Model-Based Characterization of Forgetting in Children and Across The Lifespan

Anais Capik (acpk@uw.edu)
Department of Psychology, University of Washington, Seattle, WA 98195 USA

Holly Sue Hake (hakehs@uw.edu)
Department of Psychology, University of Washington, Seattle, WA 98195 USA

S. Bahar Sener (sbsener@uw.edu)
Department of Psychology, University of Washington, Seattle, WA 98195 USA

Ariel Starr (abstarr@uw.edu)
Department of Psychology, University of Washington, Seattle, WA 98195 USA

Andrea Stocco (stocco@uw.edu)
Department of Psychology, University of Washington, Seattle, WA 98195 USA

Abstract

To fully understand human memory, it is necessary to understand its lifespan development. However, memory assessments often rely on significantly different methodologies for different age groups, and their results are typically not directly comparable. In this paper, we present a quantitative assessment of memory function spanning an age range of five to 85 years that is based on a model-based memory assessment. This approach yields a uniform metric that is directly interpretable and can be compared across different tasks and materials that are appropriate for different age groups. The results show a robust U-shape function, with long-term memory function at age 5 being comparable to that of cognitively impaired elderly individuals. These results and the method utilized could provide a new foundation for future studies on memory development across life stages.

Keywords: children, lifespan, memory, development, forgetting, adaptive fact learning system

Introduction

To attain a comprehensive understanding of human memory, it is crucial to explore how memory evolves throughout the lifespan. However, a detailed quantitative analysis that describes the progression of memory function throughout the lifespan remains elusive. Memory quality assessments often fall back on clinical tools like the memory components of the Mini-Mental State Evaluation and the WAIS-R. An inherent limitation of these tools is their dependence on accuracy scores obtained from memory tests conducted after a specific interval. Relying solely on raw accuracy rates can be problematic, as highlighted by Sherman and Hrabok (2023), and can yield incorrect results, especially when the underlying forgetting process is non-linear, as pointed out by Loftus (1978). The well-established understanding that 'forgetting' follows a non-linear process, as emphasized by Newell and Rosenbloom (1990), add a layer of complexity to the interpretation of these scores.

In response to these challenges, model-based assessments of memory have emerged as a novel approach (Pavlik and Anderson 2005; Pavlik and Anderson 2008; Sense et al. 2016). By fitting participant data to a model that reflects the dynamics of memory processes, this method creates a "cognitive twin" for each participant (Somers et al. 2020). Its parameters, indicative of cognitive functions, offer a robust alternative to traditional accuracy-based metrics. These model-based assessments can encapsulate the intricacies of forgetting and incorporate additional aspects of participants' responses, such as reaction times (Van Rijn et al. 2009) and vocal intonation (Wilschut et al. 2021). Importantly, the values of model parameters, being part of an overarching model with a highly developed and tested theoretical framework, require no standardization and possess intrinsic interpretability.

Recent applications of this methodology have demonstrated its efficacy in measuring memory function accurately and reliably across a broad demographic spectrum, including young adults (Sense et al. 2016), the elderly, and individuals experiencing memory loss, showcasing its potential to detect subtle memory function changes associated with conditions like mild cognitive impairment (Hake et al. 2023).

Pooling data from studies using these model-based techniques, we have collected information from individuals aged 18-80. These data reveal a monotonic trend, with memory function declining consistently and almost linearly over time. However, an important component is missing from this data: the development of memory during *childhood*.

Previous work has found that preschoolers are capable of forming true episodic memory as early as 3 years old (Hayne et al. 2011). Between the ages of 3 and 5 years old, we see improvements in episodic memory as children can recall for longer periods, suggesting that

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hippocampal-dependent memory systems undergo rapid development during preschool years (Saragosa-Harris et al. 2021). However, none of these studies have used model-based techniques, leaving open the possibility that these findings might have been influenced by the non-linearity of the forgetting process. Using a novel modification of model-based assessments that includes non-verbal stimuli specially designed for children, we present data on episodic memory function in 5-year-olds. Putting together this data with data from 77 participants aged 18-80, of various cognitive capabilities, we provide the first longitudinal trajectory using model-based assessments of memory across the lifespan.

Model

The memory model discussed in this article builds upon the foundational work of Anderson & Schooler (1991) and is situated within the ACT-R cognitive architecture framework. This model aligns with the principles outlined in Multiple Trace Theory as described by Nadel et al. (2000), positing that memories consist of separate traces formed upon each encounter with the same information. Each trace decays according to a power law (Newell and Rosenbloom 1990), and each re-encounter with the information generates a new trace, thereby strengthening the overall memory. The availability of a memory m at a given time t is determined by its *activation* $A(m, t)$. Thus, $A(m, t)$ is the logarithmic sum of all of its associated decaying traces:

$$A(m, t) = \log \sum_i (t - t(i))^{-d(i)} \tag{1}$$

Here, $t(i)$ represents the encoding time of the i-th trace, and $d(i)$ denotes its specific decay rate. In turn, $d(i)$ depends on the memory's activation at the time of each trace's creation, plus an individual-specific constant φ (Pavlik and Anderson 2005; Sense et al. 2016):

$$d(i) = e^{A(m,\, t\, =\, t(i))} + \varphi \tag{2}$$

By making a trace's decay rate dependent on the memory's residual activation, Equation 2 provides a natural account for the spacing effect (Cepeda et al. 2008). Note that, if the entire history of the encodings and retrievals of a memory m (that is, all of its constituent traces) are known, the probability that m can be successfully retrieved depends only on the the φ parameter, which represents an individual's characteristic *Speed of Forgetting* (SoF). High *SoF* values indicate a faster forgetting rate, suggesting lower accuracies on memory tests and accelerated forgetting over longer time periods— an observation noted in individuals experiencing memory deficits. Conversely, low *SoF* values indicate a slower forgetting rate, implying better performance and greater capacity to recall memories at longer intervals.

The practical application of this model has been previously demonstrated in educational settings, where it has been used to tailor learning experiences to individual memory profiles, enhancing the efficiency of fact memorization (Sense and van Rijn 2022; Sense et al. 2021; Van Rijn et al. 2009; Wilschut et al. 2021). Notably, the stability of the *SoF* parameter across various conditions has been affirmed (Sense et al. 2016), and its relevance to individual differences in memory function has been supported by neuroimaging studies, which have linked *SoF* to specific patterns of cortical brain activity (Zhou et al. 2021; Xu et al. 2021).

Interpreting *SoF* values

One advantage of using model-based assessments is that the interpretation of the results remains independent of the specific testing paradigm to which the model is fitted. In fact, the interpretation of the *SoF* parameter is derived directly from Equations 1 and 2. As previously mentioned, the activation of a memory reflects its availability, or more precisely, the probability $P(m, t)$ of retrieving m at time t, expressed here:

$$P(m, t) = 1 / (1 + e^{A(m,\, t)}) \tag{3}$$

In an ideal case in which a memory has been encoded and never re-encoded, the *SoF* tracks the declining probability of remembering m over time. For example, Figure 1 shows the predicted temporal memory trajectories (i.e. probability of retrievals over time) for three individuals with *SoF* values of 0.3, 0.4, and 0.5. It is easy to see how higher *SoF* values are associated with quicker forgetting, i.e., faster decline of the probability of retrieving a memory. For example, an individual with an *SoF* of 0.3 would still have a > 1% chance of remembering one week after encoding a memory, while an individual with a *SoF* value of 0.5 would have a 1% chance of remembering just one hour after encoding. Because of its computational nature, the *SoF* can be quantitatively interpreted as the speed at which a memory is forgotten.

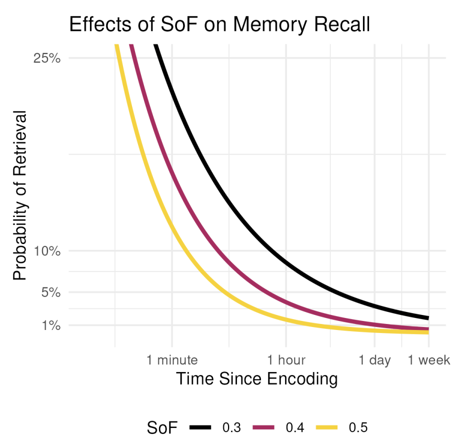

Figure 1: Probability of memory recall over time for three levels of *Speed of Forgetting* (SoF). The *x*-axis spans from 1 minute to 1 week, and the y-axis shows retrieval probability from 1% to 25%.

Experimental Hypotheses

In this paper, we use *SoF* values, computed through a model-based assessment, as an index of memory function at different ages. Because of its unambiguous mathematical interpretation, this measure is not specific to a particular test, allowing us to directly compare and interpret the performance of different individuals and age groups.

Our experimental design includes two primary objectives. The first is to assess the *SoF* in children during the period in which episodic memory is rapidly developing. This analysis will be integrated with associated demographic data to explore environmental influences on memory development.

The second objective involves a cross-sectional comparison of *SoF* across six distinct demographic cohorts. These include children aged 5, representing the initial stages of cognitive development; young adults aged 18-29, epitomizing cognitive maturity; middle-aged adults aged 30-45 and mature adults aged 46-64 providing an understanding of how memory changes incrementally throughout adulthood; senior adults aged 65 to 85, providing insight into memory retention during typical aging; and senior individuals within the same age range but with mild cognitive impairment (MCI), to examine the impact of early cognitive decline on memory decay.

Our hypotheses are the following:

1. Children will exhibit higher *SoF* values relative to other groups, reflecting the ongoing development of their cognitive processes and the relative inefficiency of their memory systems.
2. Healthy young adults will demonstrate lower *SoF* values compared to children, indicative of more stable memory retention, attributed to the maturation of their cognitive systems and the utilization of advanced memory strategies.
3. *SoF* values will increase again in normal aging, and dramatically so in individuals diagnosed with age-related cognitive impairments.

Our study aims to shed light on the computational nature of memory systems across different life stages, offering insights into the developmental trajectory of memory and retention.

Experiment 1

Our first experiment investigated children's memory using the *Speed of Forgetting* parameter and evaluated this parameter in the context of their demographic data.

Materials and Methods

Participants

Nineteen participants, all aged five years old, participated in the experiment. All participants exhibited typical development, with no diagnosed disabilities or language delays, and had regular exposure to, or fluency in, English. Of the 19 children recruited, four did not complete the task. Of the 15 remaining, 13 provided demographic data.

Adaptive Memory Assessment

An in-lab assessment was conducted using the adaptive fact learning system (AFLS), as detailed in Sense et al. (2016) and accessible at https://www.memorylab.nl/en/. This system dynamically estimates the *SoF* for each individual in real-time, adapting as the participant progresses through the learning module. The AFLS operates by initially presenting new image-image study pairs (for example, "Dinosaur / Environment") and then strategically scheduling repeated tests (such as "Environment" / Animal?") based on the real-time *SoF* estimates of the user. An illustration of the software interface is provided in Figure 2.

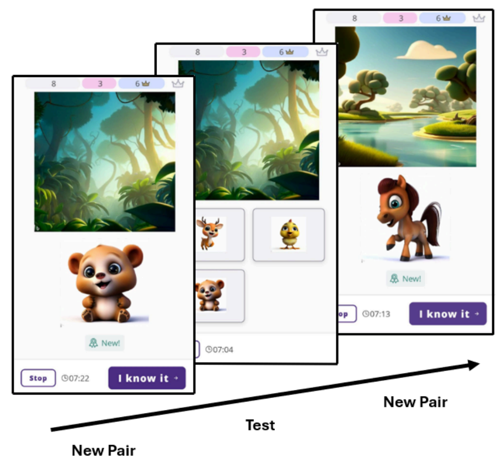

Figure 2: Interface of the Adaptive Memory Assessment.

Study Materials The study materials were created to ensure a balance between familiarity and difficulty. Utilizing AI-generated images from DALL·E, two tasks were developed: (1) an Introduction task, and (2) the Main Memory task. Figure 2 provides an illustration of the interface and two example pairs. To engage the children, a narrative was introduced: *A meteorite has scattered animals worldwide and your task is to reunite them with their homes.* This setup involved pairing 17 unique animals with corresponding habitats. The selection of animals and environments varied to maintain interest (e.g., unicorns, dinosaurs, birds, underwater creatures, reptiles, horses, etc.).

Participants were first shown an environment and its associated animal, and then just the environment with three animal options as a test probe, as illustrated in Figure 2. To maintain engagement and tailor the task's difficulty, two of the animals were more logically associated with the given environment (e.g., "dolphin"/ "underwater" and "fish"/ "underwater"), while one was clearly incongruent (e.g., "unicorn"/ "underwater"). This design aimed to ensure the task was engaging but not overly challenging.

Participants were asked to play the game for 8 minutes, and at least 6 minutes of play were required to calculate *SoF*. The number of new pairs shown or rehearsal of old pairs for each participant varied on the accuracy and reaction time collected from previous stimuli. This personalized approach was uniformly applied across all age groups, facilitating direct lifespan comparisons.

Data Processing The introduction task, designed to familiarize children with the game, was excluded from the final analysis. In the main memory task, repetition, activation, and *SoF* values for each term were calculated using specific functions from the AFLS software package. The average *SoF* for each lesson and participant was determined from the final φ value of each pair at its last repetition. Data analysis was restricted to sessions lasting a minimum of 6 minutes, filtering out instances where children were unable to focus or complete the task for the required duration.

Demographics

Alongside the collection of *SoF* data, demographic information was gathered for the children's group. This included gender, age, race, ethnicity, household income, parental education level, and languages spoken at home.

Results

Figure 3 provides an overview of the results for the children's group, which included $N = 15$ participants. Individual *SoF* varied between 0.358 and 0.590. The data was normally distributed and had a mean of φ = 0.424.

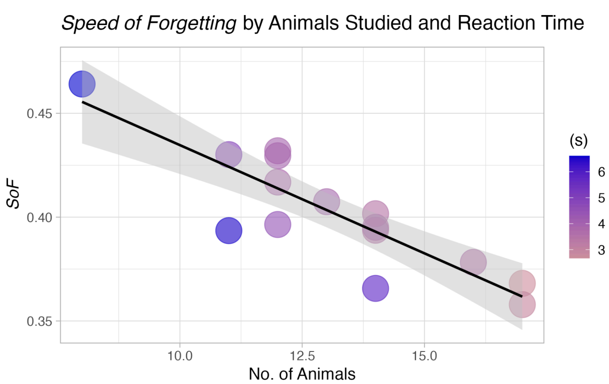

Figure 3: Correlation between *Speed of Forgetting* values and number of animal/landscape pairs memorized in the testing session. The color of each point represents the mean reaction time of each child.

Because the AFLS presents new materials at a rate adapted to each child's capacity, we expected the number of animal/environment pairs shown to each participant to be correlated with their *SoF.* As Figure 3 shows, this is indeed the case. The better participants remembered the pairs of stimuli, the more new pairs they were shown, and the lower their *SoF* was (Pearson r (15) = -0.87, $p < 0.001$).

Demographic Data Analysis No statistical significance was observed between any demographic variables and *SoF* (see Figure 4). This outcome might be attributed to the fact that the majority of our participants predominantly belonged to a middle- or upper-class socioeconomic status or to our small sample size. Consequently, limited variations in *SoF* across demographic factors within this relatively homogeneous sample were anticipated.

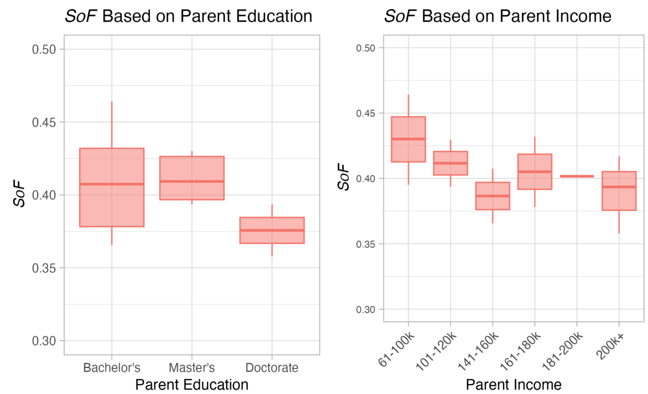

Figure 4: Relationship between children's *Speed of Forgetting* (SoF) and parent's highest level of education and household income.

Discussion

Using the *Speed of Forgetting* parameter, our study provides an understanding of children's memory. No correlation was found when analyzing *SoF* to the children's demographic data. However, while our results show no statistical significance between socioeconomic status (using household income and parent's education) and *SoF,* a larger sample size might lead to providing a statistical correlation between these parameters as previous studies have found a positive relationship between SES and episodic memory (Botdorf et al. 2022).

This study is the first to use the model-based approach pioneered by Sense et al (2016). Thus, the *SoF* parameter provides a model-based metric to quantify memory beyond the measure of overall accuracy.

Experiment 2

Our second experiment aimed to establish a lifespan developmental trajectory of the *Speed of Forgetting* metric, encompassing young children, young adults, middle-aged adults, healthy seniors, and seniors with mild cognitive impairment (MCI).

Material and Methods

Participants

This study incorporated data from 193 participants, aggregated from six distinct research projects executed within our laboratory during the previous year. The participant cohort encompassed 134 graduate and undergraduate students, termed "Early Adults", aged 18 to 29 years and enrolled at a local college, 4 "Middle Adults" aged 30 to 45, 8 "Mature Adults" aged 46 to 64, 23 "Senior Adults" aged 65 and over, and 24 senior adults with MCI.
For inclusion in the study, participants had to meet the following criteria: (1) age in the range of 18 to 85 years, (2)

proficiency in English, and (3) the absence of major medical or psychiatric conditions that could potentially interfere with cognitive performance. All individuals involved in the study participated in a minimum of four sessions, with the senior participants engaging in 30 to 52 sessions each. The recruitment of the senior participants was conducted on a rolling basis from the local NIH-designated Alzheimer's Disease Research Center.

Adaptive Memory Assessment

The adult assessment utilized the same online AFLS as described in the children's task, but with different stimuli. In this iteration, the AFLS presented study pairs such as "Pasta / Name of the Pasta" and strategically scheduled repeated tests (e.g., "Pasta" / "?") based on the participant's real-time *SoF* estimates. An example of the software interface for this assessment is depicted in Figure 5.

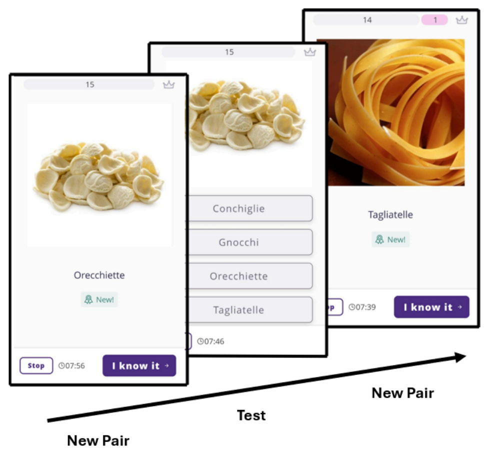

Figure 5: Interface of the Adaptive Memory Assessment for adults.

Study Materials The content for each test underwent thorough vetting and beta testing to ensure uniformity in familiarity and difficulty across tests. For each lesson, 15 pairs were crafted, linking two stimuli. Half of these lessons featured image/text associations, while the other half comprised text/text associations. The number of pairs shown was contingent on participant accuracy and reaction times.

Data Processing The methods for calculating repetition, activation, and *SoF* mirrored those used in Experiment 1.

Results

Our analysis encompassed the age spectrum from early childhood to advanced age, as depicted in Figure 6. Stratifying the data into distinct age categories revealed clear trends.

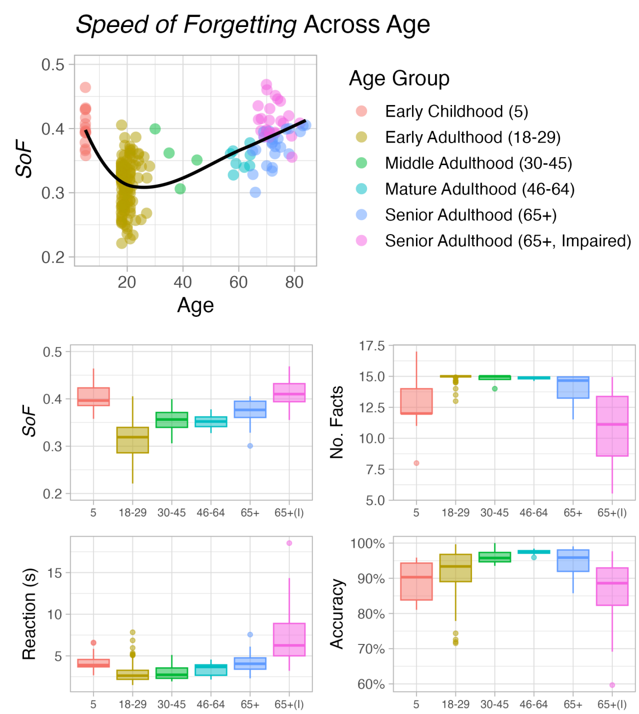

Figure 6: Comparative analysis of *Speed of Forgetting* (SoF) across age groups. Scatter plot depicting individual *SoF* values, revealing a U-shaped trend. Boxplots showing mean values across age groups for *SoF*, number of facts learned, reaction time (seconds), and accuracy (%).

Children aged five exhibited mean *SoF* rates of $\varphi = 0.42$, akin to those observed in our senior participants diagnosed with MCI ($\varphi = 0.41$). A noticeable trend toward slower forgetting speeds was found among young adults aged 18-29, with a mean $\varphi = 0.30$. The data then revealed a gradual increment in *SoF* rates in the later years of life.. This U-shaped trend was confirmed by fitting the data with a quadratic model of the form:

$$SoF \sim \beta_0 + \beta_1 Age + \beta_2 Age^2$$

The results of this model are represented in Table 1. The analysis uncovered both a significant linear ($\beta = 0.0009$, $p < 0.0001$) and a significant quadratic effect of age on *SoF* ($\beta = 0.398$, $p < 0.0001$). Together, the effects of age accounted for 39.8% of the variance in our data.

Table 1: Linear and Quadratic Effects of Age on *SoF*

Predictor	β estimate	*SE*	*t*	*p*
Intercept	0.311 ***	0.005	61.05	< 2e-16
Age (1st degree)	0.0009 ***	0.000	7.37	4.1e-12
Age (2nd degree)	0.398 ***	0.044	9.09	< 2e-16

**p < 0.05 **p < 0.01 *** p < 0.001*

The effect of age remained robust even when the age groups were used as categorical predictors. A one-way

ANOVA showed a significant main effect of group on *SoF* ($F(5,204) = 51.8$, $p < 0.0001$).

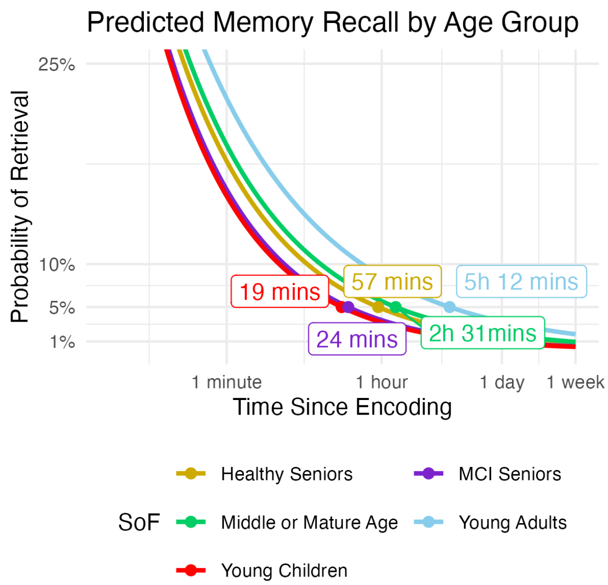

Figure 7: Probability of retrieval across different age groups' *Speed of Forgetting* (SoF) values. Points and labels refer to the time at which the probability of a memory being retrieved falls below 5%.

The use of a model-based metric like the *SoF* allows for a clearer interpretation and comparison of memory function between the six groups. As an example, Figure 7 plots the predicted memory trajectories for the mean *SoF* values of the six age groups in Figure 6. For reference, the points and labels in Figure 7 refer to the time at which the probability of successfully recalling a memory drops below 5%—an arbitrary but convenient threshold. Children and seniors with MCI, for example, cross that threshold at, respectively, 19 and 24 minutes after initial encoding; this fast forgetting would make it challenging to even follow a simple TV show because its average duration of 45 minutes exceeds their long-term memory ability.

Discussion

This paper has provided a normative trajectory of memory function over the lifetime, based on data collected from 210 individuals aged 5 to 85. Consistent with previous studies, our findings show that memory function improves rapidly between childhood and young adulthood. After that, memory function slowly decays over time, and such decay is accelerated when aging is accompanied by cognitive impairment (Schneider and Pressley, 1997; Kausler, 1994; Singer et al., 2003).

Our study not only reinforces those previous findings but is noteworthy for several reasons. First, it employs data from 210 individuals and over 4,000 individual testing sessions, yielding accurate individual measurements across a range of ages. But more importantly, it uses a model-based approach to quantifying memory, which yields directly interpretable and comparable values with only 8 minutes of testing. Additionally, the *Speed of Forgetting* values computed for each child could be directly incorporated in an educational AFLS to present study materials at an individualized pace, thus bridging the gap between memory assessment and personalized education for children.

Despite these achievements, a number of limitations should be acknowledged. Firstly, the data collected comes from different experiments, and different age groups were tested under slightly different conditions and for a different number of times. Second, while the same adaptive assessment framework was uniformly used for all individuals, the specific *stimuli* used differed across studies and age groups. Specifically, children were tested on pairs of novel visual stimuli, while adults were tested with a variety of materials that included both verbal and visual stimuli, and often included relatively unfamiliar but not entirely novel materials (i.e., pairs of country names and associated flags). While Sense et al. (2016) and Hake et al. (2023) reported that *SoF* values were not significantly affected by the specific material used, the heterogeneity of stimuli employed here made it impossible for us to systematically assess this.

An additional limitation is that the children's group only tests five-year-olds and we are missing other developmental landmark ages such as middle childhood and adolescence. Furthermore, while we were able to collect data for age groups between 30 - 64 years old, this age range is relatively undersampled compared to the young adult or senior adulthood groups. Sparse sampling may affect our ability to differentiate between different functions that define *SoF* changes across the lifespan

These limitations notwithstanding, we believe that our results provide a new foundation for understanding the nature and development of memory over the lifespan, offering new opportunities for investigating its cognitive and neural bases.

Conclusion

In conclusion, this study provides compelling evidence of the utility of the model-based *SoF* measure in characterizing memory function across the lifespan. By employing this approach, we observed a clear U-shaped trajectory of memory function, with children aged five exhibiting similar *SoF* rates as elderly individuals with MCI. Memory function improves rapidly from childhood to young adulthood and then gradually declines, with accelerated decay in older adults with MCI.

The findings underscore the value of *SoF* as a robust indicator of memory retention and forgetting. Additionally, integrating this AFLS model-based measure allows for personalized learning experiences based on each individual's memory profile. Despite the study's limitations, these results offer a new foundation for understanding the nature and development of memory over the lifespan, providing valuable insights into the factors influencing memory function and revealing opportunities for further exploration of its cognitive and neural bases.

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