Process Explanations of Age-Related Changes in Memory Specificity

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Author Note

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Abstract

Adult aging is associated with a decline in memory for the specific details of past experiences, but the reasons for these declines remain to be fully elucidated. Here, we consider the potential of computational process models of memory to reveal mechanisms underlying age-related changes in memory specificity. We define empirical benchmarks in the most widely used tasks for studying age differences in memory – recognition and free recall. We then systematically review two broad classes of process models – global matching and retrieved context models – that are well-suited to explaining these benchmarks. We discuss and at times illustrate through simulations how age differences in memory specificity can arise from different mechanisms in these models, such as reductions in encoding fidelity, cue-selectivity of retrieval, contextual reinstatement, or retrieval monitoring. These models hold great promise for uncovering the latent mechanisms of age-related memory change, but several explanatory shortcomings must be addressed for a more comprehensive theory to emerge. Because process models often incorporate simplifying shortcuts, they risk advancing descriptive rather than mechanistic explanations for age differences in memory. Furthermore, models that have identified multiple processes of age-related memory impairment have left unaddressed the ways in which these processes affect each other. By illuminating these and other challenges in current process models, our review aims to stimulate future advances that can dramatically reshape our understanding of the processes of age-related changes in memory specificity.

Keywords: aging, memory, computational models

Public Significance Statement

Failing to remember the specific details of our past experiences can have profound consequences. These failures become increasingly common as we age, yet the mechanisms underlying why older adults are more prone to forgetting specific details remain to be fully elucidated. Here, we evaluate what leading computational process models of memory have to say about these memory lapses. Our review identifies strengths and weaknesses in the abilities of current models to explain age-related memory changes, pointing to areas of improvement that could substantially improve our ability to understand, and potentially predict, why these memory changes occur.

Process Explanations of Age-Related Changes in Memory Specificity

Adult age-related declines in episodic memory have been widely reported (Light, 1991; Naveh-Benjamin & Old, 2008; Zacks, Hasher, & Li, 2000) and manifest to varying degrees on tests of recall and recognition (for meta-analyses, see Fraundorf, Hourihan, Peters, & Benjamin, 2019; Old & Naveh-Benjamin, 2008; Rhodes, Greene, & Naveh-Benjamin, 2019). These declines are evident in both cross-sectional and longitudinal studies (Salthouse, 2019) and can be detected with experimental (e.g., Craik & McDowd, 1987; Naveh-Benjamin, 2000) or self-report/interview (e.g., Dixon & Hultsch, 1983; Levine, Svoboda, Hay, Winocur, & Moscovitch, 2002) methods. Explanations for these declines range from limitations in attention (Craik & Byrd, 1982), inhibition (Hasher & Zacks, 1988), recollection (Jennings & Jacoby, 1997), or associative binding (Naveh-Benjamin, 2000); to general cognitive slowing (Salthouse, 1996) or sensory/perceptual loss (Baltes & Lindenberger, 1997); and from single- (Benjamin, 2010) to multi-component (Healey & Kahana, 2016) process impairments. Here, we consider the specific suggestion that these declines are rooted in changes in the specificity or fidelity of episodic memories with age (Greene & Naveh-Benjamin, 2023a; cf., Brainerd & Reyna, 2015; Surprenant & Neath, 2009). Our goal is to consider the etiology of these representational shifts through the lens of computational process models of memory. In doing so, we aim not only to shed light on mechanisms underlying age differences in memory specificity, but also to identify theoretical shortcomings in current models to stimulate future advances in memory theory.

What Is a Computational Process Model?

Before continuing, we first distinguish different classes of computational memory models to clarify which types of models will be placed under our microscope. Computational models encompass virtually any memory model that includes equations for relating unobserved (latent) cognitive processes to observed outcomes (e.g., recognition or recall accuracy). Latent cognitive processes are captured by free parameters, whose values depend on the data to which they are fitted (for a tutorial geared toward cognitive aging researchers, see Greene & Rhodes, 2022). All models make assumptions about how the processes they purport to measure give rise to behavior. Yet, models differ in the degree to which they formalize assumptions about how memories are represented and how they are encoded/stored and subsequently retrieved (for a review, see Kahana, 2020).

Perhaps the most widely used computational memory models are those rooted in signal detection theory (Green & Swets, 1966; Tanner & Swets, 1954), which isolate mnemonic sensitivity from response bias in choice-discrimination procedures like old/new recognition. A similar class of models – multinomial-procrcessing-tree (MPT) models (Batchelder & Riefer, 1999) – map the independent and joint contributions of unique cognitive and guessing processes to observed responses (e.g., "old" responses to similar lures). An example of an MPT model that separates the retrieval of specific details (*verbatim representations*) from the retrieval of the general meaning of an episode (*gist representations*) is depicted in Figure 1. This model, motivated by fuzzy-trace theory (Brainerd & Reyna, 1990), which we will soon review, independently estimates the probabilities of verbatim (V) versus gist (G) retrieval based on the observed rates of "old," "similar," and "new" responses to old, similar, and new/different recognition probes. Verbatim retrieval (V) yields unambiguous information about the true nature of the test probe (i.e., whether it is old, similar, or new/different). Gist retrieval in the absence of verbatim retrieval ($[1 - V] \times G$) yields uncertainty about the status of old and similar items that must be resolved through guessing. Finally, complete forgetting ($[1 - V] \times [1 - G]$) yields uncertainty for all test probes.

Signal detection and MPT models formalize assumptions about how participants make decisions under conditions of uncertainty. For example, in a conventional signal detection model, the latent strength (s_i) of recognition probe i is evaluated in light of an internal criterion (c), and an "old" response is given when $s_i \geq c$. However, these models do not formalize assumptions about how memories are represented, and they lack memory trace dynamics that explain how memories are encoded and retrieved (cf. Osth & Dennis,

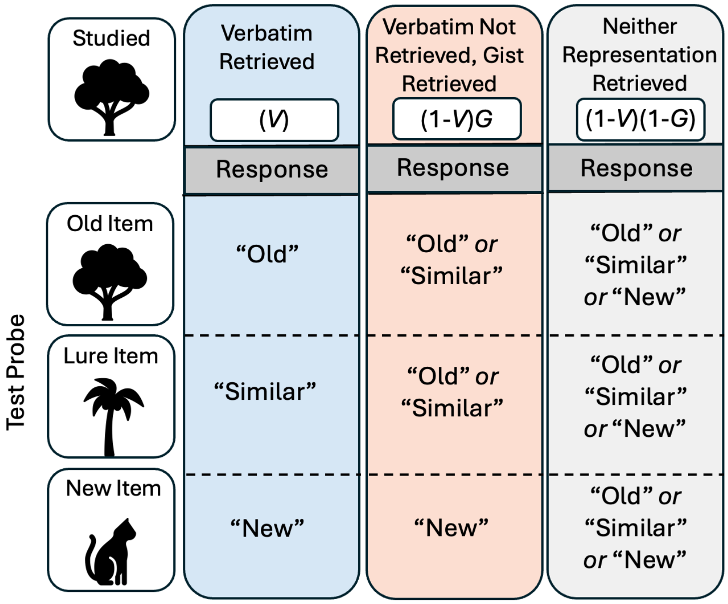

Figure 1

A Memory Model for Measuring Specific and Gist Retrieval.

In a recognition task with old items, similar lures, and new items, models can estimate the independent contributions of verbatim (V) and gist (G) retrieval to observed responses. V states yield complete certainty in the true status of any test probe relative to the studied item. In $(1 - V) \times G$ *states, one only has access to gist but not verbatim memory, resulting in uncertainty for probes that share the same gist (old items and lures) but not for unrelated items. When neither verbatim nor gist memory is retrieved* ($[1 - V] \times [1 - G]$)*, there is uncertainty for all probe types.*

2024). For example, the MPT model in Figure 1 does not specify how one stores and later accesses an item's verbatim or gist representation, and it does not define how verbatim and gist traces are represented at all.[1]

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[1] The MPT model is rooted in fuzzy-trace theory, which assumes parallel storage and retrieval of verbatim and gist traces (Brainerd & Reyna, 1990). However, these assumptions are not technically present in the model because it makes no claims about how items are encoded, and its retrieval process measures the probabilities of verbatim or gist retrieval but does not define *how* verbatim and gist representations are retrieved. These assumptions have been formalized in more recent computational models of fuzzy-trace theory (Chang, Johns, & Brainerd, 2025).

The types of computational models that we will interrogate here formalize representational assumptions and memory trace dynamics. Unlike signal detection and MPT models, these models lay bare specific assumptions about how memories are represented (e.g., as n-dimensional feature vectors), how they are encoded (e.g., by binding an item to a specific state of context), and how they are retrieved (e.g., by computing a global match between a currently attended item and all traces stored in memory). Some have used the term *generative* to describe these models (Darby & Sederberg, 2022), emphasizing their ability to explain *how* memory functions to generate observed outcomes (cf. Osth & Dennis, 2024). We focus on two broad classes of so-called *generative* computational process models – global matching (Hintzman, 1984; Shiffrin & Steyvers, 1997) and retrieved context (Howard & Kahana, 2002) models. Because these models attempt to explain how memory works, they hold great potential for revealing mechanisms of age-related changes in memory specificity.

Précis of the Present Review

We review previous computational modeling of age differences in memory, with a particular focus on global matching (Hintzman, 1984; Shiffrin & Steyvers, 1997) and retrieved context models (Howard & Kahana, 2002; Polyn, Norman, & Kahana, 2009) that have successfully explained many aspects of recognition and recall (for a more formal review, see Kahana, 2020). Efforts to extend these models to explain adult age differences in memory have been limited, despite their potential to identify latent mechanisms underlying these differences (Benjamin, 2010; Healey & Kahana, 2016; Salthouse, 1988). We pursue a didactic and theoretical approach to computational process modeling of age differences in memory specificity.

On the didactic end, we discuss computational process models in a relatively informal way, only wading into more technical territory where necessary. We are not concerned with whether any specific model constitutes the "ground truth" of how memory operates, nor do we intend to formally compare competing models. Readers interested in formal comparisons may refer to reviews by Clark and Gronlund (1996) or Osth and Dennis (2024). On the theoretical end, we aim to interrogate the assumptions that current models make regarding how memories are encoded, represented, and retrieved. The goal of this interrogation is to identify potential shortcomings in a model's ability to explain *why* older adults' episodic memories are impoverished in specific details, with the hope that this will stimulate future empirical or computational efforts to address these shortcomings.

In what follows, we first define empirical benchmarks of age differences in memory specificity. We focus on representative findings from studies of recall and recognition both because these are among the most widely used tasks for studying age differences in memory (e.g., Fraundorf et al., 2019; Rhodes et al., 2019) and because they are amenable to computational process modeling (Kahana, 2020). Other benchmarks could be identified in domains such as reading or language comprehension (Radvansky & Dijkstra, 2007; Stine-Morrow, Morrow, & Leno III, 2002; Stine & Wingfield, 1988) or autobiographical memory (Grilli & Sheldon, 2022; Levine et al., 2002); we refer the interested reader to Greene and Naveh-Benjamin (2023a) for a more comprehensive review.

After presenting these benchmarks, we briefly summarize leading theoretical explanations for age differences in memory specificity. We appeal primarily to fuzzy-trace theory (Brainerd & Reyna, 2015), given its focus on cognitive mechanisms of these differences. Fuzzy-trace theory's relatively high degree of computational formalization (Brainerd, Reyna, & Mojardin, 1999; Brainerd, Reyna, & Howe, 2009; Chang et al., 2025) also provides a bridge to our review of computational process models.

We then devote the remainder of the review to evaluating computational process model-based explanations for age differences in memory specificity. Because current models have already accounted for the observed benchmarks (e.g., Healey & Kahana, 2016), we do not intend to (re)fit the models to data. Instead, we adopt a bird's-eye view of the models, allowing us to evaluate their assumptions from a distance remote from the perspective of the original theorists who developed them. Our goal here is two-fold. First, we aim to highlight the strengths of applying computational process models to studying age differences in memory specificity. Second, we aim to identify hidden assumptions and blind spots in current models that must be addressed for a more comprehensive account of these age differences to emerge.

Benchmarks of Age Differences in Memory Specificity

Here, we summarize representative recognition and free recall findings that constitute empirical benchmarks of age differences in memory specificity. Figure 2 depicts these benchmarks. Before continuing, we acknowledge that our review primarily considers memory for items (e.g., specific words or images that were studied), for which ample evidence (discussed in the ensuing) attests to age-related declines in item specificity. However, age differences in context – remembering *where* or *when* something occurred – are also widely established and often dwarf those for item memory (Old & Naveh-Benjamin, 2008). It is conceivable that older adults' difficulties with remembering contextual features of an episode contribute to their less detailed memory for items encountered in those contexts. Indeed, some of the models we will soon review – particularly those rooted in retrieved context theory (Howard & Kahana, 2002) – emphasize the role of contextual retrieval in older adults' memory lapses.

Lure Similarity Effects in Recognition

In recognition procedures, one can infer age differences in memory specificity from the magnified effects of lure similarity on older adults' false alarms (recognizing unstudied items as“old”). Compared to younger adults (typically 18–30), older adults (typically 65–80) generally commit more false alarms to unstudied lures that share salient features (e.g., similar semantic or perceptual characteristics) with studied items, but not to unrelated novel items (Abadie, Gavard, & Guillaume, 2021; Koutstaal, 2003; Koutstaal & Schacter, 1997; Norman & Schacter, 1997; Rankin & Kausler, 1979; Stark, Yassa, Lacy, & Stark, 2013; Trelle, Henson, Green, & Simons, 2017; Tun, Wingfield, Rosen, & Blanchard, 1998; Yassa, Mattfeld, Stark, & Stark, 2011). Figure 2A depicts this typical pattern from

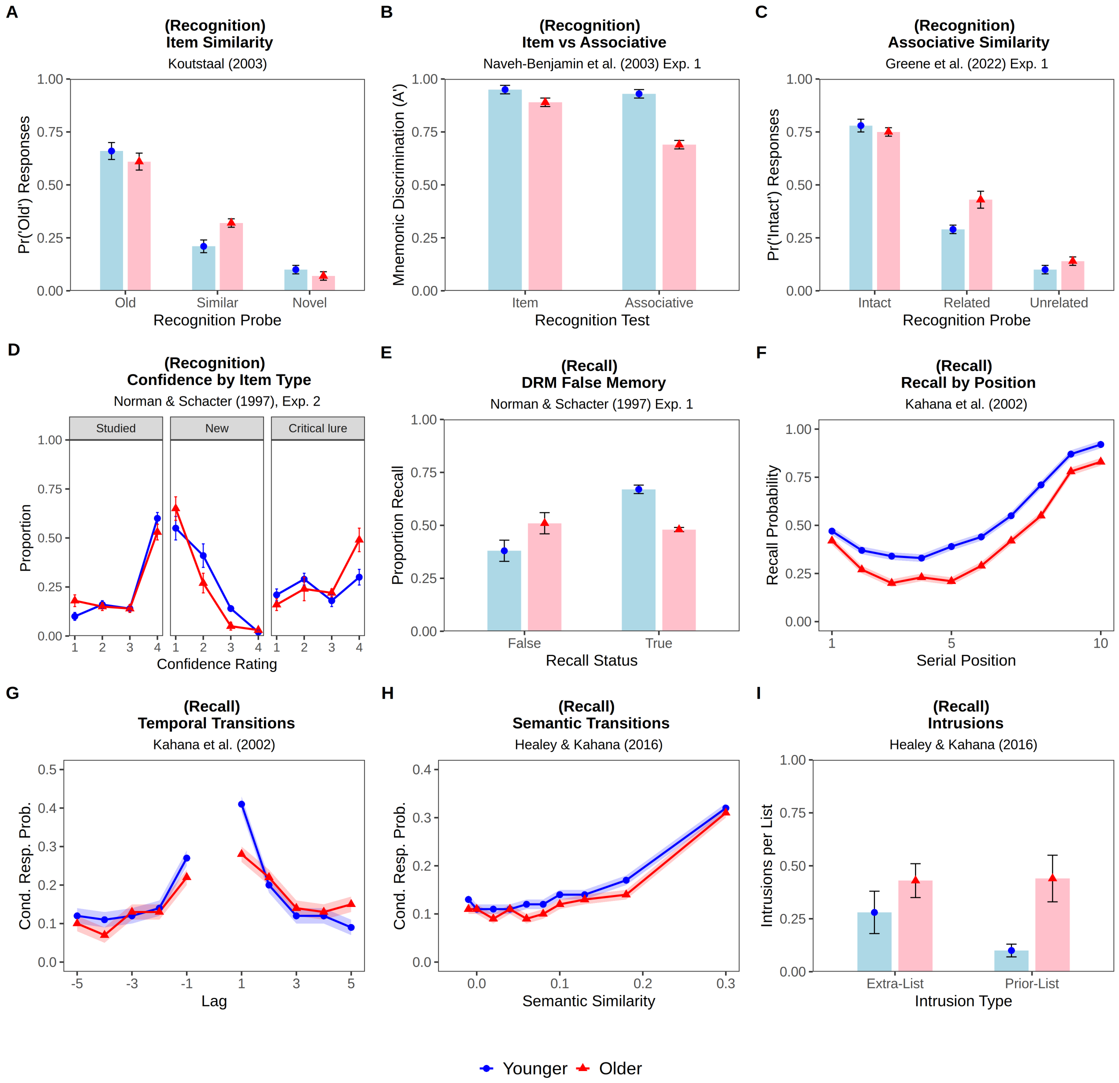

Figure 2

Benchmarks of Age Differences in Memory Specificity *Data in each panel were extracted from published figures, using WebPlotDigitizer, or from tables and re-plotted. As such, the data depicted here are approximate but may not exactly match the values in the original published works. Error bars or ribbons in all panels depict standard errors; solid circles and triangles represent group means for young and older adults, respectively. See text for more details, and online article for color reproduction.*

Koutstaal (2003), in which older adults were approximately 50% more likely than younger adults to misjudge lures (e.g., *silver keys* when *gold keys* were studied) as “old” despite comparable accuracy to novel foils (e.g., a *pen*). Older adults’ heightened sensitivity to lure similarity suggests that they often forget details (e.g., were the keys silver or gold?) but retain more general information (e.g., whether they studied keys or a pen).

Age differences in recognition are magnified on associative compared to item recognition tasks (Naveh-Benjamin, 2000; Naveh-Benjamin, Hussain, Guez, & Bar-On, 2003; Old & Naveh-Benjamin, 2008), likely owing to the greater demands these tasks place on remembering specific information (Craik, 1983; Greene & Naveh-Benjamin, 2020; Surprenant & Neath, 2009). Whereas item recognition could be mediated by familiarity with an item without awareness of when or where it was encountered, associative recognition requires explicit recollection of *which* items co-occurred during encoding (Yonelinas, 1997). For example, was A paired with B or with C? Figure 2B depicts a typical result, from Experiment 1 of Naveh-Benjamin et al. (2003), of large age differences in associative recognition (remembering which two pictures were paired together) but only a modest one in item recognition (recognizing whether a picture is old or new). Nonetheless, age differences in lure similarity effects in associative recognition resemble those in item recognition (Greene, Chism, & Naveh-Benjamin, 2022; Greene & Naveh-Benjamin, 2020, 2022, 2024b; for similar cued recall results, see Castel, 2005; Castel, Farb, & Craik, 2007). In a face-scene associative recognition task (see Figure 2C), Greene et al. (2022) reported substantial age differences in false alarms to test pairs that were similar to what was studied (e.g., an old man, who was studied with one park, appears with a *different* park) but not to those that were dissimilar (e.g., the old man now appears with a gym).

Alongside their heightened false alarms to similar lures, older adults often express high confidence that they studied these lures (Greene et al., 2022; Norman & Schacter, 1997). Figure 2D plots confidence rating data from Experiment 2 of Norman and Schacter

(1997), separately for studied items, new (unrelated) items, and critical lures in a Deese-Roediger-McDermott (DRM) task (Deese, 1959; Roediger & McDermott, 1995), a paradigm known to produce extremely high rates of false recognition and recall (see Figure 2E) among older adults (Devitt & Schacter, 2016; Schacter, Koutstaal, & Norman, 1997). Confidence ratings are ordered as 1 = “sure new,” 2 = “probably new,” 3 = “probably old,” and 4 = “sure old.” Although young and older adults assign similar confidence attributions to studied and new (unrelated) items, older adults endorse critical lures as “old” with high confidence (rating 4) at a much higher rate than younger adults do. In summary, there are both objective (increased false alarms to similar lures) and subjective (increased confidence that these lures were studied) indicators of age differences in memory specificity in recognition tasks.

Age Differences in the Dynamics of Free Recall

Whereas recognition lure similarity manipulations provide a straightforward method of measuring age differences in memory specificity, in free recall, these differences must be inferred in less obvious ways. There are typically large age differences in correct recall (Craik & McDowd, 1987; Danckert & Craik, 2013; Rhodes et al., 2019), as shown, for example, in the DRM true recall data depicted in Figure 2E. However, an isolated analysis of correct recall might *underestimate* how much one actually remembers. Most free recall tasks instruct participants to recall *only* the items from the most recent list. Given this instruction, a participant who remembers an item’s gist (e.g., that they studied a fruit) but not its exact identity (e.g., whether it was an “apple” or an “orange”) might recall no item or one that was not on the list, lowering their correct recall. Thus, to infer age differences in memory specificity in free recall, we must consider additional outcomes beyond correct recall rates.

Figure 2F through 2I depict representative findings of age differences in four key metrics from both immediate (Kahana, Howard, Zaromb, & Wingfield, 2002) and delayed (Healey & Kahana, 2016) free recall that collectively highlight age changes in memory specificity. The recall by serial position curve in Figure 2F breaks down age differences in veridical recall into the specific encoding positions in the list where these differences emerge. Although age differences are negligible for the first item (primacy) and the last couple items (recency), older adults recall fewer items from the middle of the list, suggesting they struggle the most with remembering items encountered in less distinctive positions (for similar findings in serial recall, see Golomb, Peelle, Addis, Kahana, & Wingfield, 2008).

The recall transition dynamics plotted in Figure 2G and Figure 2H provide deeper insights. The lag conditional response probability (lag CRP) curve (Kahana, 1996) in Figure 2G plots the probability of recalling item j after recalling item i based on the temporal distance (lag) between i and j during encoding (e.g., lags of 1 and -1 indicate that j was studied immediately after or before i, respectively). Young adults have a strong tendency to recall together items that were studied close in time, reflected in the much higher conditional response probabilities at small (e.g., lag = 1) versus large (e.g., lag = 5) lags in Figure 2G, particularly in the forward direction (positive lags). This tendency to temporally cluster recalls is attenuated (but not eliminated) among older adults, as reflected in the more subtle differences in CRP values for small versus large values of lag in the older adult data in Figure 2G. This points to a reduced ability of older adults to remember the specific time in which an item appeared (Kahana et al., 2002; Golomb et al., 2008; Naveh-Benjamin, 1990) – a *context* failure.

However, older adults exhibit a preserved tendency to recall together items that share similar semantic content (Figure 2H; Healey & Kahana, 2016), pointing to an intact ability to remember the meanings of items one encountered. Similar results have been reported in categorized free recall (Wingfield & Kahana, 2002; Wingfield, Lindfield, & Kahana, 1998), in which participants study multiple items belonging to each of several categories (e.g., “apple,” “orange” and “pear” from the *fruit* category, and “plane,” “truck,” and “train” from the *vehicle* category). In these tasks, older adults semantically cluster their recalls (e.g., recalling all *fruit* items before recalling *vehicle* items) to a comparable extent as younger adults do.

Finally, older adults make more intrusions – recalling items that were not present on the most recent list – than younger adults do (Figure 2I; Healey & Kahana, 2016), further pointing to age differences in memory specificity. This is particularly so because intrusions tend to be strong semantic associates of studied items (e.g., Zaromb et al., 2006). Collectively, the reduction in correct recalls (particularly for items from less distinctive serial positions; Figure 2F), the weakened tendency to recall together items studied close in time (Figure 2G), the preserved effect of semantic similarity on recall transitions (Figure 2H), and the elevated intrusions of semantically similar items (Figure 2I) indicate that older adults forget specific details in free recall – like exactly which items were studied, and when they were studied. Yet, older adults often remember more general information, like what types of items were studied, leading to their elevated false recalls of similar items.

A Current Leading Explanation for Age Differences in Memory Specificity

The empirical benchmarks highlight an age-related decline in memory specificity but do not address why these declines occur. Answers have been advanced by several theories on memory representation (e.g., Brainerd & Reyna, 2015; Craik, 2002; Robin & Moscovitch, 2017). Although these theories have rarely been formalized in computational models (for an exception, see Chang et al., 2025), we briefly discuss one leading theory as a bridge to more formal modeling of these benchmarks. We limit our focus here to fuzzy-trace theory (Brainerd & Reyna, 1990; Reyna & Brainerd, 1995) not because it is inherently the correct account of age differences in memory specificity, but because it is generally representative of most other representational theories (Greene & Naveh-Benjamin, 2023a) while enjoying a relatively higher degree of mathematical formalization (Brainerd et al., 2009; Chang et al., 2025). It also emphasizes cognitive, rather than neural, mechanisms of age differences in memory specificity, aligning it more closely with the computational models we review in the next section (for proposed neural mechanisms, see Stark, Kirwan, & Stark, 2019; Yassa et al., 2011).

Fuzzy-trace theory posits that memories are represented in two dissociated traces – a *verbatim* trace representing the specific details of the episode, and a *gist* trace representing its meaning (Brainerd & Reyna, 1990; Reyna & Brainerd, 1995). Compared to gist traces, verbatim traces consume more attention and processing time during encoding and retrieval and are more vulnerable to interference and decay. These assumptions have been upheld in empirical studies reporting more pronounced effects of divided attention (Greene & Naveh-Benjamin, 2023b; Odegard & Lampinen, 2005), speeded encoding (Greene & Naveh-Benjamin, 2023c, 2024b; Tatler, Gilchrist, & Rusted, 2003), and study-test delay (Greene & Naveh-Benjamin, 2022; Sachs, 1967; Sekeres et al., 2016) on verbatim than gist memory. Gist representations can be encoded and retrieved relatively more automatically because they are molded by prior knowledge, allowing one to rapidly make sense of an episode by connecting it with established semantic memory. Thus, individuals with less developed knowledge bases, like young children, are less prone to semantic false memories like those observed in the DRM paradigm (Brainerd, Reyna, & Forrest, 2002).

Collectively, the reduced processing demands, greater stability, and inherent connection to prior knowledge make gist traces the dominant form of memory representation among older adults (Brainerd & Reyna, 2015; cf., Greene & Naveh-Benjamin, 2024a). These properties of gist traces overcome older adults' limitations in attention (Craik & Byrd, 1982), processing speed (Salthouse, 1996), and inhibition (Hasher & Zacks, 1988), and connect with their expansive knowledge base (Umanath & Marsh, 2014), allowing them to retain the core essence of events for which they often forget more specific (verbatim) details (cf., Radvansky & Dijkstra, 2007).

Mathematical models of fuzzy-trace theory (Brainerd et al., 1999; Brainerd, Wright, Reyna, & Mojardin, 2001; Brainerd et al., 2009; Stahl & Klauer, 2008) have provided converging evidence that adult age differences in memory quality are primarily restricted to verbatim but not gist representations. Several studies testing age differences in lure similarity effects in recognition (Abadie et al., 2021; Greene & Naveh-Benjamin, 2020, 2022, 2024b) have relied upon the (simplified) conjoint recognition MPT model depicted in Figure 1. These models have consistently identified age-related declines in V (verbatim) but not G (gist) parameters (for applications to free recall, see Brainerd et al., 2009). More recently, fuzzy-trace theory's verbatim/gist distinction has been embedded within a global matching model framework (Chang et al., 2025), a class of computational models that we will soon review. To return to our earlier discussion of different classes of computational models, Chang et al.'s (2025) model more completely instantiates memory trace dynamics than the earlier conjoint recognition models. Thus, it could be a valuable tool for future research assessing *why* an age difference in V emerges at all.

Process Interpretations of Age Differences in Memory Specificity

There have been a few isolated attempts to computationally model the benchmarks of age differences in memory specificity depicted in Figure 2. Table 1 summarizes these previous attempts. Although most of these attempts were limited to explaining age differences in a single type of task like recognition (e.g., Stephens & Overman, 2018) or serial recall (e.g., Neath & Surprenant, 2007; Surprenant, Neath, & Brown, 2006), they are almost unanimous in their endorsement of representational impairments as a key driver of age differences in task performance. Global matching models (reviewed in the next section), like those based on MINERVA 2 (Hintzman, 1984) or REM (the *Retrieving Effectively from Memory* model; Shiffrin & Steyvers, 1997), attribute age differences in recognition to older adults' degraded (or reduced fidelity) representations of encoded events, which results in less diagnostic information available to discriminate new from old experiences (Benjamin, 2010; Stephens & Overman, 2018). Retrieved context models (reviewed in the section "Retrieved Context Models") have implicated multiple processes underlying age differences in free recall (Healey & Kahana, 2016), with one of these processes pertaining to noisier item representations at retrieval. Models explaining age differences in serial recall, a task similar to free recall but with added constraint of recalling items in the order in which they appeared[2], have similarly attributed these differences to reduced fidelity representations of items (Neath & Surprenant, 2007; Surprenant et al., 2006) or temporal context (Maylor et al., 1999), which blurs older adults' memories for which items appeared in which specific list positions. Finally, models based on connectionist principles (Buchler & Reder, 2007; Li, Naveh-Benjamin, & Lindenberger, 2005) assume that older adults' recognition failures stem from more diffuse association networks, which makes representations of individual episodes less distinctive.

In the next sections, we take a deeper dive into global matching models and retrieved context models. We focus specifically on these classes of models owing to their relatively widespread use in the mainstream memory literature (for a review, see Kahana, 2020). Moreover, global matching and retrieved context models have previously identified processes underlying age differences in recognition (Benjamin, 2010; Stephens & Overman, 2018) and recall (Healey & Kahana, 2016),[3] respectively. They are thus well-suited to modeling age differences in memory specificity (the benchmarks we presented in Figure 2). We will later revisit the ideas of alternative models, like connectionist models, in our closing discussion.

Global Matching Models

Overview

Global matching models describe memory retrieval as a comparison process between a probe item and multiple stored traces in memory (Clark & Gronlund, 1996; Osth & Dennis, 2024), as illustrated in Figure 3. Global matching is well suited to explaining recognition memory (e.g., Arndt & Hirshman, 1998) and has been extended to explaining

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[2] As in free recall, in serial recall, there are large age differences in correct and false recall, along with a higher incidence of order errors (recalling items in the wrong position) among older adults (Golomb et al., 2008; Maylor, Vousden, & Brown, 1999; Naveh-Benjamin, Cowan, Kilb, & Chen, 2007).

[3] Healey and Kahana (2016) extended their retrieved context model to explain age differences in item recognition, as well.

Model	**Processes of Age-Related Memory Impairment**	**Representative Papers**	**Further Reading**
DRYAD	Reduced representational fidelity, especially for context.	Benjamin (2010)	MINERVA 2 (Hintzman, 1984)
REM	Fewer item features encoded and/or similar features represent multiple items (poor distinctiveness).	Stephens & Overman (2018)	Shiffrin & Steyvers (1997), Criss & Shiffrin (2005)
SIMPLE	Degraded item representations reduce item distinctiveness	Surprenant et al. (2006)	Brown et al. (2007)
Feature Model	Less efficient encoding resulting in impoverished item representations	Neath & Surprenant (2007)	Nairne (1990)
OSCAR	Less distinctive temporal context signals associated with each item	Maylor et al. (1999)	Brown et al. (2000)
CMR2	Noisier retrieval and failures to sustain attention, retrieve contexts, and filter intrusions.	Healey & Kahana (2016)	Lohnas et al. (2015), Howard & Kahana (2002)
SAC	Diffuse semantic association networks activate similar episodes, reducing distinctiveness	Buchler & Reder (2007)	Reder et al. (2000)
Binding Model*	Neuromodulatory declines yield less distinctive stimulus representations	Li et al. (2005)	Li et al. (2001)

Table 1

Computational Modeling of Age Differences in Memory.

*Note. DRYAD = Density of Representations Yields Age-Related Dissociations. REM = Retrieving Effectively from Memory. SIMPLE = Scale-Invariant Memory, Perception, and Learning. OSCAR = OSCillator-based Associative Recall. CMR2 = Context Maintenance and Retrieval. SAC = Source of Activation Confusion. * = the full name of the model is the feature-association conjunctive-binding model.*

frequency judgments (Hintzman, 1988), categorization (Chubala, Johns, Jamieson, & Mewhort, 2016; Curtis & Jamieson, 2019), cued recall (Hintzman, 1984, 1986), and serial recall (Guitard, Saint-Aubin, Reid, & Jamieson, 2025a, 2025b), among other tasks.

Although numerous global matching frameworks exist, including MINERVA 2 (Hintzman, 1984), REM (Shiffrin & Steyvers, 1997), TODAM (*Theory of Distributed Associative Memory*; Murdock, 1982), GCM (*Generalized Context Model*; Nosofsky, 1986), and SAM (*Search of Associative Memory*; Gillund & Shiffrin, 1984), we limit our focus to MINERVA 2 as a representative global matching model. The process assumptions of MINERVA 2 serve as the bedrock of current computational theories of age-related memory change, such as Benjamin's (2010) *Density of Representations Yields Age-Related Dissociations* (DRYAD) framework (cf. Guitard, Reid, Greene, Saint-Aubin, & Jamieson, 2025). It has also recently provided a computational foundation for formalizing fuzzy-trace theory's verbatim-gist distinction (Chang et al., 2025).

MINERVA 2 (Hintzman, 1984, 1986, 1988) represents each studied item as a separate trace in memory, a standard approach in global matching models (for alternative approaches, see Murdock, 1982). Each item is represented as an n-dimensional feature vector, where each dimension corresponds to the presence or absence of a given feature. Conventionally, these vectors were randomly generated (i.e., engineered) to capture inter-item similarities (e.g., Arndt & Hirshman, 1998). Recent advances (e.g., Chang et al., 2025; Guitard, Saint-Aubin, et al., 2025a, 2025b; Osth & Zhang, 2024; Reid, Yang, & Jamieson, 2023; Reid & Jamieson, 2023) have supplanted the use of engineered feature vectors with realistic representations derived from methods like latent semantic analysis (Landauer & Dumais, 1997) or word2vec (Mikolov, Sutskever, Chen, G., & Dean, 2013) that represent similarities across items based on their co-occurrences in natural language. These advances make MINERVA 2 a scalable cognitive model (see Johns, Jamieson, & Jones, 2023), one that integrates semantic and episodic memory in a single framework (cf. Guitard, Saint-Aubin, et al., 2025a). We will soon revisit the implications

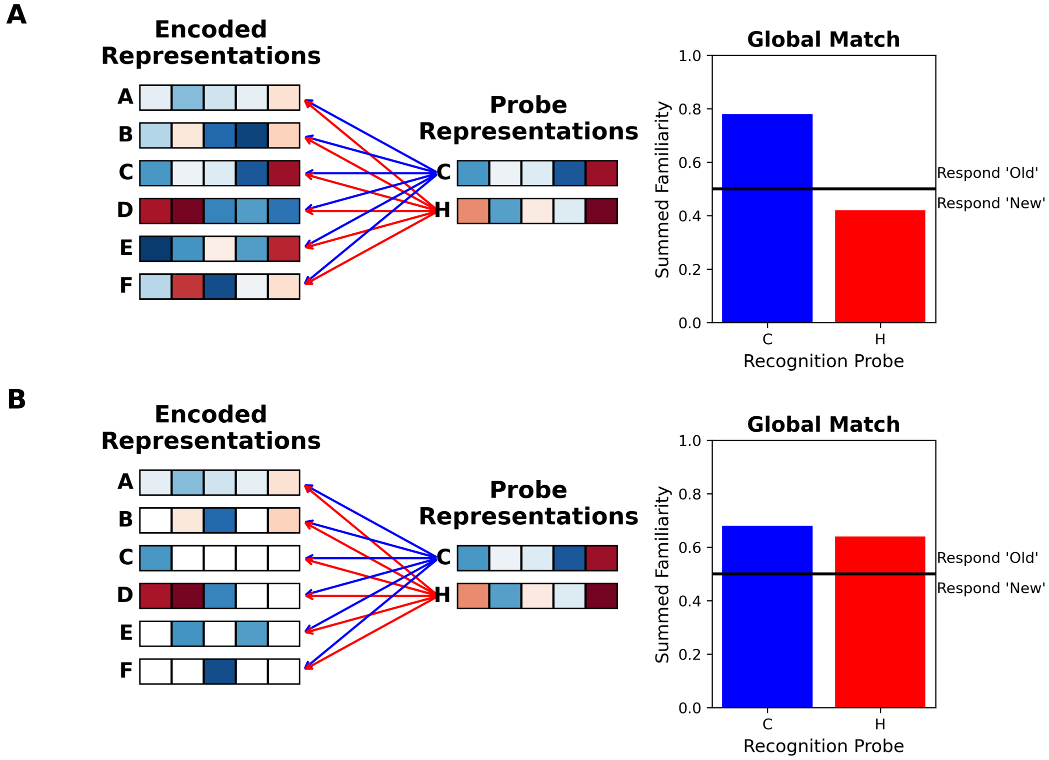

Figure 3

How Global Matching Works.

*Global matching models represent items as n-dimensional feature vectors. The learning rate (e.g., L) determines how many features are faithfully stored in memory. In **A**, the learning rate is high, ensuring high fidelity representations of each encoded item A–F (simulating a young adult). In **B**, the learning rate is low, resulting in impoverished representations of each encoded item A–F (simulating an older adult). When a recognition probe is presented, whether an old item (e.g., C) or a new one (e.g., H), its representation is compared against all encoded representations. A global match is computed based on the summed similarities of the probe with the encoded items, and if the familiarity exceeds a threshold, the probe is judged to be an old item; otherwise, it is classified as new. The sparser representations of encoded items in panel B reduces the number of available dimensions along which mismatches can be detected, increasing false alarms to unstudied items. See online article for color version.*

of these advances in understanding age differences in memory specificity.

The core parameters of MINERVA 2 are summarized in Table 2. During encoding, each item's feature vector is stored within a memory matrix M, and the success of encoding depends on the learning rate L. Higher values of L yield richer item representations, as more of their features are successfully stored in M, whereas lower values of L result in impoverished representations, where many features are replaced with random noise (e.g., 0's). During recognition, the test probe is compared against all traces stored in M simultaneously to derive a global familiarity value f. Formally, this familiarity (or global match) computation proceeds as follows:

$$f = \sum_i \left(\frac{\sum_j (q_j \times M_{ij})}{\sqrt{\sum_j p_j^2}\sqrt{\sum_j M_{ij}^2}} \right)^{\tau} \tag{1}$$

In Equation 1, q_j refers to the j^{th} feature of the memory cue (q) and M_{ij} refers to the j^{th} feature of the i^{th} memory trace stored in M. The operation inside the large parentheses computes the cosine similarity between the cue vector and the vector of the i^{th} memory trace. The parameter τ raises these cosine similarity values to an exponent, scaling the similarities to impact the "sharpness" of activations. Higher values of τ amplify the signal-to-noise ratio, such that memory traces with high cosine similarities to the cue are given more weight in the global match computation. Summing the scaled cosine similarities of the cue with each memory trace gives the overall global familiarity f of the probe. This familiarity value is then compared against a threshold T, and if it exceeds the threshold, the probe is judged to be "old."

Modeling Age Differences

The global matching computation described in the preceding section (see Equation 1) provides a simple but elegant way of modeling true and false recognition (Arndt & Hirshman, 1998; Chang et al., 2025), making it a viable model for understanding age differences in the recognition benchmarks depicted in Figure 2. Despite its relative simplicity, MINERVA 2 contains several unique ways of simulating these age

Param.	**Description**	**Modeling Age Differences**
L	Controls the learning rate (i.e, how many features of each item are stored in memory).	Lowering L yields sparser representations, reducing distinctions between old and new items.
τ	Controls the cue-specificity of retrieval (i.e., which stored traces contribute most strongly to familiarity computation).	Lowering τ makes retrieval less selective, such that weaker traces contribute to the overall familiarity of a probe.
T	Determines the decision threshold (i.e., the familiarity threshold for judging an item to be "old").	Lowering T makes recognition more liberal, increasing false alarms.

Table 2

MINERVA 2 Model Parameters and Their Relation to Age Differences in Recognition

differences (see Table 2).

To demonstrate how age differences could arise in the model, we conducted a small-scale simulation using a variant of MINERVA 2 that incorporates structured semantic representations derived through latent semantic analysis (Reid & Jamieson, 2022). We trained the model on 10 six-item DRM-style lists of semantic associates to an unpresented critical lure. Lists were created by selecting words with similar University of South Florida word association, rhyme, and word fragment norms (Nelson, McEvoy, & Schreiber, 2004) to maximize the probability of producing false recognition for the critical lures; complete details can be found in in Experiment 1 of Guitard, Saint-Aubin, et al. (2025b). At test, the model was presented with the 60 studied items, 10 corresponding critical lures, and 70 unrelated distractors. We simulated the recognition behavior of the model under four conditions, each with 200 simulations (corresponding to 200 participants performing the task under the same condition), to demonstrate two approaches of modeling age differences. In all conditions, we held the decision threshold T constant between the young and older adult version of the model; we fixed T to the 42.86th percentile of the familiarity distribution to match the study-to-test ratio (i.e., 60 studied items out of 140 total test items). Model simulation code can be found at `https://osf.io/7mfh4/overview?view_only=6cce1ea4ef7940daa0b3793054cb2747`.

Figure 4 represents the results of our simple demonstration. In Figure 4A, we specified a different learning rate for simulating young adult ($L = 0.6$) and older adult ($L = 0.4$) performance, while holding $\tau = 3$ constant across conditions. Lowering L increases the probability that a given feature value is replaced by 0, resulting in sparser or more impoverished representations. As a consequence, when cosine similarity is computed (see Equation 1), the surviving (i.e., non-zero) features receive proportionally greater weight. This is a consequence of the normalization of the feature vectors in computing cosine similarity; it *amplifies* coincidental matches on the few remaining active dimensions. This can lead to a modest increase in summed familiarity for distractors (as illustrated in Figure 3), even though encoding accuracy is overall poorer. Indeed, the lower learning rate resulted in a pattern of results somewhat aligned with the benchmark finding of lure similarity effects on item recognition in Figure 2A. Although the difference in false alarms to similar lures is smaller in the simulations than in the observed data, directionally, the model predicts more false alarms when L is reduced.

Meanwhile, in Figure 4B, the learning rate was held constant across age groups ($L = 0.6$), but τ varied, with a higher value for young adults ($\tau = 5$) than older adults ($\tau = 3$). Recall from Equation 1 that τ scales the magnitude of the cosine similarity value between the memory probe q and each individual memory trace M_i. If $\tau = 1$, then we just add together the cosine similarities for q with all traces in memory. But as τ increases, the relative weights of the cosine similarity values become apparent; items that are *more* similar to the probe play a greater role in the global match computation. Consider, for example, that the cosine similarities between the memory probe q and three items M_1, M_2, and M_3

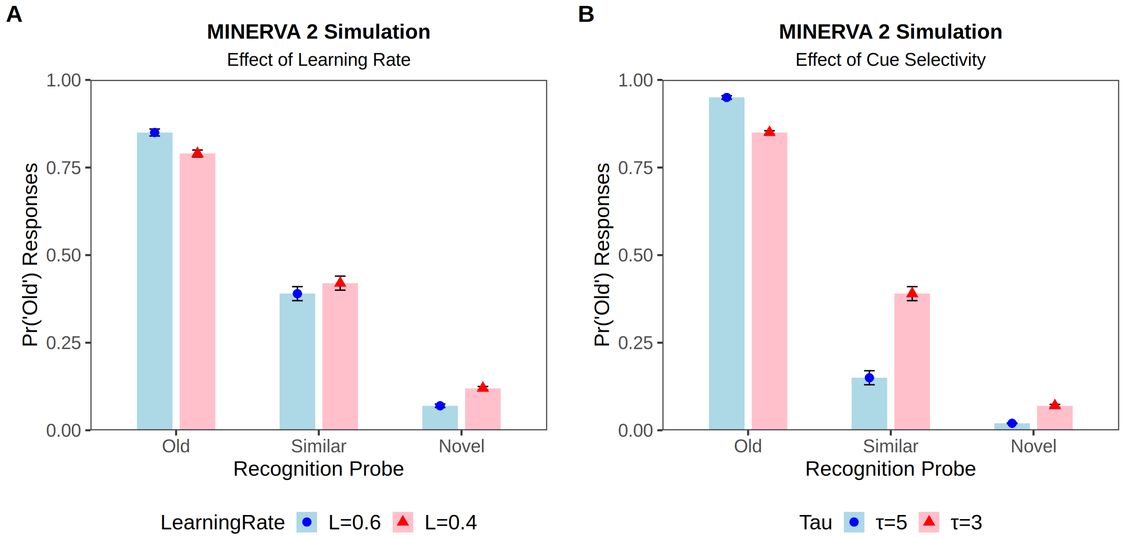

Figure 4

MINERVA 2 Simulation of Age Differences in Recognition

We simulated the recognition performance of 200 hypothetical participants per condition using MINERVA 2. Each simulation involved learning 10 six-item lists of semantic associates to an unpresented critical lure (see text for details). Recognition tests featured the 60 studied items, 10 corresponding lures, and 70 novel (unrelated) items. In ***A****, a lower learning rate (L) was used to simulate the performance of older relative to younger adults, while holding τ constant. In* ***B****, different settings of cue selectivity (τ) were used to simulate these age differences, while holding L constant. See online article for color version.*

in memory are 0.2, 0.3, and 0.4, respectively. At $\tau = 1$, the memory item most resembling the probe (M_3) contributes twice as strongly to the global match as the memory item least like the probe (M_1). But if we square these cosine similarities ($\tau = 2$), now M_3 contributes four times as much information as M_1 ($0.4^2 = 0.16$ versus $0.2^2 = 0.04$). The relative weight of M_3 over M_1 doubles yet again if we set $\tau = 3$. Thus, as τ increases, retrieval increasingly favors matches with high similarity to the probe. Indeed, the higher setting of τ resulted in more selective retrievals for younger adults, dramatically lowering their false alarm rates.

The foregoing simulation demonstrates two ways in which an age difference in effects of lure similarity on recognition accuracy could arise in a global matching framework. The change in learning rate in Figure 4A aligns with conventional approaches of modeling age differences in recognition with global matching models (Benjamin, 2010; Guitard, Reid, et al., 2025; Stephens & Overman, 2018). A viable alternative to the lower learning rate was demonstrated in our second simulation (Figure 4B), which revealed that age differences in effects of lure similarity could stem from the cue selectivity of retrieval (differences in τ). Although typically researchers set $\tau = 3$ (Hintzman, 1984, 1986, 1988), τ is a free parameter that could vary across conditions (e.g., Chang et al., 2025). When τ is lower, items that are weakly activated by a cue nonetheless contribute noise to the signal, inflating the global match of the probe with the contents of memory. Thus, even if older adults encode as many features of each item as younger adults do (i.e., $L_{old} = L_{young}$), an age difference in τ (i.e., $\tau_{old} < \tau_{young}$) would make older adults more prone to false alarms to unstudied items, especially to similar lures that enjoy higher cosine similarities with studied items, a finding confirmed by our demonstrative simulation.

Explanatory Gaps in Global Matching Models

As our foregoing discussion highlights, global matching models like MINERVA 2 can readily explain age differences in memory specificity in recognition tasks. Yet, these models have several explanatory shortcomings.

Can Global Matching Explain Age Differences in Recall? Global matching works by comparing a probe to existing memory traces, but in free recall, no probes are provided at retrieval. Thus, whether the mechanisms these models use to explain age differences in recognition would similarly explain age differences in free recall cannot be ascertained currently. Any future application of global matching models to free recall would have to contend with the temporal contiguity effect (Kahana, 1996), necessitating a role of context in the model.

Some promising developments suggest that MINERVA 2 may one day be suited to modeling free recall. Recent work has extended MINERVA 2 to the domain of serial recall by incorporating positional representations into the model (Guitard, Saint-Aubin, et al., 2025a, 2025b; Guitard, Reid, et al., 2025). Each item is represented by both its lexical content (e.g., its semantic or phonological features) and its positional content (i.e., which position it occupies in a list), and a free parameter governs the similarities between positional representations of adjacent items in a list. These additions make MINERVA 2 well-suited to explaining order errors in serial recall, but it remains to be seen whether they can also account for the free recall dynamics depicted in Figure 2.

What Causes Poorer-Fidelity Encoding? Global matching models typically attribute age differences in recognition to reduced fidelity of encoding, captured by a lower learning rate in older adults (Benjamin, 2010; Guitard, Reid, et al., 2025; Stephens & Overman, 2018). Although these models are more formal than verbal theories, they do not reveal *why* older adults have more impoverished representations. In MINERVA 2, for instance, there is no theoretical justification for why L is lower in one condition than another; it is simply a necessity for the model to be able to simulate a specific pattern of data, like age differences in recognition. In a sense, although the model itself is a *process* model (in that it explains a process of how memory operates), its explanation for age differences in memory is descriptive. Without defining the role of processes that affect the learning rate (e.g., how attention is deployed to different features of an item), the model cannot reveal the causes of poorer-fidelity encoding on its own. One could of course observe a lower setting of L in empirical conditions of divided versus full attention that implicates a role of attention in the learning rate (e.g., Chang et al., 2025), yet this would still rely on *ad hoc* assumptions about how attention and memory interact to influence encoding fidelity. Note that this limitation also applies to our simulation of varying τ. Although higher τ makes retrieval more selective (favoring items that are more similar to the probe), the model does not explicate mechanisms that dictate the value τ assumes.

The point is that global matching models like MINERVA 2 do not generally explain what unmeasured processes affect their parameters, and thus they do not fully explain *why* older adults encode or retrieve less detailed memories.[4] But there is reason for optimism. The incorporation of structured item representations derived from natural language models into MINERVA 2 and similar models (Chang et al., 2025; Guitard, Saint-Aubin, et al., 2025a, 2025b; Osth & Zhang, 2024; Reid et al., 2023; Reid & Jamieson, 2022, 2023) holds great promise for advancing more process-pure theories of age changes in memory specificity. Because these models derive their representations from item co-occurrences in natural language, there are opportunities to explain age differences in the fidelity of representations in more mechanistic ways. For example, following the approach of Johns, Jones, and Mewhort (2012), tuning parameters that affect the model's lexicon (its "long-term memory") could directly influence the representations it stores for each item in a memory experiment. If, for example, item representations were derived from a larger lexicon (simulating an older adult's more expansive long-term memory), then there could be potential for more diffuse associations across items that would be otherwise unrelated in a model possessing a smaller lexicon (like a younger adult's long-term memory). This approach would echo the idea of connectionist models like SAC (Buchler & Reder, 2007) that attribute older adults' recognition errors to more diffuse association networks, whereby each item activates more features distributed across more items, reducing the distinctiveness of each trace in memory. Exploring the downstream consequences of changes to a global matching model's long-term memory constitutes a highly promising direction for future computational modeling of age differences in memory specificity.

Retrieved Context Models

Overview

Retrieved context theory (Howard & Kahana, 1999, 2002) posits that items bind to the specific contexts in which they occur; retrieving an item retrieves its previous contexts,

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[4] To be clear, global matching models can be more sophisticated than what we have described here. For example, some models include temporal dynamics that capture the speed with which competing representations enter the global match computation (Cox & Shiffrin, 2017; Osth, Zhang, & Williams, 2025).

and vice versa. Retrieving an item's past contexts also cues items encountered in temporally similar contexts or those that are semantically related, thus facilitating temporal or semantic recall transitions like those observed in Figure 2G and 2H, respectively. These assumptions have been formalized in TCM (Howard & Kahana, 2002) and the *Context Maintenance and Retrieval* (CMR; Polyn et al., 2009) and CMR2 (Lohnas, Polyn, & Kahana, 2015) models.

Table 3 summarizes the representational assumptions of retrieved context models, while Table 4 summarizes the core parameters of the CMR2 model. Each time an item is encoded or retrieved, it activates its unique feature representation on F (the feature vector). No two items are represented by the same feature, ensuring complete orthogonality in item representations. Nonetheless, items with similar semantic content, or those encountered in similar temporal contexts, become associated through their co-activation in context. Because context is a continuously evolving state, the context active at the time item i is presented resembles the context associated with items $i-1$ and $i+1$ more strongly than items from the remote past. Furthermore, when item i is presented, it co-activates semantically associated items, increasing those items' representations in the current state of context. Associative matrices M^{FC} and M^{CF} store feature-to-context and context-to-feature associations, respectively. These associations are a weighted sum of pre-experimental (*semantic*) associations, derived from item co-occurences in natural language (Landauer & Dumais, 1997; Mikolov et al., 2013), and newly formed experimental (*episodic*) associations acquired through learning. Free parameters γ_{FC} and γ_{CF} weight the influence of experimental to pre-experimental associations; higher values of these parameters yield stronger emphasis on newly formed over long-standing associations (see Table 4).

Figure 5 illustrates the encoding and retrieval processes in CMR2. During encoding, an item (e.g., the word "cat") activates its feature representation $\mathbf{f}_i$ on F. Passing $\mathbf{f}_i$

Component	**How it is Represented in the Model**
Context	The state of contextual experience at time i is represented by the vector $\mathbf{c}_i$, which represents items based on recency, such that more recently encoded items are more strongly represented in $\mathbf{c}_i$ than distantly encoded items are.
Items (Features)	Each item activates a single (localist) feature on F (the n-dimensional feature vector), such that $\mathbf{f}_i \neq \mathbf{f}_j$ for any items i and j.
Associations Between Items and Contexts	Associative matrices M^{FC} and M^{CF} store feature-to-context and context-to-feature connections, respectively. Each element in M^{FC} and M^{CF} is a weighted sum of pre-experimental (semantic) and experimental (episodic) associations formed through Hebbian learning.

Table 3

Representational Assumptions of Retrieved Context Models.

through M^{FC} retrieves the item's prior contexts.[5] Blending this retrieved context with the current context yields a new state of context that carries over into the next encoding episode. A free parameter β_{enc} weights how strongly context updates with each encoding event, effectively controlling how similar the context is between adjacent items (see Table 4). If β_{enc} is high, context drifts substantially between items, yielding more distinctive item-context associations, whereas if β_{enc} is low, context remains relatively stagnant across encoding, blurring contextual distinctions among items. Over the course of learning items in a sequence, earlier context states gradually fade, such that the relative activation of items in the current context is determined by how recently they were encoded.

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[5] This process is formalized by the equation $\mathbf{c}_i^{\mathbf{retr}} = M^{FC} \cdot \mathbf{f}_i$, where $\mathbf{c}_i^{\mathbf{retr}}$ denotes the retrieved context of the i^{th} item. Context then updates according to the equation $\mathbf{c}_{i+1} = \rho_i \mathbf{c}_i + \beta_{enc} \mathbf{c}_i^{\mathbf{retr}}$, where $\mathbf{c}_{i+1}$ is the new state of context, $\mathbf{c}_i$ is the current state of context, β_{enc} is a free parameter controlling how strongly context updates to the retrieved context ($\mathbf{c}_i^{\mathbf{retr}}$), and ρ_i is a normalizing constant (see Polyn et al., 2009).

Parameters	**Description**
β_{enc}, β_{retr}*, β_{post}^{recall}	Control how much context updates following each encoding (β_{enc}) or retrieval (β_{retr}) event or between lists (β_{post}^{recall}). Higher values yield greater context drift between successive events.
γ_{FC}, γ_{CF}	Weight the relative influence of experimental versus pre-experimental feature-to-context (γ_{FC}) and context-to-feature (γ_{CF}) associations. Higher values emphasize experimental associations.
s_{FC}, s_{CF}	Scale the magnitude of pre-experimental (semantic) feature-to-context (s_{FC}) and context-to-feature (s_{CF}) associations. Higher values make these associations stronger.
ϕ_s*, ϕ_d*	Increases encoding strength for the first item (ϕ_s) and decays this added strength with each additional item (ϕ_d) to capture the primacy gradient in recall. Higher values of both result in a steeper primacy effect.
κ, λ*, η*	Control the retrieval race. κ determines how fast item activations decay (higher κ = faster decay). λ determines how much each item inhibits other items during the race (higher λ = stronger inhibition). η governs the amount of noise in the retrieval process (higher η = more noise).
c_{thresh}*	Threshold for filtering recalls based on similarity between an item's retrieved context and the current context. Higher values yield more conservative recalls.
α, ω	Scale an item's retrieval threshold after it is successfully recalled. ω increases the item's threshold for the next recall attempt, making re-recall less likely, and α gradually lowers the threshold back to baseline with each successive recall attempt.

Table 4

CMR2 Model Parameters

Note. Values of the asterisked parameters reported to differ between young and older adults (Healey & Kahana, 2016)

For example, when “ball” is encoded as the sixth item in the list in Figure 5A, the newly generated context $\mathbf{c}_i$ strongly represents “ball” and “tool” (the fifth item) but only weakly represents items from much earlier in the list (e.g., “cat,” “tree”). A pair of primacy parameters ϕ_s and ϕ_d (see Table 4) controls the primacy gradient – the well-established tendency for superior recall of the first item(s) in a list relative to middle-position items (see Figure 2F) – by increasing the encoding strength for the first item in the list.

The recall process depicted in Figure 5B is a modeled as a competitive race among recall candidates (cf. Usher & McClelland, 2001).[6] Items are cued for recall in proportion to their relative representation in the current context at the start of retrieval, which determines their starting point in the recall race. For example, in the first panel of Figure 5B, the most recently encoded item (“ball”) has the strongest activation in the start-of-retrieval context, so it enjoys the highest starting point (closest to its retrieval threshold) in the second panel. During the course of the race (second panel of Figure 5B), evidence in favor of each item accumulates gradually (see Table 4 for a description of parameters governing this process). Given the stochastic nature of the recall process, the first item to reach its threshold is not always the item with the strongest activation in the current context. For example, despite being the item with the third highest activation at the start of the race, “frog” wins the competition in Figure 5B.

Once an item wins the competition, it reactivates its feature $\mathbf{f}_i$ on F (third panel in Figure 5B). The ensuing process plays out like encoding, whereby passing $\mathbf{f}_i$ through M^{FC} retrieves the past context associated with the item. Next, this retrieved context ($\mathbf{c}_i^{\mathbf{retr}}$) is compared to the current state of context (fourth panel in Figure 5B). If the similarity between the two context states exceeds a threshold (i.e., $\mathbf{c}_i^{\mathbf{retr}} \cdot \mathbf{c}_i \geq c_{thresh}$), the item is

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[6] For recognition, the process begins at the third panel, where a given memory probe activates its corresponding feature. This in turn retrieves its past contexts, which are then compared against the current context to determine whether the context associated with the probe is familiar enough to warrant an “old” response.

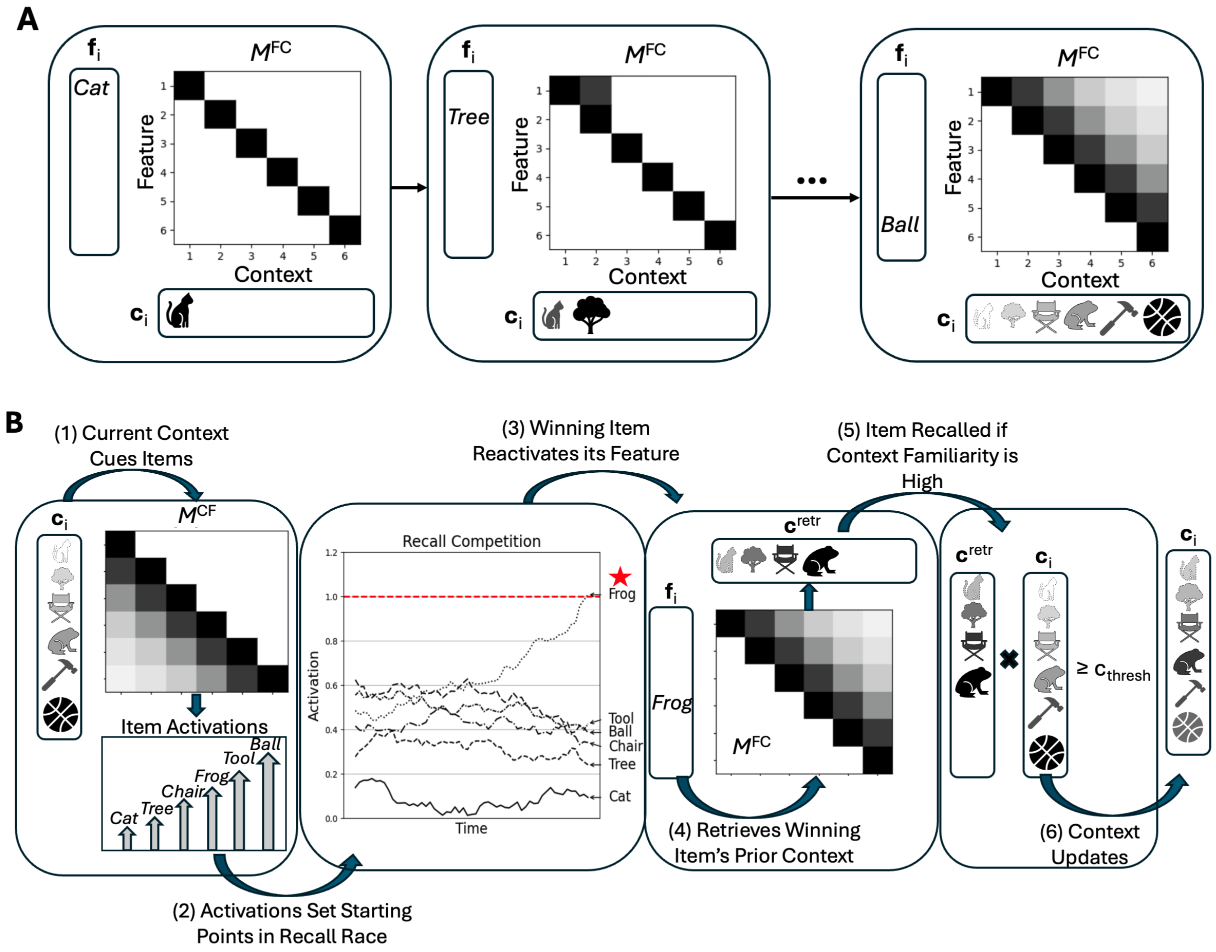

Figure 5

Encoding and Retrieval in Retrieved Context Models.

A. *When an item is encoded (shown separately for the first, second, and sixth items in a list), it activates its feature* $\mathbf{f}_i$*, which retrieves past context states through* M^{FC}*. A new context representation* $\mathbf{c}_i$ *is formed by integrating the context evoked by the present item with past states of contexts weighted by their recency.* ***B.*** *At retrieval, the current state of context* $\mathbf{c}_i$ *cues items through* M^{CF}*, yielding a set of item activations that pass into a competitive race for retrieval. The first item to cross the recall threshold (dashed red line in the second panel) wins the competition and reactivates its corresponding feature* $\mathbf{f}_i$*. Passing this feature through* M^{FC} *retrieves the item's previous context* $\mathbf{c}^{retr}$*. This retrieved context is then compared against the current context, and if the resulting similarity* $\mathbf{c}^{retr} \cdot \mathbf{c}_i$ *exceeds a threshold (*c_{thresh}*), the item is recalled. A new state of context* $\mathbf{c}_{i+1}$ *is formed by blending* $\mathbf{c}^{retr}$ *and* $\mathbf{c}_i$*, and this new context becomes* $\mathbf{c}_i$ *in the next evolution of retrieval.*

deemed familiar enough to recall it or to recognize it as “old.” If an item is recalled, context updates by blending the item’s retrieved context with the current context. A free parameter β_{retr} controls the degree of context updating with each successful retrieval much like β_{enc} does during encoding (see Table 4 and Footnote 5). The recall process then repeats with this updated context as the new $\mathbf{c}_i$, such that items that were encoded near the just-recalled item enjoy stronger activations at the start of the next race.[7] This process continues until a maximum time is reached, at which point the recall period terminates.

Modeling Age Differences

Given its complexity, a retrieved context model like CMR2 must simulate multiple outcomes in tandem for its parameter space to be identifiable. Thus, rather than simulate these outcomes ourselves, we summarize the prior work of Healey and Kahana (2016), who applied CMR2 to the free recall benchmarks of age differences in memory specificity (Figure 2F–I). They first simulated young adult data from Kahana et al. (2002) to find the best-fitting parameters that could account for the recall performance of young adults. They then selectively “lesioned” (i.e., freed) parameters of the model to fit older adult data from that study, allowing them to identify which parameters accounted for age differences. Next, they validated the model in an independent sample from the Penn Electrophysiology of Encoding and Retrieval Study (PEERS). Their approach identified six free parameters, representing four unique processes, that differed between young and older adults (see Figure 6). These parameters, and the processes they represent, are summarized in Table 4.

First, β_{retr} was lower for older than younger adults, such that the retrieval context remains more stagnant with each recall among older adults. Healey and Kahana (2016) interpret this as evidence that older adults are less likely to reinstate the contexts in which items were encoded. We revisit this interpretation in the next section.

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[7] To avoid successively recalling the same item, the retrieval threshold for an item is augmented by a parameter ω after it is recalled (see Table 4). The elevated threshold is gradually reduced by α with each additional recall attempt.

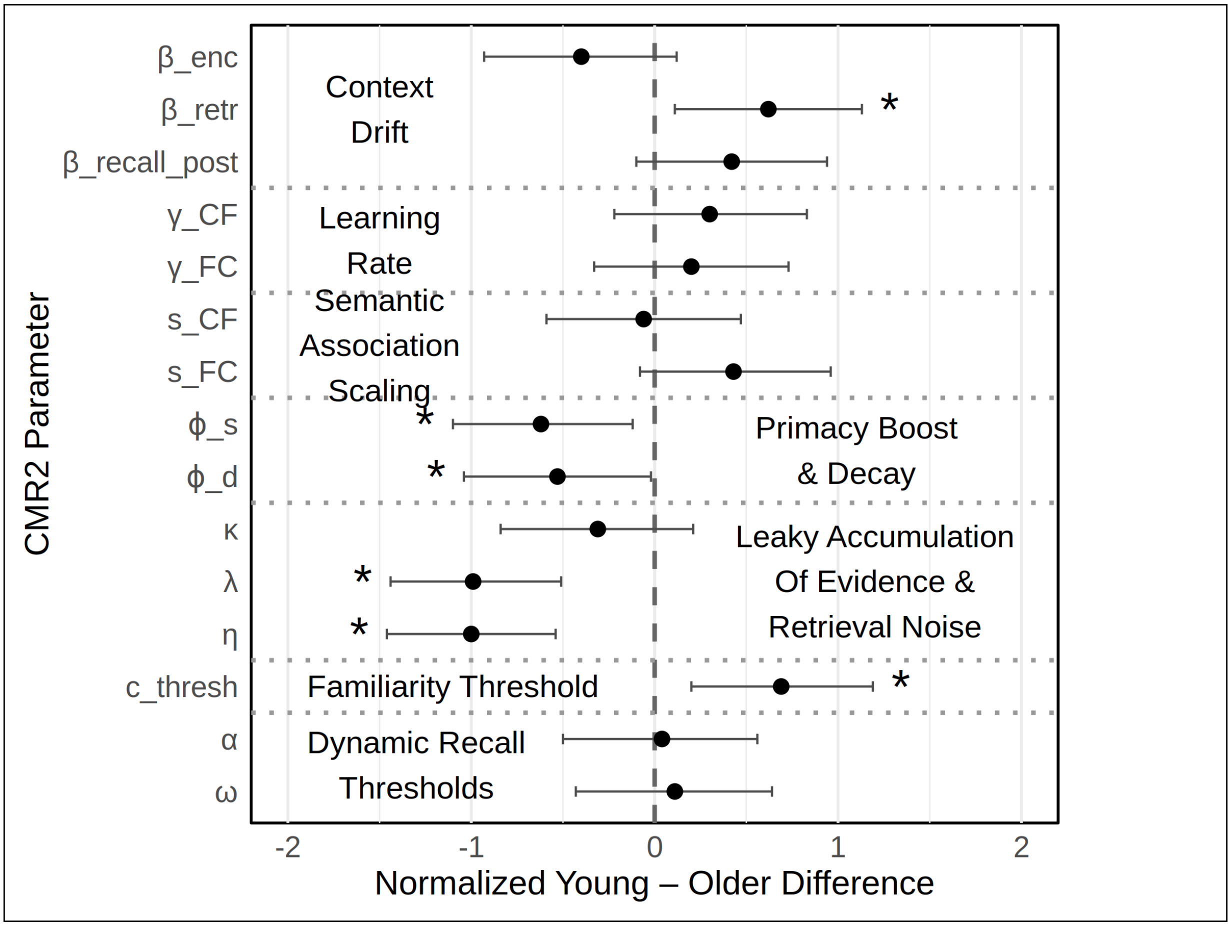

Figure 6

Age Differences in Retrieved Context Model Parameters.

Parameter difference scores re-plotted from Healey & Kahana (2016) using WebPlotDigitizer, so values may not be exact. The Context Maintenance and Retrieval (CMR2) model was fitted to individual participant data from Kahana et al. (2002); participant-level estimates were then z-scored and averaged within age group. Points denote the mean difference (young - older adults), and error bars correspond to the 95% confidence interval (CI) of the difference. If the 95% CI excludes 0, the parameter significantly differs between age groups. These parameters are denoted with asterisks. Parameter descriptions are given in Table 4.

Second, older adults had higher estimates of both primacy parameters – ϕ_s and ϕ_d – than younger adults did. The higher value of ϕ_s gives a greater encoding boost for the first item in the list, while the higher value of ϕ_d yields faster decay of this encoding boost with each additional item in the list. Healey and Kahana (2016) interpret the age-related increase in these parameters as evidence that older adults fail to sustain their attention across an encoding episode. As above, we revisit this interpretation in the next section.

Third, older adults had higher estimates of the lateral inhibition parameter (λ) and the retrieval noise parameter (η). These parameters affect overlapping aspects of the competitive retrieval race. Higher values of η contribute more random noise to the evidence accumulation process (see Figure 5B, second panel), blurring distinctions among studied and unstudied items. Higher values of λ increase inhibition, such that items with stronger activations more effectively inhibit items with weaker activations, which is generally advantageous. Healey and Kahana (2016) reported a near unity correlation between λ and η, $r = 0.93$, arguing that they measure approximately the same process (noisy retrieval), which is at odds with the original conception of these parameters: higher λ yields more organized retrieval, while higher η yields less organized retrieval (Polyn et al., 2009; Sederberg, Howard, & Kahana, 2008).

Finally, older adults had a more liberal (lower) context familiarity threshold c_{thresh} than younger adults did, making them more prone to recall or recognize items that are only weakly similar to the current context. Healey and Kahana (2016) interpret the more liberal setting of c_{thresh} among older adults as reflecting an impaired ability to monitor for intrusions.

This impressive modeling revealed that multiple processes, affecting both encoding and retrieval, underlie age differences in memory specificity. This multi-component account challenges more conventional single-process theories of age-related memory decline, such as those that attribute these declines to slower processing speed (Salthouse, 1996), attentional limitations (Craik & Byrd, 1982), inhibition failures (Hasher & Zacks, 1988), or binding deficits (Naveh-Benjamin, 2000).

Explanatory Gaps in Retrieved Context Models

Retrieved context models have uncovered multiple processes of age changes in memory specificity in free recall (Healey & Kahana, 2016). However, several explanatory gaps remain to be addressed.

Inter-Dependency in Processes of Impairment? Although each parameter in CMR2 purportedly measures a specific process (see Table 4), they also exhibit some degree of collinearity. As noted earlier, for example, Healey and Kahana (2016) found that λ and η were highly positively correlated ($r = 0.93$), despite the fact that these parameters exert *opposite* effects on retrieval, with higher λ yielding more organized retrieval, and higher η more disorganized retrieval (Polyn et al., 2009).[8] Even if all parameters were orthogonal, the *processes* those parameters represent might exhibit some degree of inter-dependency. Put simply, are there truly four *independent* processes of age-related memory "impairment," or does one process *cause* the others? For example, could a faster decay of the primacy boost (i.e., higher ϕ_d), arising perhaps from attentional lapses, weaken item encoding sufficiently to render the ensuing retrieval competition noisier (affecting the values of η and λ) or the participant more liberal in their recalls (lowering the value of c_{thresh})?

If there exists a superordinate process that exerts downstream effects on other processes, then what appears to be a multi-component account of age-related memory change might be a single-process model in disguise. If, for example, one could eradicate an age difference in primacy decay and, in turn, observe no age differences in the level of noise in the retrieval competition, or in the degree of context updating at retrieval, then the primacy decay *causes* the other impairments. This inter-dependency question must be resolved any time a multi-component theory of age-related memory change is advanced. To be clear, we do not object to the idea that there are multiple mnemonic processes that

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[8] Is it even fair to call an age-related increase in λ an "impairment" if the increase in inhibition might be acting to combat the increased noise in the retrieval process?

differ between young and older adults, but from a causal perspective, knowing how one process affects other processes is critical, even if their respective parameters are uncorrelated. A possible first step toward addressing this inter-dependency question would be to identify the latent structure of the parameter space, using dimensionality reduction methods like principal component analysis or factor analysis.

Process-Based or Descriptive Explanations? Echoing our earlier critique of global matching models, some of the processes of age-related memory impairment identified by retrieved context models are merely descriptive rather than explanatory. Specifically, the primacy parameters ϕ_s and ϕ_d do not define a specific process of how primacy arises; rather, they operate descriptively to fit a specific pattern of primacy in a given dataset. Here, a brief history lesson is in order. The original TCM (Howard & Kahana, 2002) lacked any mechanisms to simulate the widely-established (e.g., Murdock & Metcalfe, 1978; Rundus, 1971) primacy effect in free recall. To address this short-coming, Sederberg et al. (2008) added an initial encoding boost for the first item (ϕ_s) that ensured stronger item-context binding. For each additional item in the sequence, this encoding boost decayed exponentially at a rate determined by ϕ_d.[9] This descriptive mechanism enabled TCM and CMR/CMR2 to simulate different primacy gradients in free recall by selectively tuning the settings of ϕ_s and ϕ_d without explicating a process (e.g., rehearsal) that causes primacy. To quote Sederberg et al. (2008), p. 901, “Not wanting to complicate [TCM] by including a rehearsal mechanism during encoding, we chose to model primacy as an exponentially decaying boost in the learning rate for early serial positions.”

Because the primacy parameters do not measure a process of how primacy arises, any connection to a process, like rehearsal or fluctuations in attention, is merely *ad hoc*. The model itself does not include a rehearsal mechanism, nor does it explicate a role of attention in encoding or retrieval. Accordingly, it is unsurprising to observe different values of ϕ_s and ϕ_d among young and older adults (e.g., Healey & Kahana, 2016) because there

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[9] Formally, the added learning rate for the i^{th} item in a list, ϕ_i, is given by: $\phi_i = \phi_s e^{-\phi_d(i-1)} + 1$.

are different primacy gradients in each age group (see, for example, Figure 2F). This makes the observed age differences in ϕ_s and ϕ_d tautological rather than explanatory. Nonetheless, the finding of different primacy gradients among young and older adults (e.g., Kahana et al., 2002) warrants a model-based explanation for these differences. A major leap forward for retrieved context models would be to formalize the processes that generate primacy in a mechanistic way. For example, if a rehearsal mechanism were incorporated into CMR2, it could reveal whether age-related changes in rehearsal causes the differences in memory specificity.

What Do the Identified Processes Actually Measure? Verbal theories leave ambiguous how proposed processes operate. Although computational models remove much of this ambiguity (Oberauer & Lewandowsky, 2019), some interpretative barriers still persist. Different researchers might interpret what a process means in different ways. For example, Healey and Kahana (2016) interpret the age difference in β_{retr} as evidence of reduced context reinstatement among older than young adults. However, technically speaking, β_{retr} does not measure context reinstatement. Instead, it weights how strongly the retrieval context updates each time an item is successfully recalled; that is, how strongly the retrieved context blends in to the current context to generate a new context state. Thus, older adults' lower estimates of β_{retr} could reflect a *preference* to "stay" in the current context, even if a previous context state was initially reinstated. Older adults might retrieve these past contexts but reorient their attention to the test context, perhaps because they deem it important to stay focused on the task.

Nonetheless, evidently the lower value of β_{retr} affects how well older adults recall items that were encountered in neighboring temporal contexts, whether because they fail to reinstate those earlier contexts or because they do reinstate an item's context initially but then weight the current context more strongly. Yet, if older adults' reduced tendency to merge retrieved contexts with the current retrieval context stem from a preference to stay focused on the retrieval context, then presumably the age-related declines in temporal contiguity (e.g., Figure 2G) could be eliminated through cuing manipulations that shift retrieval intentions, as by making retrieval more spontaneous rather than deliberate. Indeed, under incidental retrieval conditions, older adults can successfully retrieve the details of past experiences as well as younger adults (Koutstaal, 2003), suggesting that older adults conceivably can access past memory states, but they do so less effectively based on retrieval intentions (e.g., incidental versus intentional).

Alternative Processes of Age Differences? A significant challenge for explaining age differences in memory with a model as complex as CMR2 (Lohnas et al., 2015) is that the number of parameters that could differ between age groups ranges from one to 15 (see Figure 6). For the model to be identifiable, one must fit it to a rich set of behavioral metrics, like the entire ensemble of free recall benchmarks in Figure 2F–I. This was the approach taken by Healey and Kahana (2016). Although their approach identified significant age differences in only six parameters in the data from Kahana et al. (2002), it is conceivable that were the model initially validated on a larger sample, reduced uncertainty in estimates of some of the parameters (e.g., β_{enc} or s_{FC}) in Figure 6 could have identified other processes that differed between age groups.

Our confidence in the four-component model is increased by its ability to produce a good account of age differences in an independent sample. However, it is worth pointing out that model fit was evaluated on the basis of *relative* fit, that is, the degree to which one version of CMR2 (in which the six identified parameters differed between age groups) fit the data better than alternative versions (in which different subsets of parameters differed between age groups). Relative fit was evaluated both by Bayesian information criteria (BIC) and root-mean-square deviation (RMSD) metrics. Given a candidate set of models, the one with the lowest BIC and RMSD is the preferred model. In the validation sample from Kahana et al. (2002), the four-component model bested a number of alternative models on the basis of both BIC and RMSD, but an unrestricted model in which *all* parameters were free to vary between age groups yielded a superior fit (lower BIC; its

RMSD value was not reported). Meanwhile, in the independent sample from PEERS, the four-component model was only evaluated against one single alternative model and was deemed to better fit the data on the basis of a lower BIC. In this sample, the unrestricted model was not reported, so it is conceivable that other processes, beyond those implicated in the four-component model, could have differed between age groups in this independent sample. Our argument is not intended to cast doubt on the four-component account of age differences in memory. Rather, it is to encourage further validation of the model in other independent samples and, ideally, other tasks.

Discussion

In many ways, the present review is a sequel to the work of Greene and Naveh-Benjamin (2023a). Their extensive review of age differences in memory attributed age-related quantitative performance declines across diverse memory tasks to *qualitative* changes in the specificity of episodic memories (cf. Brainerd & Reyna, 2015). Building on this prior work, we reviewed current computational process model-based explanations of these qualitative changes in memory specificity. Along the way, we highlighted explanatory shortcomings in current models to stimulate future theoretical advances. Here, we summarize what was learned by this review and propose solutions to the challenges confronting current process models as they endeavor to explain these changes.

Key Insights Advanced by the Present Review

We began our review by defining a set of empirical benchmarks of age differences in memory specificity in recognition and recall (Figure 2). This constitutes the first attempt to group these well-established findings from the most widely used tasks for studying age differences in memory (for meta-analyses, see Fraundorf et al., 2019; Rhodes et al., 2019; Old & Naveh-Benjamin, 2008) under a common framework. These empirical benchmarks represent behavioral manifestations of underlying processes that cannot be observed directly. To make inferences about these latent processes, researchers often turn to mathematical measurement models that can estimate the contributions of a given process (e.g., verbatim or gist retrieval; see Figure 1) to the observed outcome (e.g., Brainerd et al., 1999, 2009; Stahl & Klauer, 2008). Yet, measurement models do not define memory trace dynamics; they simply measure the outputs of some undefined process. Computational process models formalize assumptions about how memories are encoded, represented, and retrieved and thus hold great promise for understanding the *processes* that underlie age changes in memory specificity.

Although limited, previous attempts to computationally model age differences in memory (see Table 1) have generally converged on the idea that impairments in the representational quality or fidelity of encoded events (captured by a free parameter in the model) underlie older adults' errors in recognition and play a contributing role in their recall failures. Thus, one of the major insights of the present review is that there is substantial consistency between verbal and computational theories in their endorsement of age changes in the specificity of memory as key to older adults' episodic memory errors. This majorly extends the empirical review of Greene and Naveh-Benjamin (2023a) by showing that the proposed principle that memory becomes "fuzzier" or less precise with aging is also largely upheld in computational models.

In recognition, global matching models like MINERVA 2 (Hintzman, 1984) can simulate age differences in effects of lure similarity on recognition accuracy by setting the learning rate (L) to a lower value for older than younger adults, thereby yielding sparser representations of each event in memory (Benjamin, 2010; Guitard, Reid, et al., 2025; Stephens & Overman, 2018). However, our demonstrative simulation with a recent variant of MINERVA 2 (Reid & Jamieson, 2022) identified that differences in the cue selectivity of retrieval might constitute an alternative mechanism of older adults' heightened false alarms to similar lures (see Figure 4). We revisit the implications of this finding in the next section (see "Challenges to Current Process Models").

In serial recall, models like SIMPLE (*Scale-Invariant Memory, Perception, and Learning*; Surprenant et al., 2006), the Feature Model (Neath & Surprenant, 2007, cf.;

Nairne, 1990), and OSCAR (*OSCillator-based Associative Recall*; Maylor et al., 1999) all incorporate mechanisms of representational imprecision into their explanations of older adults' poorer serial recall. For example, echoing the effects of lowering the learning rate in MINERVA 2, in the Feature Model, less efficient encoding leads to sparse representations of each item in older adults' memory, yielding downstream effects on older adults' abilities to recall items in the order in which they appeared.

Meanwhile, age differences in the free recall benchmarks in Figure 2 have been simulated with the CMR2 model of retrieved context theory (Healey & Kahana, 2016). As summarized in Figure 6 and Table 4, several CMR2 parameters controlling different encoding and retrieval processes assume different values in modeling young versus older adult free recall data. Healey and Kahana (2016) interpret these parameter differences as broadly reflecting four components of age-related memory impairment: (1) failures to sustain attention during encoding, (2) increased noise in retrieval competition, (3) decreased sensitivity for monitoring intrusions, and (4) reduced contextual reinstatement following each recalled event. Nonetheless, we identified several explanatory gaps in retrieved context model explanations that we summarize in the ensuing section.

Challenges to Current Process Models

As our focused review of global matching and retrieved context models highlighted, several gaps need to be filled for these models to advance a more comprehensive theory of why memories become less detailed as we age. In fact, it is the very effort to extend these models to explain age differences in memory that illuminates some of their hidden assumptions and philosophical shortcomings. When the purpose of computational modeling is to explain how task performance in one condition arises, then certain shortcuts in the model – like providing a descriptive method of simulating primacy without explicating a process that gives rise to primacy (e.g., Sederberg et al., 2008) – probably do not majorly limit the inferences we can draw. This is so because we make no claim about how the process the shortcut circumvents differs across conditions. But when one seeks to identify processes that differ between two conditions or groups (e.g., young versus older adults), then these shortcuts can be problematic, particularly if the parameters that differ between groups relate to these undefined processes. This makes applying computational models to cognitive aging data a powerful way of identifying hidden (or sometimes not so hidden) assumptions of the models.

We identified two examples in which so-called "processes" that differed between young and older adults in a given model operate in a more descriptive rather than mechanistic way. First, in global matching models like MINERVA 2 (Hintzman, 1984), a lower learning rate (L) yields sparser representations for older than younger adults, but it does not define *why* the learning rate is reduced with aging. What causes older adults to store fewer features of each item faithfully into memory? The model has no mechanism in place to resolve this question, so the difference in learning rate acts more descriptively than mechanistically to explain age differences in recognition (see Smyth & Naveh-Benjamin, 2016, for a similar critique). Second, in retrieved context models like CMR2 (Lohnas et al., 2015), primacy parameters ϕ_s (encoding boost for the first item in the list) and ϕ_d (decay in this added boost with each additional item) ensure the model can successfully simulate the primacy gradient in free recall. However, these parameters operate at a descriptive level but do not explicate a specific process (e.g., rehearsal) of how primacy arises (Sederberg et al., 2008). Thus, the fact that these parameters differ between young and older adults (Healey & Kahana, 2016) does not in itself reveal a mechanistic process that gives rise to different primacy gradients across age groups.

Other challenges arise when models contain multiple (sometimes competing) ways of simulating an age difference in memory. In CMR2, for example, the fact that there are (at least) four processes of age-related impairment (Healey & Kahana, 2016) warrants additional consideration of whether any of these processes operates at a superordinate level over the others. That is, does one process of impairment *cause* the others? In addition, because CMR2 is a highly complex model, containing at least 15 free parameters (Table 4), it is conceivable that other combinations of parameter changes could underlie age-related performance differences in free recall or recognition in different (e.g., larger) samples than those on which the four-component model was validated. This poses a substantial challenge to proposing the four-component model as a universal theory of age-related memory change, especially as noted earlier that, even in the samples on which the model was validated (namely, Kahana et al., 2002), an unrestricted model in which *all* parameters varied between groups exhibited superior fit to the data based on BIC values (BIC = -251 for the unrestricted model; BIC = -230 for the four-component model).

This issue might appear to be less endemic to a simpler model like MINERVA 2, though the relative simplicity of the model has other drawbacks (e.g., the model is not currently suited to simulating free recall). However, even in a model with as few parameters as MINERVA 2, it is possible that an age difference could be simulated from several different combinations of those parameters. Although most applications of global matching models to cognitive aging data have focused on the effects of changing the learning rate (e.g., Benjamin, 2010; Stephens & Overman, 2018), it is possible that selectively tuning the cue-selectivity of retrieval might offer a viable alternative way of simulating age differences. As noted earlier, we conducted a simple demonstrative simulation in which we selectively tuned either the learning rate (L) or the cue-specificity of retrieval (τ) between age groups (see Figure 4) and found that, in both cases, lower settings of the respective parameter increased recognition false alarms. As before, we caution reading too much into this demonstration, because we did not fit the model to a specific experimental dataset. However, the fact that the demonstration revealed that changes in other parameters besides L can also influence the relative proportions of hits and false alarms warrants a deeper consideration of this issue in future global matching modeling of age differences in recognition.

Promising Directions for Future Research

Despite (or perhaps because of) the foregoing challenges to current process models that our review identified, there are several promising directions to extend these models in the future, which will have enormous implications for memory theory broadly, and for understanding age changes in memory more specifically. One of the most promising directions will be for the models to formalize assumptions about mechanistic processes that can supplant some of their more descriptive components. For example, adding rehearsal to CMR2 could provide retrieved context models with a specific mechanism that generates primacy, replacing the descriptive ϕ parameters all together (Sederberg et al., 2008). Then age differences in the primacy gradient in free recall (e.g., Kahana et al., 2002, see Figure 2F) could arise from different ways in which young and older adults rehearse items. For example, perhaps rehearsing earlier items preserves the primacy boost for the initial items in a list across age groups but induces more interference for later items in the list for older than younger adults.

Similarly, in global matching models like MINERVA 2 (Hintzman, 1984), defining processes that affect the fidelity of encoding could yield valuable insights into why the learning rate inherently differs between age groups. Here, there are several viable options whose seeds have already been planted. First, the emerging use of structured item representations into global matching models (e.g., Chang et al., 2025; Guitard, Saint-Aubin, et al., 2025a, 2025b; Reid & Jamieson, 2023) provides opportunities for modeling how experience shapes the nature of the representations the model learns in a given context. Inter-item similarities might be more diffuse if the model's long-term memory (its lexicon) was derived from a larger corpora of words (perhaps simulating the more expansive long-term memory of an older adult), potentially increasing ambiguities between studied and novel items in a recognition task (cf. Johns et al., 2012). Second, representing an item with different types of features (e.g., phonological versus semantic), each derived in a structured way, has potential to reveal whether older adults selectively attend to different features than younger adults do. For example, Chang et al.'s (2025) recent incorporation of fuzzy-trace theory's dual verbatim/gist distinction into MINERVA 2 allows each item to be represented by both its surface-level, orthographic features (derived from holographic word-form vectors; see Cox, Kachergis, Recchia, & Jones, 2011) and its gist-level semantic features (derived from BEAGLE; see Jones & Mewhort, 2007). This innovative use of multiple representational types for each item could supplant the need to simulate an age-related reduction in learning rate (L) all together by instead allowing the model to prioritize encoding different feature types for young versus older adults (cf. Caplan, 2023; Caplan & Guitard, 2024).

Another highly promising direction for future modeling will be to blend elements of both global matching and retrieved context models to create a more unified theory of memory and how it changes with age. As noted earlier, global matching mechanisms have been extended beyond recognition to categorization (Chubala et al., 2016), frequency judgments (Hintzman, 1988), cued recall (Hintzman, 1986), and serial recall (Guitard, Saint-Aubin, et al., 2025b), yet challenges persist in the ability to extend global matching to free recall. The main challenge is that, in the absence of a specific memory cue, one must define a role of context in driving recalls. This is well handled in retrieved context models (Howard & Kahana, 2002; Polyn et al., 2009), which have also been extended to modeling recognition (Healey & Kahana, 2016; Jin, Halpern, & Kahana, Submitted). Indeed, given that retrieved context models can already model both free recall and item or associative recognition, one might question the need to combine these two classes of models at all. What we see as the main benefit is that embedding structured item representations, the emerging standard in global matching models, into retrieved context models could have huge consequences for understanding age differences in memory specificity across recall and recognition in a unified way. Because retrieved context models represent each item as a single localist feature, they possess no mechanism for modeling what types of features (e.g., semantic versus phonological) of an item bind to a given context and thus no way of modeling whether older adults differentially associate a certain type of feature (e.g., semantic) to its encoding context than younger adults do. In fact, the models only represent long-standing semantic associations among items (stored in the pre-experimental associations in M^{FC} and M^{CF}) but have no way of jointly representing other types of associations (e.g., phonological or orthographic associations), which limits their ability to measure true and false recall across non-semantic domains. But if the localist representational assumption (a current shortcut in models like CMR2) was relaxed, and items were instead represented by structured representations as in recent global matching models (e.g., Guitard, Saint-Aubin, et al., 2025a; Reid & Jamieson, 2023), then there would be a whole host of ways in which to model age differences in memory that previously were not feasible in CMR2.

Finally, although our review has focused on the implications of computational modeling for understanding “normal” age-related changes in memory, future applications to pathological aging are certainly needed. A computational model could potentially identify processes of memory that differ between healthy older adults and cognitively-impaired older adults, making it a valuable tool in the diagnosis and prediction of cognitive impairment in older adults.

Conclusions

Computational process models have enormous, untapped potential for revealing the processes underlying age-related changes in memory specificity. Here, we discussed how two of the most widely used classes of process models in the mainstream memory literature – global matching and retrieved context models (Kahana, 2020) – explain empirical benchmarks of age differences in memory specificity in recognition and free recall. Nonetheless, several gaps remain to be filled for a more comprehensive theory of these differences to emerge. We meticulously laid out these gaps and provided future modelers with a roadmap of how to address them. Accordingly, this review not only serves to illuminate the potential of computational modeling for cognitive aging research but also sets the stage for critical new developments in process models that will reverberate far beyond.

References

Abadie, M., Gavard, E., & Guillaume, F. (2021). Verbatim and gist memory in aging. *Psychology and Aging*, *36*(8), 891–901. doi: 10.1037/pag0000635

Arndt, J., & Hirshman, E. (1998). True and false recognition in MINERVA2: Explanations from a global matching perspective. *Journal of Memory and Language*, *39*(3), 371–391.

Baltes, P. B., & Lindenberger, U. (1997). Emergence of a powerful connection between sensory and cognitive functions across the adult life span: a new window to the study of cognitive aging? *Psychology and Aging*, *12*(1), 12–21. doi: 10.1037/0882-7974.12.1.12

Batchelder, W. H., & Riefer, D. M. (1999). Theoretical and empirical review of multinomial process tree modeling. *Psychonomic Bulletin & Review*, *6*(1), 57–86. doi: 10.3758/BF03210812

Benjamin, A. (2010). Representational explanations of "process" dissociations in recognition: The DRYAD theory of aging and memory judgments. *Psychological Review*, *117*(4), 1055–1079. doi: 10.1037/a0020810

Brainerd, C. J., & Reyna, V. F. (1990). Gist is the grist: Fuzzy-trace theory and the new intuitionism. *Developmental Review*, *10*(1), 3–47. doi: 10.1016/0273-2297(90)90003-M

Brainerd, C. J., & Reyna, V. F. (2015). Fuzzy-trace theory and lifespan cognitive development. *Developmental Review*, *38*, 89–121. doi: 10.1016/j.dr.2015.07.006

Brainerd, C. J., Reyna, V. F., & Forrest, T. J. (2002). Are young children susceptible to the false-memory illusion? *Child Development*, *73*(5), 1363–1377. doi: 10.1111/1467-8624.00477

Brainerd, C. J., Reyna, V. F., & Howe, M. L. (2009). Trichotomous processes in early memory development, aging, and neurocognitive impairment: A unified theory. *Psychological Review*, *116*(4), 783–832. doi: 10.1037/a0016963

Brainerd, C. J., Reyna, V. F., & Mojardin, A. H. (1999). Conjoint recognition. *Psychological Review*, *106*(1), 160–179. doi: 10.1037/0033-295X.106.1.160

Brainerd, C. J., Wright, R., Reyna, V. F., & Mojardin, A. H. (2001). Conjoint recognition and phantom recollection. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *27*(2), 307–327. doi: 10.1037/0278-7393.27.2.307

Brown, G. D. A., Neath, I., & Chater, N. (2007). A temporal ratio model of memory. *Psychological Review*, *114*(3), 539–576. doi: doi:10.1037/0033-295X.114.3.539

Brown, G. D. A., Preece, T., & Hulme, C. (2000). Oscillator-based memory for serial order. *Psychological Review*, *107*(1), 127–181. doi: 10.1037/0033-295X.107.1.127

Buchler, N. E. G., & Reder, L. M. (2007). Modeling age-related memory deficits: A two-parameter solution. *Psychology and Aging*, *22*(1), 104–121. doi: 10.1037/0882-7974.22.1.104

Caplan, J. B. (2023). Sparse attentional subsetting of item features and list-composition effects on recognition memory. *Journal of Mathematical Psychology*, *116*, 102802. doi: 10.1016/j.jmp.2023.102802

Caplan, J. B., & Guitard, D. (2024). A feature-space theory of the production effect in recognition. *Experimental Psychology*, *71*(1), 64–82. doi: 10.1027/1618-3169/a000611

Castel, A. D. (2005). Memory for grocery prices in younger and older adults: The role of schematic support. *Psychology and Aging*, *20*(4), 718–721. doi: 10.1037/0882-7974.20.4.718

Castel, A. D., Farb, N. A. S., & Craik, F. I. M. (2007). Memory for general and specific value information in younger and older adults: Measuring the limits of strategic control. *Memory & cognition*, *35*(4), 689–700. doi: 10.3758/BF03193307

Chang, M., Johns, B. T., & Brainerd, C. J. (2025). True and false recognition in MINERVA2: Integrating fuzzy-trace theory and computational memory modeling. *Psychological Review*, *132*(4), 857–894. doi: 10.1037/rev0000541

Chubala, C. M., Johns, B. T., Jamieson, R. K., & Mewhort, D. J. K. (2016). Applying an exemplar model to an implicit rule-learning task: Implicit learning of semantic structure. *The Quarterly Journal of Experimental Psychology*, *69*(6), 1049–1055. doi: 10.1080/17470218.2015.1130068

Clark, S. E., & Gronlund, S. D. (1996). Global matching models of recognition memory: How the models match the data. *Psychonomic Bulletin and Review*, *3*, 37-60. doi: 10.3758/BF03210740

Cox, G. E., Kachergis, G., Recchia, G., & Jones, M. N. (2011). Toward a scalable holographic word-form representation. *Behavior Research Methods*, *43*(3), 602–615. doi: 10.3758/s13428-011-0125-5

Cox, G. E., & Shiffrin, R. M. (2017). A dynamic approach to recognition memory. *Psychological review*, *124*(6), 795. doi: 10.1037/rev0000076

Craik, F. I. M. (1983). On the transfer of information from temporary to permanent memory. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *302*(1110), 341–359. doi: 10.1098/rstb.1983.0059

Craik, F. I. M. (2002). Levels of processing: Past, present... and future? *Memory*, *10*(5-6), 305–318. doi: 10.1080/09658210244000135

Craik, F. I. M., & Byrd, M. (1982). Aging and cognitive deficits: The role of attentional resources. In F. I. M. Craik & S. Trehub (Eds.), *Aging & cognitive processes: Advances in the study of communication and affect* (Vol. 8, p. 191-211). New York: Plenum Press.

Craik, F. I. M., & McDowd, J. M. (1987). Age differences in recall and recognition. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *13*(3), 474–479. doi: 10.1037/0278-7393.13.3.474

Criss, A., & Shiffrin, R. (2005). List discrimination in associative recognition and implications for representation. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *31*(6), 1199–1212. doi: 10.1037/0278-7393.31.6.1199

Curtis, E. T., & Jamieson, R. K. (2019). Computational and empirical simulations of selective memory impairments: Converging evidence for a single-system account of memory dissociations. *The Quarterly Journal of Experimental Psychology*, *72*(4), 798–817. doi: 10.1177/1747021818768502

Danckert, S. L., & Craik, F. I. M. (2013). Does aging affect recall more than recognition memory? *Psychology and Aging*, *28*(4), 902–909. doi: 10.1037/a0033263

Darby, K. P., & Sederberg, P. B. (2022). Transparency, replicability, and discovery in cognitive aging research: A computational modeling approach. *Psychology and Aging*, *37*(1), 10–29. doi: 10.1037/pag0000665

Deese, J. (1959). On the prediction of occurrence of particular verbal intrusions in immediate recall. *Journal of Experimental Psychology*, *58*(1), 17-22. doi: 10.1037/h0046671

Devitt, A. L., & Schacter, D. L. (2016). False memories with age: Neural and cognitive underpinnings. *Neuropsychologia*, *91*, 346–359. doi: 10.1016/j.neuropsychologia.2016.08.030

Dixon, R. A., & Hultsch, D. F. (1983). Structure and development of metamemory in adulthood. *Journal of Gerontology*, *38*(6), 682–688. doi: 10.1093/geronj/38.6.682

Fraundorf, S. H., Hourihan, K. L., Peters, R. A., & Benjamin, A. S. (2019). Aging and recognition memory: A meta-analysis. *Psychological Bulletin*, *145*(4), 339–371. doi: 10.1037/bul0000185

Gillund, G., & Shiffrin, R. M. (1984). A retrieval model for both recognition and recall. *Psychological Review*, *91*(1), 1-67. doi: 10.1037/0033-295X.91.1.1

Golomb, J. D., Peelle, J. E., Addis, K. M., Kahana, M. J., & Wingfield, A. (2008). Effects of adult aging on utilization of temporal and semantic associations during free and serial recall. *Memory & Cognition*, *36*(5), 947–956. doi: 10.3758/MC.36.5.947

Green, D. M., & Swets, J. A. (1966). *Signal detection theory and psychophysics.* Oxford, England: Wiley.

Greene, N. R., Chism, S., & Naveh-Benjamin, M. (2022). Levels of specificity in episodic memory: Insights from response accuracy and subjective confidence ratings in older adults and in younger adults under full or divided attention. *Journal of Experimental Psychology: General*, *151*(4), 804–819. doi: 10.1037/xge0001113

Greene, N. R., & Naveh-Benjamin, M. (2020). A specificity principle of memory: Evidence from aging and associative memory. *Psychological Science*, *31*(3), 316–331. doi: 10.1177/0965797620901760

Greene, N. R., & Naveh-Benjamin, M. (2022). Adult age differences in specific and gist associative episodic memory across short- and long-term retention intervals. *Psychology and Aging*, *37*(6), 681–697. doi: 10.1037/pag0000701

Greene, N. R., & Naveh-Benjamin, M. (2023a). Adult age-related changes in the specificity of episodic memory representations: A review and theoretical framework. *Psychology and Aging*, *38*(2), 67–86. doi: 10.1037/pag0000724

Greene, N. R., & Naveh-Benjamin, M. (2023b). Differential attentional costs of encoding specific and gist episodic memory representations. *Journal of Experimental Psychology: General*, *152*(11), 3292–3299. doi: 10.1037/xge0001448

Greene, N. R., & Naveh-Benjamin, M. (2023c). The formation of specific and gist associative episodic memory representations during encoding: Effects of rate of presentation. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *49*(7), 1099–1118. doi: 10.1037/xlm0001173

Greene, N. R., & Naveh-Benjamin, M. (2024a). On the adaptive reliance on fuzzy memory representations in adult aging. In M. Toglia, H. Otgaar, J. Altarriba, & B. Erickson (Eds.), *Interdisciplinary perspectives and advances in understanding adaptive memory* (pp. 276–297). Oxford University Press.

Greene, N. R., & Naveh-Benjamin, M. (2024b). The time course of encoding specific and gist episodic memory representations among young and older adults. *Journal of Experimental Psychology: General*, *153*(6), 1671–1697. doi: 10.1037/xge0001589

Greene, N. R., & Rhodes, S. (2022). A tutorial on cognitive modeling for cognitive aging research. *Psychology and Aging*, *37*(1), 30–42. doi: 10.1037/pag0000637

Grilli, M. D., & Sheldon, S. (2022). Autobiographical event memory and aging: Older adults get the gist. *Trends in Cognitive Sciences*, *26*(12), 1079–1089. doi: 10.1016/j.tics.2022.09.007

Guitard, D., Reid, J. N., Greene, N. R., Saint-Aubin, J., & Jamieson, R. K. (2025). An embedded computational framework of age-related memory change. *PsyArXiv*. doi: https://doi.org/10.31234/osf.io/j6pmv_v1

Guitard, D., Saint-Aubin, J., Reid, J. N., & Jamieson, R. K. (2025a). An embedded computational framework of memory: Accounting for the influence of semantic infomration in verbal short-term memory. *Journal of Memory and Language*, *140*, 104573. doi: 10.1016/j.jml.2024.104573

Guitard, D., Saint-Aubin, J., Reid, J. N., & Jamieson, R. K. (2025b). An embedded computational framework of memory: The critical role of representations in veridical and false recall predictions. *Psychonomic Bulletin & Review*, 1–55. doi: 10.3758/s13423-025-02669-7

Hasher, L., & Zacks, R. T. (1988). Working memory, comprehension, and aging: A review and a new view. In G. H. Bower (Ed.), *The psychology of learning and motivation: Advances in research and theory* (p. 193-225). San Diego: Academic Press.

Healey, M. K., & Kahana, M. J. (2016). A four-component model of age-related memory change. *Psychological Review*, *123*(1), 23–69. doi: 10.1037/rev0000015

Hintzman, D. L. (1984). MINERVA 2: A simulation of human memory. *Behavioral Research Methods, Instrumentation, and Computers*, *16*(2), 96–101. doi: 10.3758/BF03202365

Hintzman, D. L. (1986). 'Schema abstraction' in a multiple-trace memory model. *Psychological Review*, *93*, 411-428. doi: 10.1037/0033-295X.93.4.411

Hintzman, D. L. (1988). Judgments of frequency and recognition memory in multiple-trace memory model. *Psychological Review*, *95*(4), 528-551. doi: 10.1037/0033-295X.95.4.528

Howard, M. W., & Kahana, M. J. (1999). Contextual variability and serial position effects in free recall. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *25*(4), 923–941. doi: 10.1037/0278-7393.25.4.923

Howard, M. W., & Kahana, M. J. (2002). A distributed representation of temporal context. *Journal of Mathematical Psychology*, *46*(3), 269–299. doi: 10.1006/jmps.2001.1388

Jennings, J. M., & Jacoby, L. L. (1997). An opposition procedure for detecting age-related deficits in recollection: Telling effects of repetition. *Psychology and Aging*, *12*(2), 352–361. doi: 10.1037/0882-7974.12.2.352

Jin, B. J., Halpern, D. J., & Kahana, M. J. (Submitted). A theory of memory for items and associations. *PsyArXiv*. doi: https://doi.org/10.31234/osf.io/xm8v6

Johns, B. T., Jamieson, R. K., & Jones, M. N. (2023). Scalable cognitive modelling: Putting Simon's 1969 ant back on the beach. *Canadian Journal of Experimental Psychology/Revue canadienne de psychologie expérimentale*, *77*(3), 185–201. doi: 10.1037/cep0000306

Johns, B. T., Jones, M. N., & Mewhort, D. J. K. (2012). A synchronization account of false recognition. *Cognitive Psychology*, *65*, 486–518. doi: 10.1016/j.cogpsych.2012.07.002

Jones, M. N., & Mewhort, D. J. K. (2007). Representing word meaning and order information in a composite holographic lexicon. *Psychological Review*, *114*(1), 1–37. doi: 10.1037/0033-295X.114.1.1

Kahana, M. J. (1996). Associative retrieval processes in free recall. *Memory & Cognition*, *24*(1), 103–109. doi: 10.3758/BF03197276

Kahana, M. J. (2020). Computational models of memory search. *Annual Review of Psychology*, *71*(1), 107–138. doi: 10.1146/annurev-psych-010418-103358

Kahana, M. J., Howard, M. W., Zaromb, F., & Wingfield, A. (2002). Age dissociates recency and lag recency effects in free recall. *Journal of Experimental Psychology:*

Learning, Memory, and Cognition, *28*(3), 530–540. doi: 10.1037/0278-7393.28.3.530

Koutstaal, W. (2003). Older adults encode—but do not always use—perceptual details: Intentional versus unintentional effects of detail on memory judgments. *Psychological Science*, *14*(2), 189–193.

Koutstaal, W., & Schacter, D. L. (1997). Gist-based false recognition of pictures in older and younger adults. *Journal of Memory and Language*, *37*(4), 555–583. doi: 10.1006/jmla.1997.2529

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*, 211–240.

Levine, B., Svoboda, E., Hay, J. F., Winocur, G., & Moscovitch, M. (2002). Aging and autobiographical memory: Dissociating episodic from semantic retrieval. *Psychology and Aging*, *17*(4), 677–689. doi: 10.1037/0882-7974.17.4.677

Li, S. C., Lindenberger, U., & Sikstrom, S. (2001). Aging cognition: From neuromodulation to representation. *Trends in Cognitive Science*, *5*(11), 479–486. doi: 10.1016/s1364-6613(00)01769-1

Li, S.-C., Naveh-Benjamin, M., & Lindenberger, U. (2005). Aging neuromodulation impairs associative binding: A neurocomputational account. *Psychological Science*, *16*(6), 445–450. doi: 10.1111/j.0956-7976.2005.01555.x

Light, L. (1991). Memory and aging: Four hypotheses in search of data. *Annual Review of Psychology*, *42*, 333-376. doi: 10.1146/annurev.ps.42.020191.002001

Lohnas, L. J., Polyn, S. M., & Kahana, M. J. (2015). Expanding the scope of memory search: Modeling intralist and interlist effects in free recall. *Psychological Review*, *122*(2), 337–363. doi: 10.1037/a0039036

Maylor, E. A., Vousden, J. I., & Brown, G. D. A. (1999). Adult age differences in short-term memory for serial order: Data and a model. *Psychology and Aging*, *14*(4), 572–594. doi: 10.1037/0882-7974.14.4.572

Mikolov, T., Sutskever, I., Chen, K., G., C., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. *arXiv*. doi: 10.48550/arXiv.1310.4546

Murdock, B. B. (1982). A theory for the storage and retrieval of item and associative information. *Psychological Review*, *89*, 609-626.

Murdock, B. B., & Metcalfe, J. (1978). Controlled rehearsal in single-trial free recall. *Journal of Verbal Learning and Verbal Behavior*, *17*(3), 309-324. doi: 10.1016/S0022-5371(78)90201-3

Nairne, J. S. (1990). A feature model of immediate memory. *Memory & Cognition*, *18*(3), 251-269. doi: 10.3758/BF03213879

Naveh-Benjamin, M. (1990). Coding of temporal order information: An automatic process? *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *16*(1), 117–126. doi: 10.1037/0278-7393.16.1.117

Naveh-Benjamin, M. (2000). Adult-age differences in memory performance: Tests of an associative deficit hypothesis. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *26*(5), 1170–1187. doi: 10.1037/0278-7393.26.5.1170

Naveh-Benjamin, M., Cowan, N., Kilb, A., & Chen, Z. (2007). Age-related differences in immediate serial recall: Dissociating chunk formation and capacity. *Memory & Cognition*, *35*(4), 724–737. doi: 10.3758/BF03193310

Naveh-Benjamin, M., Hussain, Z., Guez, J., & Bar-On, M. (2003). Adult age differences in episodic memory: Further support for an associative-deficit hypothesis. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *29*(5), 826–837. doi: 10.1037/0278-7393.29.5.826

Naveh-Benjamin, M., & Old, S. R. (2008). Aging and memory. In J. H. Bryne, H. Eicenbaum, R. Menzel, H. L. Roediger, & D. Sweatt (Eds.), *Learning and memory: A comprehensive reference* (pp. 787–808). Oxford, U. K.: Elsevier.

Neath, I., & Surprenant, A. M. (2007). Accounting for age-related differences in working memory using the feature model. In N. Osaka, R. H. Logie, & M. D'Esposito (Eds.), *The cognitive neuroscience of working memory* (pp. 165–180). New York, NY: Oxford University Press.

Nelson, D. L., McEvoy, C. L., & Schreiber, T. A. (2004). The University of South Florida free association, rhyme, and word fragment norms. *Behavior Research Methods, Instruments and Computers*, *36(3)*, 402-407. doi: 10.3758/BF03195588

Norman, K. A., & Schacter, D. L. (1997). False recognition in younger and older adults: Exploring the characterisitics of illusory memories. *Memory & Cognition*, *25*(6), 838–848. doi: 10.3758/BF03211328

Nosofsky, R. M. (1986). Attention, similarity, and the identification-categorization relationship. *Journal of Experimental Psychology: General*, *115*, 39-57.

Oberauer, K., & Lewandowsky, S. (2019). Addressing the theory crisis in psychology. *Psychonomic Bulletin & Review*, *26*(5), 1596–1618. doi: 10.3758/s13423-019-01645-2

Odegard, T. N., & Lampinen, J. M. (2005). Recollection rejection: Gist cuing of verbatim memory. *Memory & Cognition*, *33*(8), 1422–1430. doi: 10.3758/BF03193375

Old, S. R., & Naveh-Benjamin, M. (2008). Differential effects of age on item and associative measures of memory: A meta-analysis. *Psychology and Aging*, *23*(1), 104–118. doi: 10.1037/0882-7974.23.1.104

Osth, A. F., & Dennis, S. (2024). Global matching models of recognition memory. In M. J. Kahana & A. D. Wagner (Eds.), *Oxford handbook of human memory* (Vol. 1, pp. 895–922). Oxford University Press.

Osth, A. F., & Zhang, L. (2024). Integrating word-form representations with global similarity computation in recognition memory. *Psychonomic Bulletin & Review*, *31*(3), 1000-1031. doi: 10.3758/s13423-023-02402-2

Osth, A. F., Zhang, L., & Williams, S. (2025). A global matching model of choice and response times in the Deese-Roediger-Mcdermott semantic and structural false recognition paradigms. *Psychological Review*, Advance online publication. doi: 10.1037/rev0000596

Polyn, S. M., Norman, K. A., & Kahana, M. J. (2009). A context maintenance and retrieval model of organizational processes in free recall. *Psychological Review*, *116*(1), 129–156. doi: 10.1037/a0014420

Radvansky, G. A., & Dijkstra, K. (2007). Aging and situation model processing. *Psychonomic Bulletin & Review*, *14*(6), 1027–1042. doi: 10.3758/BF03193088

Rankin, J. L., & Kausler, D. H. (1979). Adult age differences in false recognitions. *Journal of Gerontology*, *34*(1), 58–65. doi: 10.1093/geronj/34.1.58

Reder, L. M., Nhouyvanisvong, A., Schunn, C. D., Ayers, M. S., Angstadt, R., & Hiraki, K. A. (2000). A mechanistic account of the mirror effect for word frequency: A computational model of remember-know judgments in a continuous recognition paradigm. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *26*(2), 294–320. doi: 10.1037/0278-7393.26.2.294

Reid, J. N., & Jamieson, R. K. (2022). A computational model of item-based directed forgetting. *Canadian Journal of Experimental Psychology/Revue canadienne de psychologie expérimentale*, *76*(2), 75–86. doi: 10.1037/cep0000281

Reid, J. N., & Jamieson, R. K. (2023). True and false recognition in MINERVA 2: Extension to sentences and metaphors. *Journal of Memory and Language*, *129*, 104397. doi: 10.1016/j.jml.2022.104397

Reid, J. N., Yang, H., & Jamieson, R. K. (2023). A computational account of item-based directed forgetting for nonwords: Incorporating orthographic representations in MINERVA 2. *Memory & Cognition*, *51*(8), 1785–1806. doi: 10.3758/s13421-023-01433-3

Reyna, V. F., & Brainerd, C. J. (1995). Fuzzy-trace theory: An interim synthesis. *Leaning and Individual Differences*, *7*(1), 1–75. doi: 10.1016/1041-6080(95)90031-4

Rhodes, S., Greene, N. R., & Naveh-Benjamin, M. (2019). Age-related differences in recall and recognition: a meta-analysis. *Psychonomic Bulletin & Review*, *26*(5), 1529–1547. doi: 10.3758/s13423-019-01649-y

Robin, J., & Moscovitch, M. (2017). Details, gist, and schema: Hippocampal-neocortical interactions underlying recent and remote episodic and spatial memory. *Current Opinion in Behavioral Sciences*, *17*, 114–123. doi: 10.1016/j.cobeha.2017.07.016

Roediger, H. L., & McDermott, K. B. (1995). Creating false memories: Remembering words not presented in lists. *Journal of Experimental Psychology: Learning, Memory and Cognition*, *21*, 803-814. doi: 10.1037/0278-7393.21.4.803

Rundus, D. (1971). An analysis of rehearsal processes in free recall. *Journal of Experimental Psychology*, *89*, 63-77. doi: 10.1037/h0031185

Sachs, J. S. (1967). Recognition memory for syntactic and semantic aspects of connected discourse. *Perception & Psychophysics*, *2*(9), 437–442. doi: 10.3758/BF03208784

Salthouse, T. A. (1988). Initiating the formalization of theories of cognitive aging. *Psychology and Aging*, *3*(1), 3–16. doi: 10.1037//0882-7974.3.1.3

Salthouse, T. A. (1996). The processing-speed theory of adult age differences in cognition. *Psychological Review*, *103*(3), 403–428. doi: 10.1037/0033-295x.103.3.403

Salthouse, T. A. (2019). Trajectories of normal cognitive aging. *Psychology and Aging*, *34*(1), 17–24. doi: 10.1037/pag0000288

Schacter, D. L., Koutstaal, W., & Norman, K. A. (1997). False memories and aging. *Trends in Cognitive Sciences*, *1*(6), 229–236. doi: 10.1016/S1364-6613(97)01068-1

Sederberg, P. B., Howard, M. W., & Kahana, M. J. (2008). A context-based theory of recency and contiguity in free recall. *Psychological Review*, *115*(4), 893–912. doi: 10.1037/a0013396

Sekeres, M. J., Bonasia, K., St-Laurent, M., Pishdadian, S., Winocur, G., Grady, C., & Moscovitch, M. (2016). Recovering and preventing loss of detailed memory: Differential rates of forgetting for detail types in episodic memory. *Learning & Memory*, *23*(2), 72–82. doi: 10.1101/lm.039057.115

Shiffrin, R. M., & Steyvers, M. (1997). A model for recognition memory: REM—retrieving effectively from memory. *Psychonomic Bulletin & Review*, *4*(2), 145–166. doi: 10.3758/BF03209391

Smyth, A. C., & Naveh-Benjamin, M. (2016). Can DRYAD explain age-related associative memory deficits? *Psychology and Aging*, *31*(1), 1–13. doi: 10.1037/a0039071

Stahl, C., & Klauer, K. C. (2008). A simplified conjoint recognition paradigm for the measurement of gist and verbatim memory. *Journal of Memory and Language*, *60*(1), 180–193. doi: 10.1016/j.jml.2008.08.001

Stark, S. M., Kirwan, C. B., & Stark, C. E. (2019). Mnemonic similarity task: A tool for assessing hippocampal integrity. *Trends in cognitive sciences*, *23*(11), 938–951.

Stark, S. M., Yassa, M. A., Lacy, J. W., & Stark, C. E. (2013). A task to assess behavioral pattern separation BPS in humans: Data from healthy aging and mild cognitive impairment. *Neuropsychologia*, *51*(12), 2442–2449. doi: 10.1016/j.neuropsychologia.2012.12.014

Stephens, J. D. W., & Overman, A. A. (2018). Modeling age differences in effects of pair repetition and poractive interference using a single parameter. *Psychology and Aging*, *33*(1), 182–194. doi: 10.10137/pag0000195

Stine, E. A. L., & Wingfield, A. (1988). Memorability functions as an indicator of qualitative age differences in text recall. *Psychology and Aging*, *3*(2), 179–183. doi: 10.1037/0882-7974.3.2.179

Stine-Morrow, E. A. L., Morrow, D. G., & Leno III, R. (2002). Aging and the representation of spatial situations in narrative understanding. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, *57*(4), 291–297. doi: 10.1093/geronb/57.4.P291

Surprenant, A. M., & Neath, I. (2009). *Principles of memory.* New York, NY: Psychology Press.

Surprenant, A. M., Neath, I., & Brown, G. D. A. (2006). Modeling age-related differences in immediate memory using SIMPLE. *Journal Of Memory And Language*, *55*(4), 572–586. doi: 10.1016/j.jml.2006.08.001

Tanner, W. P., & Swets, J. A. (1954). A decision-making theory of visual detection. *Psychological Review*, *61*(6), 401–409. doi: 10.1037/h0058700

Tatler, B. W., Gilchrist, I. D., & Rusted, J. (2003). The time course of abstract visual representation. *Perception*, *32*(5), 579–592. doi: 10.1016/0010-0285(77)90005-6

Trelle, A. N., Henson, R. N., Green, D. A. E., & Simons, J. S. (2017). Declines in representational quality and strategic retrieval processes contribute to age-related increases in false recognition. *Journal Experimental Psychology: Learning, Memory and Cognition*, *43*(12), 1883–1897. doi: 10.1037/xlm0000412

Tun, P. A., Wingfield, A., Rosen, M. J., & Blanchard, L. (1998). Response latencies for false memories: Gist-based processes in normal aging. *Psychology & Aging*, *13*(2), 230–241. doi: 10.1037//0882-7974.13.2.230

Umanath, S., & Marsh, E. J. (2014). Understanding how prior knowledge influences memory in older adults. *Perspectives on Psychological Science*, *9*(4), 408–426. doi: 10.1177/1745691614535933

Usher, M., & McClelland, J. L. (2001). The time course of perceptual choice: The leaky, competing accumulator model. *Psychological Review*, *108*(3), 550–592. doi: 10.1037/0033-295x.108.3.550

Wingfield, A., & Kahana, M. J. (2002). The dynamics of memory retrieval in older adulthood. *Canadian Journal of Experimental Psychology*, *56*, 187–199. doi: 10.1037/h0087396

Wingfield, A., Lindfield, K. C., & Kahana, M. J. (1998). Adult age differences in the temporal characteristics of category free recall. *Psychology and Aging*, *13*(2), 256–266. doi: 10.1037/0882-7974.13.2.256

Yassa, M. A., Mattfeld, A., Stark, S. M., & Stark, C. E. L. (2011). Age-related memory deficits linked to circuit-specific disruptions in the hippocampus. *Proceedings of the*

National Academy of Sciences, USA, *108*(21), 8873–8878. doi: 10.1073/pnas.1101567108

Yonelinas, A. P. (1997). Recognition memory ROCs for item and associative information: The contribution of recollection and familiarity. *Memory & Cognition*, *25*(6), 747–763. doi: 10.3758/BF03211318

Zacks, R., Hasher, L., & Li, K. Z. H. (2000). Human memory. In F. I. M. Craik & T. A. Salthouse (Eds.), *The handbook of aging and cognition* (p. 293-358). Mahwah, NJ: Lawrence Erlbaum and Associates.

Zaromb, F. M., Howard, M. W., Dolan, E. D., Sirotin, Y. B., Tully, M., Wingfield, A., & Kahana, M. J. (2006). Temporal associations and prior-list intrusions in free recall. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *32*(4), 792–804. doi: 10.1037/0278-7393.32.4.792