $HDI_{95\%} = [1.53, 2.05]$; 7-8yrs: BL, $M = 2.54$, $HDI_{95\%} = [2.19, 2.97]$, MS, $M = 2.36$, $HDI_{95\%} = [1.92, 2.91]$, LG, $M = 1.96$, $HDI_{95\%} = [1.66, 2.28]$; adults: BL, $M = 3.07$, $HDI_{95\%} = [2.51, 3.79]$, MS, $M = 3.20$, $HDI_{95\%} = [2.66, 3.96]$, LG, $M = 2.66$, $HDI_{95\%} = [2.30, 3.11]$.

(A.1.6) Source recognition frequency effect results (see Fig. 3d) -- 4-5yrs: low-freq. $M = 1.96$, $HDI_{95\%} = [1.72, 2.23]$, high-freq. $M = 1.85$, $HDI_{95\%} = [1.61, 2.12]$; 7-8yrs: low-freq. $M = 2.39$, $HDI_{95\%} = [2.07, 2.75]$, high-freq. $M = 2.09$, $HDI_{95\%} = [1.82, 2.39]$; adults: low-freq. $M = 3.12$, $HDI_{95\%} = [2.72, 3.62]$, high-freq. $M = 2.58$, $HDI_{95\%} = [2.25, 2.98]$.

A.2. Hit rate

Hit rates from the item recognition task was analyzed using a hierarchical Bayesian binomial model. The group parameters were derived by equation (A2).

$$\begin{aligned} \omega &\sim \text{Beta}(1, 1) \\ \kappa &\sim \text{Gamma}(.01, .01) \\ \theta_i &\sim \text{Beta}(\omega*\kappa+1, (1-\omega)*\kappa+1) \\ y_{ij} &\sim \text{Binomial}(n_i, \theta_i) \end{aligned} \tag{A2}$$

$i=1, \dots, N_s$
 $j=1, \dots, N_{it}$

where y_{ij} is the accuracy for trial j of participant i , θ_i is the rate parameter for each participant i and, ω and κ are group accuracy rate and concentration respectively. N_s is the total number of participants and N_{it} is the total number of trials for each participant i . All Bayes factors used for comparison were calculated using the Savage-Dickey ratio (Wagenmakers et al., 2010) with the effect-size as a measure of difference and a Cauchy prior of scale 1.0.

(A.2.1) Age effect in the item recognition task -- 4-5yrs-adults: $BF_{10} = 2.89$; 4-5yrs-7-8yrs: $BF_{10} = 7.22$; 7-8yrs-adults: $BF_{10} = 3830678$; 4-5yrs: $M = 0.81$, $SD = 0.17$; 7-8yr: $M = 0.75$, $SD = 0.13$; adults: $M = 0.87$, $SD = 0.12$.

(A.2.2) Item recognition list length and strength effects -- (a) List length: 4-5yrs, $BF_{10} = .17$; 7-8yrs, $BF_{10} = 1.44$; adults, $BF_{10} = .58$, (b) List strength: 4-5yrs, $BF_{10} = .47$; 7-8yrs, $BF_{10} = 1.40$; adults, $BF_{10} = 1.37$. 4-5yrs: baseline (BL), $M = .80$, $SD = .21$, mixed strength (MS), $M = .81$, $SD = .20$, long (LG), $M = .81$, $SD = .23$; 7-8yrs: BL, $M = .78$, $SD = .18$, MS, $M = .74$, $SD = .18$, LG, $M = .74$, $SD = .18$; adults: BL, $M = .89$, $SD = .14$, MS, $M = .85$, $SD = .17$, LG, $M = .87$, $SD = .17$.

(A.2.3) Item recognition frequency effect results -- 4-5yrs, $BF_{10} = 53.61$; 7-8yrs, $BF_{10} = 3.66E13$; adults, $BF_{10} = 2.6E13$. 4-5yrs: low-freq. $M = .83$, $SD = .78$, high-freq. $M = .78$, $SD = .19$; 7-8yrs: low-freq. $M = .82$, $SD = .13$, high-freq. $M = .68$, $SD = .17$; adults: low-freq. $M = .93$, $SD = .12$, high-freq. $M = .81$, $SD = .16$.

A.3. False alarm rate

False alarm rates were also analyzed using a hierarchical Bayesian binomial model.

(A.3.1) Age effect in the item recognition task -- 4-5yrs-adults: $BF_{10} = 9.6E23$; 4-5yrs-7-8yrs: $BF_{10} = 4.2E14$; 7-8yrs-adults: $BF_{10} = 1.53$; 4-5yrs: $M = 0.36$, $SD = 0.33$; 7-8yr: $M = 0.07$, $SD = 0.13$; adults: $M = 0.04$, $SD = 0.10$.

(A.3.2) Item recognition list length and strength effects -- (a) List length: 4-5yrs, $BF_{10} = .41$; 7-8yrs, $BF_{10} = .50$; adults, $BF_{10} = 2.7$, (b) List strength: 4-5yrs, $BF_{10} = .38$; 7-8yrs, $BF_{10} = .60$; adults, $BF_{10} = .66$. 4-5yrs: baseline (BL), $M = .34$, $SD = .41$, mixed strength (MS), $M = .37$, $SD = .36$, long (LG), $M = .37$, $SD = .41$; 7-8yrs: BL, $M = .07$, $SD = .19$, MS, $M = .08$, $SD = .17$, LG, $M = .05$, $SD = .15$; adults: BL, $M = .04$, $SD = .16$, MS, $M = .03$, $SD = .10$, LG, $M = .05$, $SD = .17$.

(A.3.3) Item recognition frequency effect results -- 4-5yrs, $BF_{10} = .51$; 7-8yrs, $BF_{10} = .79$; adults, $BF_{10} = 1.73$. 4-5yrs: low-freq. $M = .35$, $SD = .34$, high-freq. $M = .38$, $SD = .37$; 7-8yrs: low-freq. $M = .06$, $SD = .14$, high-freq. $M = .08$, $SD = .17$; adults: low-freq. $M = .03$, $SD = .12$, high-freq. $M = .04$, $SD = .12$.

B. Source recognition task analyzed by Bayesian hierarchical binomial model

In the main text, the source recognition task was analyzed using a Bayesian hierarchical signal detection model so that the results are comparable to the item recognition task. An alternative way to analyze this data is examining the raw accuracy (proportion of correct) instead of using the signal detection model. Here we present the results analyzing the proportion of correct in the source recognition task using a hierarchical Bayesian binomial model that was used for analyzing the hit rate and false alarm rate for the item recognition task. We only analyzed the trials with correct item recognition.

Performance, measured by the group accuracy (ω), showed an increase across age groups (4yr-adults: $BF_{10} = 2.66e+9$; 4yr-7yr: $BF_{10} = 2.57$; 7yr-adults: $BF_{10} = 15.67$; 4yrs: $M = .87$, $HDI_{95\%} = [.82 .92]$, 7yrs: $M = .94$, $HDI_{95\%} = [.88 .99]$; adults: $M = .97$, $HDI_{95\%} = [.94 1.00]$), but there was a null effect for frequency across age groups with an ambiguous effect for adults (4yrs: $BF_{10} = .19$, low-freq. $M = .87$, $HDI_{95\%} = [.82 .92]$, high-freq. $M = .85$, $HDI_{95\%} = [.80 .91]$; 7yrs: $BF_{10} = .30$, low-freq. $M = .94$, $HDI_{95\%} = [.88 .99]$, high-freq. $M = .88$, $HDI_{95\%} = [.83 .90]$; adults: $BF_{10} = 1.01$, low-freq. $M = .97$, $HDI_{95\%} = [.94 .99]$, high-freq. $M = .94$, $HDI_{95\%} = [.89 .99]$). We also find null effects for list length in 4-year-olds and adults, but a small effect for 7-year-olds (4yrs: $BF_{10} = .21$; 7yrs: $BF_{10} = 2.71$; adults: $BF_{10} = .23$), and null effects for strength (4yrs: $BF_{10} = .25$; 7yrs: $BF_{10} = .46$; adults: $BF_{10} = .74$; 4yrs: baseline (BL), $M = .89$, $HDI_{95\%} = [.82 .98]$, mixed strength (MS), $M = .88$, $HDI_{95\%} = [.82 .96]$, long (LG), $M = .84$, $HDI_{95\%} = [.79 .90]$; 7yrs: BL, $M = .94$, $HDI_{95\%} = [.89 .99]$, MS, $M = .93$, $HDI_{95\%} = [.86 1.00]$, LG, $M = .88$, $HDI_{95\%} = [.82 .97]$; adults: BL, $M = .97$, $HDI_{95\%} = [.92 1.00]$, MS, $M = .97$, $HDI_{95\%} = [.93 1.00]$, LG, $M = .94$, $HDI_{95\%} = [.89 .99]$).

C. Computational Model

C.1. Description

A similar description of the model is also presented in (Osth, Fox, et al., 2018). Here, we describe the previous model with additional constraints, which was included in the current model in order to better capture the developmental changes. The model assumes that each dimension of an event is represented as a vector, and a memory trace of an event is the outer product of these vectors producing a tensor representation. The model also assumes that pre-experimentally formed traces (M_{pre}) exists, which also follows a tensor representation. Therefore, the sum of all memory traces (M) after the study phase of the experiment will be expressed as equation D1.

$$M = \sum r \cdot (I \otimes C \otimes S) + M_{pre} \quad (C1)$$

where r is a learning rate, I is the item (i.e., the word that was presented during study), C is the context (i.e., context of the study phase), and S is the source representation (i.e., either the female or male speaker). The memory strength (s) at test is defined as a dot product between the cue at test and the memory representation M as in equation C2.

$$s = (I_t' \otimes C_s' \otimes S_a') \cdot M \quad (C2)$$

where $(I_t' \otimes C_s' \otimes S_a')$ is the cue presented at test. The model further decomposes the memory representation (M) into different parts such as pre-experimental memory traces and traces that were formed during the study phase (see equation C3).

$$\begin{aligned}
s = & (l_t' \otimes C_s' \otimes S_a') \cdot [r(l_t \otimes C_s \otimes S_a) & \dots \text{ Self Match} & (C3) \\
& + \sum_{i \in A, i \neq t} r(l_i \otimes C_s \otimes S_a) & \dots \text{ Item Noise (A)} & \\
& + \sum_{i \in B, i \neq t} r(l_i \otimes C_s \otimes S_b) & \dots \text{ Item Noise (B)} & \\
& + \sum_{u \in P, u \neq s} (l_t \otimes C_u \otimes S_a) & \dots \text{ Context Noise (A)} & \\
& + \sum_{u \in P, u \neq s} (l_t \otimes C_u \otimes S_b) & \dots \text{ Context Noise (B)} & \\
& + \sum_{u \in P, u \neq s} (l_t \otimes C_u \otimes S_c) & \dots \text{ Context Noise (C)} & \\
& + \sum_{u \in P, u \neq s, z \notin L} (l_z \otimes C_u \otimes S_a) & \dots \text{ Background Noise (A)} & \\
& + \sum_{u \in P, u \neq s, z \notin L} (l_z \otimes C_u \otimes S_b) & \dots \text{ Background Noise (B)} & \\
& + \sum_{u \in P, u \neq s, z \notin L} (l_z \otimes C_u \otimes S_c) & \dots \text{ Background Noise (C)} &]
\end{aligned}$$

where Self Match is the trace that exactly matches the cue at test, Item Noise (A) is the trace that does not match the item with the cue but was in the study list (context match) and matches the source (i.e., was presented with source A, for example the female speaker), Item Noise (B) is the trace that does not match the item with the cue but was in the study list (context match) and was presented with source B (e.g., male speaker). Context Noise (A), (B), (C) are the traces that match the item with the cue but not with the context, and matches either the source (source A), matches the other source in the study (source B), or a source that did not appear in experiment (source C). Also note that learning r was applied separately for words that were presented once and words that were presented three times in the mixed condition.

C.2. Source decomposition and model parameterization

Using properties in linear algebra, equation C3 could be re-expressed by distributing the cue $(l_t' \otimes C_s' \otimes S_a')$ into each component and rearranging each term as below:

$$\begin{aligned}
s = & r(l_t' \cdot l_t)(C_s' \cdot C_s)(S_a' \cdot S_a) & (C4) \\
& + \sum_{i \in A, i \neq t} r(l_t' \cdot l_i)(C_s' \cdot C_s)(S_a' \cdot S_a) \\
& + \sum_{i \in B, i \neq t} r(l_t' \cdot l_i)(C_s' \cdot C_s)(S_a' \cdot S_b)
\end{aligned}$$

$$\begin{aligned}
& + \sum_{u \in P, u \neq s} (l_t' \cdot l_t) (C_s' \cdot C_u) (S_a' \cdot S_a) \\
& + \sum_{u \in P, u \neq s} (l_t' \cdot l_t) (C_s' \cdot C_u) (S_a' \cdot S_b) \\
& + \sum_{u \in P, u \neq s} (l_t' \cdot l_t) (C_s' \cdot C_u) (S_a' \cdot S_c) \\
& + \sum_{u \in P, u \neq s, z \notin L} (l_t' \cdot l_z) (C_s' \cdot C_u) (S_a' \cdot S_a) \\
& + \sum_{u \in P, u \neq s, z \notin L} (l_t' \cdot l_z) (C_s' \cdot C_u) (S_a' \cdot S_b) \\
& + \sum_{u \in P, u \neq s, z \notin L} (l_t' \cdot l_z) (C_s' \cdot C_u) (S_a' \cdot S_c)
\end{aligned}$$

This method of re-expression provides a way to formulate the equation in terms of match and mis-match components. Therefore, in the model, each component is parameterized as a normal distribution with a certain mean and variance as follows:

$l_t' \cdot l_t \sim \text{Normal}(\mu_{tt}, \sigma_{tt})$	... Item Match
$l_t' \cdot l_i \sim \text{Normal}(0, \sigma_{ti})$	... Item Mismatch
$C_s' \cdot C_s \sim \text{Normal}(\mu_{ss}, \sigma_{ss})$	... Context Match
$C_s' \cdot C_u \sim \text{Normal}(0, \sigma_{su})$	... Context Mismatch
$S_a' \cdot S_a \sim \text{Normal}(\mu_{aa}, \sigma_{aa})$	... Source Match
$S_a' \cdot S_b \sim \text{Normal}(0, \sigma_{ab})$	... Source Mismatch (B)
$S_a' \cdot S_c \sim \text{Normal}(0, \sigma_{ac})$	... Source Mismatch (C)

The normal distribution is used for mathematical convenience since each term in equation C4 is a multiplication of three normal distributions, which becomes a modified Bessel function of the third kind, and the mean and variance of each term follows the below rule:

$$\begin{aligned}
E(X_1, \dots, X_n) &= \prod E(X_i) \\
\text{Var}(X_1, \dots, X_n) &= \prod [\text{var}(X_i) + E(X_i)^2] - \prod E(X_i)^2
\end{aligned}$$

Additionally, when the summation notations are specified for the current study, the equation could be re-express as C5.

$$\begin{aligned}
s = & r \cdot \text{Normal}(\mu_{tt}, \sigma_{tt}) \cdot \text{Normal}(\mu_{ss}, \sigma_{ss}) \cdot \text{Normal}(\mu_{aa}, \sigma_{aa}) \quad (C5) \\
& + [(1/2) - 1] \cdot \text{Normal}(0, \sigma_{ti}) \cdot \text{Normal}(\mu_{ss}, \sigma_{ss}) \cdot \text{Normal}(\mu_{aa}, \sigma_{aa}) \\
& + 1/2 \cdot \text{Normal}(0, \sigma_{ti}) \cdot \text{Normal}(\mu_{ss}, \sigma_{ss}) \cdot \text{Normal}(0, \sigma_{ab}) \\
& + n_a \cdot \text{Normal}(\mu_{tt}, \sigma_{tt}) \cdot \text{Normal}(0, \sigma_{su}) \cdot \text{Normal}(\mu_{aa}, \sigma_{aa}) \\
& + n_b \cdot \text{Normal}(\mu_{tt}, \sigma_{tt}) \cdot \text{Normal}(0, \sigma_{su}) \cdot \text{Normal}(0, \sigma_{ab}) \\
& + n_c \cdot \text{Normal}(\mu_{tt}, \sigma_{tt}) \cdot \text{Normal}(0, \sigma_{su}) \cdot \text{Normal}(0, \sigma_{ac}) \\
& + m_a \cdot \text{Normal}(0, \sigma_{ti}) \cdot \text{Normal}(0, \sigma_{su}) \cdot \text{Normal}(\mu_{aa}, \sigma_{aa}) \\
& + m_b \cdot \text{Normal}(0, \sigma_{ti}) \cdot \text{Normal}(0, \sigma_{su}) \cdot \text{Normal}(0, \sigma_{ab}) \\
& + m_c \cdot \text{Normal}(0, \sigma_{ti}) \cdot \text{Normal}(0, \sigma_{su}) \cdot \text{Normal}(0, \sigma_{ac})
\end{aligned}$$

where the sum of m_a , m_b , and m_c is the total number of words that a participant would have experienced (i.e., m_{total}). Following previous empirical literature (Hart & Risley, 1995), we approximated

that participants experience 10,950,000 words each year, and used the logged value for each participant's m_{total} . Therefore, $m_{total} = \log(10,950,000 \times \text{age}_{\text{year}})$. Further, we assumed that m_a and m_b each approximates to $\log(.1 \times 10,950,000 \times \text{age}_{\text{year}})$ and m_c to $\log(.8 \times 10,950,000 \times \text{age}_{\text{year}})$. The sum of n_a , n_b , and n_c is the total number of times (or contexts) that the word was experienced (i.e., n_{total}) prior to the experiment. n_{total} was calculated by multiplying the per-million frequency for the specific word at the specific age group to the total number of words experienced divided by a million. Frequency information was extracted using the CHILDES corpus for the children groups and TASA corpus for adults. Therefore, $n_{total} = \log(\text{word_frequency}_{\text{per_million@year}} \times 10.95 \times \text{age}_{\text{year}})$. n_a , n_b , and n_c was proportional as was for the m_{total} case. Finally, l is the length of the list (i.e., 8 or 16 depending on the condition).

C.3. Calculating memory strength

For item recognition, memory strength is calculated by assuming that participants use a generic source cue that matches the source that was presented with the item during study with a mean of one and variance of zero. Therefore, the target distribution (i.e., when the items were studied item) and the noise distribution (i.e., when the items were not studied) in the SDT framework follows as below:

$$\mu_{old} = r \cdot \mu_{tt} \cdot \mu_{ss} \quad (C6)$$

$$\mu_{new} = 0$$

$$\begin{aligned} \sigma_{old}^2 &= r^2 \cdot [(\sigma_{tt}^2 + \mu_{tt}^2) \cdot (\sigma_{ss}^2 + \mu_{ss}^2) - (\mu_{tt}^2 \cdot \mu_{ss}^2)] \quad \dots \text{Self Match} \\ &+ r^2 \cdot (1 - r) \cdot [\sigma_{tt}^2 \cdot (\sigma_{ss}^2 + \mu_{ss}^2)] \quad \dots \text{Item Noise} \\ &+ n_{item} \cdot [\sigma_{su}^2 \cdot (\sigma_{tt}^2 + \mu_{tt}^2)] \quad \dots \text{Context Noise} \\ &+ m_{item} \cdot (\sigma_{ti}^2 \cdot \sigma_{su}^2) \quad \dots \text{Background Noise} \end{aligned}$$

$$\begin{aligned} \sigma_{new}^2 &= r^2 \cdot l \cdot [\sigma_{tt}^2 \cdot (\sigma_{ss}^2 + \mu_{ss}^2)] \quad \dots \text{Item Noise} \\ &+ n_{item} \cdot [\sigma_{su}^2 \cdot (\sigma_{tt}^2 + \mu_{tt}^2)] \quad \dots \text{Context Noise} \\ &+ m_{item} \cdot (\sigma_{ti}^2 \cdot \sigma_{su}^2) \quad \dots \text{Background Noise} \end{aligned}$$

where $n_{item} = n_a + n_b + n_c$ and $m_{item} = m_a + m_b + m_c$

For source recognition, memory strength is calculated by taking the difference between the strength when source A (e.g., female speaker) is cued and the strength when source B (e.g., male speaker) is cued. First, the mean and variance of the distribution when source A was cued when source A was actually studied (a|a) and when source B was cued when source A was studied (b|a) follows:

$$\mu_{a|a} = r \cdot \mu_{tt} \cdot \mu_{ss} \cdot \mu_{aa} \quad (C7)$$

$$\mu_{b|a} = 0$$

$$\begin{aligned} \sigma_{a|a}^2 = & r^2 \cdot [(\sigma_{tt}^2 + \mu_{tt}^2) \cdot (\sigma_{ss}^2 + \mu_{ss}^2) \cdot (\sigma_{aa}^2 + \mu_{aa}^2) - (\mu_{tt}^2 \cdot \mu_{ss}^2 \cdot \mu_{aa}^2)] \quad \dots \text{Self Match} \\ & + r^2 \cdot (1/2 - 1) \cdot [\sigma_{tt}^2 \cdot (\sigma_{ss}^2 + \mu_{ss}^2) \cdot (\sigma_{aa}^2 + \mu_{aa}^2)] \quad \dots \text{Item Noise A} \\ & + r^2 \cdot (1/2) \cdot [\sigma_{tt}^2 \cdot (\sigma_{ss}^2 + \mu_{ss}^2) \cdot (\sigma_{ab}^2)] \quad \dots \text{Item Noise B} \\ & + n_a \cdot [\sigma_{su}^2 \cdot (\sigma_{tt}^2 + \mu_{tt}^2) \cdot (\sigma_{aa}^2 + \mu_{aa}^2)] \quad \dots \text{Context Noise A} \\ & + n_b \cdot [\sigma_{su}^2 \cdot (\sigma_{tt}^2 \cdot \sigma_{ab}^2)] \quad \dots \text{Context Noise B} \\ & + n_c \cdot [\sigma_{su}^2 \cdot (\sigma_{tt}^2 \cdot \sigma_{ac}^2)] \quad \dots \text{Context Noise C} \\ & + m_a \cdot [(\sigma_{tt}^2 \cdot \sigma_{su}^2) \cdot (\sigma_{aa}^2 + \mu_{aa}^2)] \quad \dots \text{Background Noise A} \\ & + m_b \cdot (\sigma_{tt}^2 \cdot \sigma_{su}^2 \cdot \sigma_{ab}^2) \quad \dots \text{Background Noise B} \\ & + m_c \cdot (\sigma_{tt}^2 \cdot \sigma_{su}^2 \cdot \sigma_{ac}^2) \quad \dots \text{Background Noise C} \end{aligned}$$

$$\begin{aligned} \sigma_{b|a}^2 = & r^2 \cdot [(\sigma_{tt}^2 + \mu_{tt}^2) \cdot (\sigma_{ss}^2 + \mu_{ss}^2) \cdot (\sigma_{ab}^2)] \quad \dots \text{Self Match} \\ & + r^2 \cdot (1/2 - 1) \cdot [\sigma_{tt}^2 \cdot (\sigma_{ss}^2 + \mu_{ss}^2) \cdot (\sigma_{ba}^2)] \quad \dots \text{Item Noise A} \\ & + r^2 \cdot (1/2) \cdot [\sigma_{tt}^2 \cdot (\sigma_{ss}^2 + \mu_{ss}^2) \cdot (\sigma_{bb}^2)] \quad \dots \text{Item Noise B} \\ & + n_a \cdot [\sigma_{su}^2 \cdot (\sigma_{tt}^2 + \mu_{tt}^2) \cdot (\sigma_{ba}^2)] \quad \dots \text{Context Noise A} \\ & + n_b \cdot [\sigma_{su}^2 \cdot (\sigma_{tt}^2 + \mu_{tt}^2) \cdot (\sigma_{bb}^2 + \mu_{bb}^2)] \quad \dots \text{Context Noise B} \\ & + n_c \cdot [\sigma_{su}^2 \cdot (\sigma_{tt}^2 + \mu_{tt}^2) \cdot (\sigma_{bc}^2)] \quad \dots \text{Context Noise C} \\ & + m_a \cdot (\sigma_{tt}^2 \cdot \sigma_{su}^2 \cdot \sigma_{ba}^2) \quad \dots \text{Background Noise A} \\ & + m_b \cdot [(\sigma_{tt}^2 \cdot \sigma_{su}^2) \cdot (\sigma_{bb}^2 + \mu_{bb}^2)] \quad \dots \text{Background Noise B} \end{aligned}$$

$$+ m_c \cdot (\sigma_{ti}^2 \cdot \sigma_{su}^2 \cdot \sigma_{bc}^2) \quad \dots \text{Background Noise C}$$

where we assume symmetry between source A and B and that $\mu_{aa} = \mu_{bb}$, $\sigma_{aa} = \sigma_{bb}$, $\sigma_{ab} = \sigma_{ba}$, $\sigma_{ac} = \sigma_{bc}$.

Then, the difference between the two distributions (i.e., a|a and b|a) becomes the following (see simulation results of this approximation in Osth, Fox, et al. (2018):

$$\mu_{(a|a)-(b|a)} = \mu_{a|a} - \mu_{b|a} \quad (C8)$$

$$\sigma_{(a|a)-(b|a)}^2 = \sigma_{a|a}^2 + \sigma_{b|a}^2$$

C.4. Log-likelihood ratio transformation

Using the distributions of the memory strengths in the previous section, we apply a likelihood ratio (λ) transformation (Glanzer et al., 2009; Osth et al., 2017) using discriminability (d) and relative variance of the target distribution (S) in SDT. For item recognition the transformation follows:

$$\text{where} \quad (C9)$$

$$d_i = \mu_{old} / \sigma_{new}$$

$$S_i = \sigma_{old} / \sigma_{new}$$

the means and standard deviations of λ are

$$\mu_{\lambda_new} = -[(d_i^2/2) \cdot \{(S_i^2 + 3)/(4 \cdot S_i^2)\} + \log(S_i)]$$

$$\mu_{\lambda_old} = d_i^2 \cdot \{(S_i^2 + 1)/(2S_i^2)\} + \mu_{\lambda_new}$$

$$\sigma_{\lambda_new} = d_i \cdot \{(S_i^2 + 1)/(2S_i^2)\}$$

$$\sigma_{\lambda_old} = S_i \cdot \sigma_{\lambda_new}$$

For source recognition the transformation follows:

$$\text{where} \quad (C10)$$

$$d_s = (\mu_A - \mu_B) / \sigma_A$$

the means and standard deviations of λ are

$$\mu_{\lambda_A} = d_s^2 / 2$$

$$\mu_{\lambda_B} = -d_s^2 / 2$$

$$\sigma_{\lambda_A}, \sigma_{\lambda_B} = d_s^2$$

C.5. Model fitting procedures

Additionally, we fix the following parameters for computational efficiency. We fixed the means of the match parameters (i.e., μ_{tt} , μ_{ss} , μ_{aa}) to 1.0, and the variances of the match parameters to 0.0. Variance of between-source-option mismatch (i.e., μ_{ba} , μ_{ab}) were constrained to have the same value as μ_{aa} . Learning

rates for the weak items were fixed to 1.0 while learning rates for the strong items were free parameters. These values were derived from previous studies (Osth, Fox, et al., 2018; Osth & Dennis, 2015) where additional data was provided from the experiment such as reaction time and confidence judgement in that the model was more constrained to accurately estimate the parameters.

D. Modelling Results

D.1. Noise estimated from the item recognition task -- 4-5yrs: ItemNoise-Baseline, $M = .11$, $HDI_{95\%} = [.05, .18]$, ItemNoise-Long, $M = .22$, $HDI_{95\%} = [.10, .36]$, ItemNoise-MixedStrength, $M = .27$, $HDI_{95\%} = [.12, .44]$, Context-Noise-Low-Freq., $M = .26$, $HDI_{95\%} = [.19, .32]$, Context-Noise-High-Freq., $M = .35$, $HDI_{95\%} = [.26, .44]$, Background-Noise, $M = .008$, $HDI_{95\%} = [.004, .01]$; 7-8yrs: ItemNoise-Baseline, $M = .001$, $HDI_{95\%} = [9.8E-5, .002]$, ItemNoise-Long, $M = .002$, $HDI_{95\%} = [.0002, .004]$, ItemNoise-MixedStrength, $M = .002$, $HDI_{95\%} = [.0003, .005]$, Context-Noise-Low-Freq., $M = .16$, $HDI_{95\%} = [.14, .18]$, Context-Noise-High-Freq., $M = .21$, $HDI_{95\%} = [.18, .24]$, Background-Noise, $M = 3.9E-5$, $HDI_{95\%} = [4.6E-6, 8.4E-5]$; adults: ItemNoise-Baseline, $M = 5.1E-5$, $HDI_{95\%} = [2.5E-6, 1.3E-4]$, ItemNoise-Long, $M = 1.0E-4$, $HDI_{95\%} = [5.0E-6, 2.6E-4]$, ItemNoise-MixedStrength, $M = 1.3E-4$, $HDI_{95\%} = [6.8E-6, 3.3E-4]$, Context-Noise-Low-Freq., $M = .07$, $HDI_{95\%} = [.06, .08]$, Context-Noise-High-Freq., $M = .1$, $HDI_{95\%} = [.08, .12]$, Background-Noise, $M = 1.1E-6$, $HDI_{95\%} = [4.9E-8, 2.6E-6]$.

D.2. Noise estimated from the source recognition task -- 4-5yrs: ItemNoise-Baseline, $M = .06$, $HDI_{95\%} = [.03, .10]$, ItemNoise-Long, $M = .13$, $HDI_{95\%} = [.06, .20]$, ItemNoise-MixedStrength, $M = .27$, $HDI_{95\%} = [.11, .47]$, Context-Noise-Low-Freq., $M = .20$, $HDI_{95\%} = [.15, .25]$, Context-Noise-High-Freq., $M = .30$, $HDI_{95\%} = [.22, .37]$, Background-Noise, $M = .007$, $HDI_{95\%} = [.004, .01]$; 7-8yrs: ItemNoise-Baseline, $M = 6.2E-4$, $HDI_{95\%} = [6.3E-5, .001]$, ItemNoise-Long, $M = .001$, $HDI_{95\%} = [1.3E-4, .003]$, ItemNoise-MixedStrength, $M = .005$, $HDI_{95\%} = [4.6E-4, .01]$, Context-Noise-Low-Freq., $M = .14$, $HDI_{95\%} = [.12, .16]$, Context-Noise-High-Freq., $M = .21$, $HDI_{95\%} = [.18, .23]$, Background-Noise, $M = 4.4E-5$, $HDI_{95\%} = [4.8E-6, 9.4E-5]$; adults: ItemNoise-Baseline, $M = 2.6E-5$, $HDI_{95\%} = [1.3E-6, 6.4E-5]$, ItemNoise-Long, $M = 5.1E-5$, $HDI_{95\%} = [2.5E-6, 1.3E-4]$, ItemNoise-MixedStrength, $M = 5.3E-5$, $HDI_{95\%} = [2.8E-6, 1.3E-4]$, Context-Noise-Low-Freq., $M = .18$, $HDI_{95\%} = [.14, .23]$, Context-Noise-High-Freq., $M = .29$, $HDI_{95\%} = [.22, .36]$, Background-Noise, $M = 3.1E-6$, $HDI_{95\%} = [1.5E-7, 7.9E-6]$.

E. Model parameters

Table E. Description and range of the free parameters used in the model.

Parameter	Range	Description
σ_{ti}	$0 : \infty$	Variance of the item mismatch parameter, which is linked to how well one discriminates the cued item from other items in the study list.
σ_{su}	$0 : \infty$	Variance of the context mismatch parameter, which is linked to how well one discriminates the study context from other contexts that one has experienced in the past.
σ_{aa}	$0 : \infty$	Variance of the source match parameter, which is linked to how well one discriminates the two sources in the current experiment.
σ_{ac}	$0 : \infty$	Variance of the source mismatch parameter, which is linked to how well one discriminates the two sources in the current experiment from other sources that one has experienced in the past.
Φ_{item}	$-\infty : \infty$	Response criteria for the item recognition task, where a negative value represents 'Yes' bias and positive represents 'No' bias.
Φ_{source}	$-\infty : \infty$	Response criteria for the source recognition task, where a negative value represents 'Female' bias and positive represents 'Male' bias.
r_{strong}	$0 : \infty$	Learning rate for items presented three times.

F. Estimated model parameter.

Figure F. Estimated model parameters across age groups. **a**, bias from the item recognition task (note that negative values represent Yes response and positive values represent No response). **b**, bias from the source recognition task (note that negative values represent female response and positive values represent male response). **c**, logged learning rate for the items repeated three times. **d**, logged variance of the source-match parameter. **e**, logged variance of the source-mismatch parameter. Note that parameters that are ‘logged’ are log transformed for an easier visual comparison among the parameters. Also note that the variance of the item-mismatch parameter and the variance of the context-mismatch parameter are presented in the main text.

We find that the model captures a slight ‘Yes’ response bias for 4-year-olds while a ‘No’ response bias for 7-year-olds and adults in the item recognition task (see Figure Fa; 4yrs: $M = -.40$, $HDI_{95\%} = [-.60, -.22]$, 7yrs: $M = .73$, $HDI_{95\%} = [.56, .90]$, adults: $M = .80$, $HDI_{95\%} = [.54, 1.05]$, negative values represent Yes response and positive values represent No response). A bias was also shown in the source recognition task, where 4-year-olds had a slight female speaker bias while adults had a slight male speaker bias (see Figure Fb; 4yrs: $M = -.22$, $HDI_{95\%} = [-.29, -.14]$, 7yrs: $M = .01$, $HDI_{95\%} = [-.11, .13]$, adults: $M = .39$, $HDI_{95\%} = [.23, .56]$, where negative values represent female response and positive values represent male response). Logged learning rate for the items that were shown three times ($\log(r_{strong})$) also showed a developmental increase (see Figure Fc; 4yrs: $M = -.96$, $HDI_{95\%} = [-1.05, -.87]$, 7yrs: $M = -.65$, $HDI_{95\%} = [-.74, -.57]$, adults: $M = -.50$, $HDI_{95\%} = [-.59, -.42]$). Additionally, the logged

variance of the source match parameter ($\log(\sigma_{aa})$), which is linked to how well one discriminates between the two sources in the experiment, shows a developmental decrease (Figure Fd; 4yrs: $M = -2.84$, $\text{HDI}_{95\%} = [-3.23, -2.48]$, 7yrs: $M = -2.02$, $\text{HDI}_{95\%} = [-2.20, -1.84]$, adults: $M = -5.64$, $\text{HDI}_{95\%} = [-7.10, -4.34]$). On the other hand, we see that the logged variance of the source mismatch parameter ($\log(\sigma_{ac})$), which is linked to how well one discriminates between the sources from the experiment and the sources from prior experience, increases with development (Figure Fe; 4yrs: $M = -9.60$, $\text{HDI}_{95\%} = [-12.44, -6.55]$, 7yrs: $M = -7.08$, $\text{HDI}_{95\%} = [-9.80, -4.41]$, adults: $M = .72$, $\text{HDI}_{95\%} = [.49, .94]$). The flipped pattern of the source mismatch parameter should be interpreted with caution since they are not constrained enough as the context mismatch parameter. The context mismatch parameter is constrained by how many times an item (i.e., words in the current experiment) has been experienced across development using empirical data. However, the assumptions regarding the source parameters are derived from previous adult studies and do not change across development in the model. Future studies will be required to understand these parameters more accurately.

G. Model simulation.

Figure G. Model simulations where recognition performance in terms of hit rates and false alarm rates are shown as a function of item noise, context noise, and decision bias. (a) recognition performance when item noise was changed in the model (solid lines are hit rates and dotted lines are false alarm rates). As item noise is a multiplication between the length of the study list and the variance of the item mismatch parameter, we changed each component separately. (b) recognition performance when context noise was changed in the model (solid lines are hit rates and dotted lines are false alarm rates). As context noise is a multiplication of the frequency of the item (i.e., word) and the variance of the context mismatch parameter, we changed each component separately. Figure (a) and (b) presents simulation results where there is no decision bias involved. (c), (d) show simulation results of (a) and (b) respectively but when a Yes response bias is added. (e), (f) show simulation results of (a) and (b) but when a No response bias is added.

H. Relationship between item noise and the list-length, list-strength effects in the experiment

Figure H. Relationship between individual proportion of item noise, the list-length effect score, and list-strength effect score across age groups. The proportion of item noise was calculated by dividing the item noise with the sum of item noise, context noise, and background noise. The individual list-length effect score was calculated by subtracting the d-prime value of the long condition from the d-prime value of the baseline condition. The individual list-strength effect score was calculated by subtracting the d-prime value of the mixed strength condition from the d-prime value of the baseline condition. Then, we calculated Spearman's rho, where the results only showed a statistically significant effect of the relationship between the 4-year-olds' proportion of item noise and list-strength effect score. The plots show the data divided into quartiles for better visualization. (a) 4-year-olds' proportion of item noise and list-length effect score ($\rho = .012$, $p = .91$), (b) 7-year-olds' proportion of item noise and list-length effect score ($\rho = -.075$, $p = .54$), (c) adults' proportion of item noise and list-length effect score ($\rho = -.071$, $p = .56$), (d) 4-year-olds' proportion of item noise and list-strength effect score ($\rho = .755$, $p < .001$), (e) 7-year-olds' proportion of item noise and list-strength effect score ($\rho = .205$, $p = .07$), (f) adults' proportion of item noise and list-strength effect score ($\rho = .087$, $p = .48$). Error bars represent ± 1 SEM.