Psychology and Aging

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Online First Publication, July 20, 2023. https://dx.doi.org/10.1037/pag0000769

CITATION

Sheldon, S., Sheldon, J., Zhang, S., Setton, R., Turner, G. R., Spreng, R. N., & Grilli, M. D. (2023, July 20). Differences in the Content and Coherence of Autobiographical Memories Between Younger and Older Adults: Insights From Text Analysis. *Psychology and Aging*. Advance online publication. https://dx.doi.org/10.1037/pag0000769

AMERICAN PSYCHOLOGICAL ASSOCIATION

Psychology and Aging

ISSN: 0882-7974

https://doi.org/10.1037/pag0000769

Differences in the Content and Coherence of Autobiographical Memories Between Younger and Older Adults: Insights From Text Analysis

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Several studies have shown that older adults generate autobiographical memories with fewer specific details than younger adults, a pattern typically attributed to age-relate declines in episodic memory. A relatively unexplored question is how aging affects the content used to represent and recall these memories. We recently proposed that older adults may predominately represent and recall autobiographical memories at the gist level. Emerging from this proposal is the hypothesis that older adults represent memories with a wider array of content topics and recall memories with a distinct narrative style when compared to younger adults. We tested this hypothesis by applying natural language processing approaches to a data set of autobiographical memories described by healthy younger and older adults. We used topic modeling to estimate the distribution (i.e., diversity) of content topics used to represent a memory, and sentence embedding to derive an internal similarity score to estimate the shifts in content when narrating a memory. First, we found that older adults referenced a wider array of content topics (higher content diversity) than younger adults when recalling their autobiographical memories. Second, we found older adults were included more content shifts when narrating their memories than younger adults, suggesting a reduced reliance on choronology to form a coherent memory. Third, we found that the content diversity measures were positively related to specific detail generation for older adults, potentially reflecting age-related compensation for episodic memory difficulties. We discuss how our results shed light on how younger and older adults differ in the way they remember and describe the past.

Public Significance Statement

A classic finding in cognitive aging research is that older adults describe autobiographical memories with less specific details than younger adults. Whether there are other age differences in how autobiographical memories are described remains unclear. Using novel text analysis, we found evidence that older adults tend to recall memories by referencing and shifting between more content than younger adults, indicating an age difference in memory content as well as narrative style. The tendency for older adults to generate more content topics in their memories was linked to better use of specific details during recall. These results indicate that older adults might bring to mind a broader range of content topics to compensate for episodic memory decline.

Keywords: autobiographical memory, healthy aging, episodic memory, text analysis, topic modeling

The authors gratefully acknowledge funding from a Natural Sciences and Engineering Research Council of Canada Discovery Grant (No. RGPIN-04241) awarded to Signy Sheldon. Preliminary results from this research were presented at the Memory Disorders Research Society Meeting (Philadelphia, 2022) and at the Annual Meeting for the Cognitive Neuroscience Society (San Francisco, 2023). The authors have no known conflicts of interest to disclose.

The data set generated and analyzed for the present study are available through the Open Science Framework, project “Psychometrics of Autobiographical Memory” contributed by R. Nathan Spreng (https://osf.io/fzkm7/) or from the corresponding author.

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Research on young versus older adult differences in autobiographical memory has largely focused on assessing the detail specificity of past events (e.g., Levine et al., 2002). This line of work has revealed that the specificity in which event memories are recalled tends to be lower among older adults, such that older adults recall fewer event-specific details and more generalized semantic details compared to younger adults (Addis et al., 2008; Gaesser et al., 2011; Levine et al., 2002; Madore & Schacter, 2014; Peters et al., 2019; Setton, Mwilambwe-Tshilobo, et al., 2022; Setton, Sheldon, et al., 2022). Whether there are younger versus older age differences in the content of autobiographical memories—and how such content relates to the ability to provide detail-rich memories—is a relatively unexplored topic. The present study addressed this knowledge gap. In the sections to follow, we first describe prior research on young versus older age differences in autobiographical memory and how this research informed the tested hypotheses about the way the content of a memory may differ between younger and older adults. We then describe how we leveraged natural language processing (NLP) methods to test these hypotheses.

Aging and Autobiographical Memory

To document how older adults describe past personal experiences, many researchers have compared the autobiographical memory descriptions of younger and older adults by scoring these memories for the presence of specific details. This method involves using validated protocols like the Autobiographical Interview (AI) (Levine et al., 2002). In the Autobiographical Interview, participants are asked to describe a series of single past life events in as much detail as possible. These descriptions are transcribed and manually scored by trained raters for the presence of details that are internal or external to the chosen event. Internal details refer to specific event-unique descriptors including context, objects, actions, thoughts, and perceptual details. External details include general facts and statements about the event. With the Autobiographical Interview, several studies have found that older adults provide significantly fewer internal but not external details compared to younger adults, a pattern that has been primarily interpreted as evidence of episodic memory decline in older age (Addis et al., 2008; Gaesser et al., 2011; Madore & Schacter, 2014; Peters et al., 2019; Setton, Sheldon, et al., 2022; Sheldon et al., 2011).

While scoring memories for the number of details is a useful approach to document young versus older age differences in the specificity of autobiographical memories, this approach lacks the ability to describe differences in the type of content contained in a memory. Take, for example, the following descriptions from a memory of an evening out: “I ate cheesecake and I watched TV” and “I ate cheesecake with whipped cream.” According to detail scoring methods, both description statements are equally specific, containing two internal details, and thus are considered to rely on episodic memory to the same degree. However, these descriptions clearly contain different types of content. Whether there are meaningful differences in the type of content contained in the autobiographical memories of younger and older adults remains relatively unexplored.

There is prior work, to suggest that older adults access memory representations with more content. Despite reduced specificity, older adults retain higher order gist-level features of memories (Castel et al., 2007; Gallo et al., 2019; Koutstaal & Schacter, 1997; Rhodes et al., 2008; Whatley et al., 2021). For example, older adults remember the underlying meaning of an encoded narrative story, akin to the gist of the story (Adams et al., 1997). Similarly, older adults seem to flexibly access the gist from other types of learned information (e.g., knowing which days to carry an umbrella from a learned weather forecast), while recalling fewer specific details (e.g., the expected temperature on certain days from a forecast; Gallo et al., 2019). The gist of a memory often involves making inferences and referencing related knowledge outside of the perceived event. Thus, representing a memory at a gist level is likely to include a broader scope of content than when representing a memory specifically, which centers on reproducing a precise representation of the experience at the heart of a memory (Hall, 1990). Given that older adults may favor gist representations of autobiographical memories and that a gist memory representation may be enriched with a variety of topics (Grilli & Sheldon, 2022), autobiographical memories of older adults may be more likely to be represented with enriched content, or more “content diversity,” than the memories of younger adults.

A compelling idea is that age differences in autobiographical memory content reflect differences in how event-specific details are generated by younger and older adults. This notion follows compensation-based theories of cognitive aging which propose that older adults recollect gist-level memories in order to compensate for deficits in episodic memory (Festini et al., 2018; Nilsson, 2003; Reuter-Lorenz & Cappell, 2008; Reuter-Lorenz & Lustig, 2005). According to these theories, individuals can use generalized prior knowledge, supported by semantic memory processes that are retained into older age, to help guide access to episodic memory during retrieval (Irish, 2016; Irish & Piguet, 2013). Thus, we may expect that drawing on more diverse content topics, reflecting the inclusion of more prior knowledge and the representation of memories at a gist level, would positively relate to the specific detail generation exclusively for older adults. In other words, using a wider sampling of content topics to represent an autobiographical memory may help older adults retrieve details, which may partly be a response to an episodic memory system with reduced capacity.

The inclusion of more content among older adults may also influence the narrative style used to recall autobiographical memories (Reese et al., 2011). Theories of personal narrative coherence have proposed that there are separate dimensions for providing a coherent narrative, with many of these theories distinguishing between a chronological (narrating the order of the original actions in the event) and a less constrained meaning/thematic (narrating the relevance and importance of a memory) form of coherence (Adler et al., 2007; Reese et al., 2011). This line of research has shown that chronological coherence dominates the narratives of younger adults while the use of a less constrained thematic/meaning-based form of coherence is associated with older age (Reese et al., 2011). This research suggests that in older age, we organize memories with a broader focus, which could result in more shifts or “asides” in content as a past event is narrated (Arbuckle et al., 2000; Arbuckle & Gold, 1993; Bluck et al., 2016; Gold & Arbuckle, 1995). Our view is that how a person constructs a coherent account of their past may be less closely tied to episodic memory capacity and instead may reflect a natural difference in younger versus older adult memory organization and motivations (Grilli & Sheldon, 2022). Indeed, research suggests that younger and older adults are motivated to recall autobiographical memories with different goals in mind, which may promote the use of different narrative styles (Bluck & Alea, 2009). Specifically, we suggest that younger adults tend to recall past events to guide future behavior, and thus recall associated memories close to how an event originally occurred. In contrast, older adults tend to recall memories to share meaning, form social bonds, and reflect on identity, leading to past experiences narrated with a focus on thematic coherence (Demiray et al., 2019; Grilli & Verfaellie, 2015; Hess, 2005). Under this view, younger versus older differences in narrative coherence do not reflect compensation for episodic memory, but rather a preferred or motivated difference in memory narrative style.

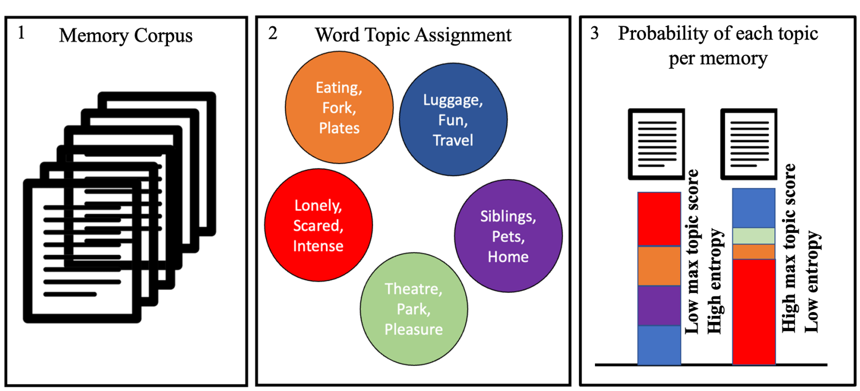
Natural Language Processing

NLP approaches are powerful, data-driven computational methods to estimate content in written descriptions (Hirschberg & Manning, 2015) and can be used to test for age differences in autobiographical memory content and coherence. In this study, we used topic modeling, Latent Dirichlet allocation (LDA; Blei et al., 2003), to measure the spread of content topics in memories. LDA is a data-driven probabilistic model that estimates the presence and distribution of common content units, or topics, in large data sets of text (Puschmann & Scheffler, 2016). As illustrated in Figure 1, LDA first searches through a collection of documents to create a topic dictionary, which contains clusters of word embeddings that share a common underlying meaning represented in the documents. Next, LDA estimates the probability distribution of each of these topics within each document of the larger data set. These distribution scores can provide two measures of topic or content diversity, a maximum topic score and an entropy score. The maximum topic score is the value of the topic most strongly represented within a document. Given that topic scores are probability values (/1), a high maximum topic score (close to one) indicates that most of a document's content is explained by a single topic and a document with a low maximum topic score is one in which there are more content topics expressed, or higher content/subject matter diversity. In parallel, LDA estimates the entropy of each of the content topics within a model based on the number of high probability words that are contained within a topic. The entropy score of a document (memory) is calculated by taking the average entropy over the expressed topics contained within it. Topics with few higher probability words have higher entropy or randomness than topics with many high probability words, which are considered more focused on the content of the topics and therefore low in entropy. For the purposes of the present study, maximum topic scores and entropy scores are used to test for age differences in the content diversity within a memory representation.

Second, we applied an unsupervised sentence embedding technique, Google's Universal Sentence Encoder, to examine narrative coherence. This technique embeds segments of text into a high-dimensional vector space and measures the similarity of neighboring segments using cosine similarity [$\cos(\theta) = (A \cdot B)/|A||B|$], (Lahitani et al., 2016). The similarity of two neighboring segments indicates the degree to which the types of words present in both vectors are related. When averaged across a document, this similarity measure gives an estimate of narrative coherence. A low internal similarity score represents a document that has neighboring phrases with less similarity, reflecting a reduced reliance on coherently organizing information in a straightforward (i.e., chronological) manner. A high internal similiarity score, on the other hand, represents a document in which the semantics, or content, of neighboring phrases are relatively similar. For example, a description of a memory that includes phrases that reference the same semantic topic (e.g., kittens) would have a high internal similiarity score ("I made the big mistake of trying to take on two little kittens. My cousin's brother had found some kittens on a dock in the bay, and they looked like they were abandoned by their mother. They couldn't really tell if people had dropped them off or if the mother cat had abandoned them or something happened to her"). In contrast, a description of a memory that includes phrases that reference different types of content as the memory is narrated (e.g., kittens and fishing) would have a low internal similiarity score ("I made the big mistake of trying to take on two little kittens. My cousin's brother had found some kittens on a dock in the bay. We were just passing time.

Figure 1

A Schematic Depiction of the LDA Analysis Approach



Note. (1) LDA determines the number of topics represented within a set of documents (memories). (2) The terms (words) that best reflect each topic are used to create a topic dictionary. (3) This dictionary is applied to each document (memory) from the analyzed set, and the probability that each topic is included in a document is calculated. Maximum topic scores and entropy scores are calculated using the topic probability distribution. LDA = Latent Dirichlet allocation. See the online article for the color version of this figure.

The dock had a lot of sailboats, and a lot of people ready to go fishing since it was the season for it. Anyway, about the cats, they couldn't really tell if people had dropped them off or if the mother cat had abandoned them or something happened to her").

The Present Study

The overall aim of the present study was to document age differences in the content diversity and narrative coherence (organization) of autobiographical memories, and then test if these measures relate to episodic memory use when recalling these memories. To this end, we re-analyzed a data set that contained autobiographical memories recalled from three different life periods given by 352 younger and older adults. We first implemented LDA to evaluate the number of content topics represented within each memory (maximum topic and entropy scores) and then used a sentence embedding algorthim to determine the internal similarity scores of these memories, an estimate of narrative coherence. Within a subset of participants for which memories that were scored for the presence of internal and external details using the Autobiographical Interview (Lockrow et al., 2023), we related these new text analysis measures to these detail scores. Our predictions were the following: First, if older adults reference a greater diversity of content topics when recalling past events, older adults' memories will be associated with lower maximum topic scores and higher entropy scores than those of younger adults. Second, if older adults narrate their memories with more frequent shifts to new information, reflecting the use of thematic instead of chronological forms of narrative coherence, older adults' memories will be associated with lower internal similarity scores (i.e., more shifting) than those of younger adults. Third, if content diversity represents an age-related compensatory mechanism to generate episodic details when recalling the past, the reported topic modeling scores will be associated with higher internal but not external detail generation in the older adult sample An additional exploratory aim was to determine if the NLP measures differed as a function of time period from which a memory was described, as theories suggest that different cognitive processes, particularly episodic memory processes, are involved when retrieving recent versus remote autobiographical memories (Gilboa & Moscovitch, 2021).

Method

Transparency and Openness

This study used a previously analyzed deidentified data set collected by coauthors R. Nathan Spreng and Gary R. Turner, available on Open Science Framework (Spreng, 2023; https://osf.io/fzkm7/). The conducted analysis received ethical review board approval at McGill University. We report all the manipulations and measures used to test our hypotheses. The study design, hypotheses, and analytic plan were not preregistered; however, we have made our analytic code available at https://github.com/signysheldon/Autobiographical-Memory-Text-Analysis-Code-.git (Sheldon et al., 2023).

Participants

Two hundred one younger adults (mean: 22.4 ± 3, 3 years, age range: 18–34, M/F: 87/114) and 151 older adults (mean: 68.8 ± 6.7 years, age range: 60–92, M/F: 69/82) from Ithaca, New York and Toronto, Ontario were included in the present report, with a full description of the collected behavioral data reported in the published report, Spreng et al. (2022). Younger adults were recruited from nearby universities while older adults were community-dwelling participants recruited through local advertisements between 2014 and 2017. Sample size determination and exclusions can be found in these reports. The sample size for each age group was determined to provide sufficient statistical power for group-wise individual difference analyses, and group interactions in slope. The average correlation between measures that do not share method variance is between 0.20 and 0.30 (Fraley & Marks, 2007; Gignac & Szodorai, 2016; Hemphill, 2003). A sample size greater than 120 participants provides 80% power to detect correlations $r \geq 0.20$ with 95% confidence intervals not crossing zero. Participants were screened to rule out individuals with a history of neurological or other medical illness impacting cognition, including acute or chronic psychiatric illness. All participants were screened for depressive symptoms and global cognition. Four younger adult and 16 older adult participants had scores below 27/30 on the Mini Mental Status Exam (Folstein et al., 1975) and/or above 20/30 on the Geriatric Depression scale (Yesavage & Sheikh, 1986), indicative of mild cognitive impairment or moderate to severe depression, and were removed from the data set. Demographic information for the analyzed participants are shown in Table 1. Participants provided written informed consent in accord with the institutional review board at Cornell University and Research Ethics Board at York University under the project title "Goal Directed Cognition in Older and Younger Adults."

Autobiographical Interview

As part of a larger behavioral data set, participants completed the Autobiographical Interview (Levine et al., 2002). Younger adults were asked to recall and describe single events from "early childhood" (childhood to 11 years old), "teenage years" (ages 11–18), as well as from the most recent year ("early adulthood"). Older adults were asked to recall events from five life periods: "early childhood" (childhood to 11 years old), "teenage years" (ages 11–18), "early adulthood" (18–30), "middle adulthood" (ages 30–55) and from the most recent year ("late adulthood"). Participants freely recalled each event until a natural stop was reached and then the interviewers used probes to prompt the recall of more details (Levine et al., 2002). These descriptions were audio recorded and transcribed. We selected transcriptions of events described prior to the probes (i.e., when participants were freely recalling the event) from the three life periods common among the age groups: "early childhood," "teenage years," and the "recent" year, thus equating the content of events experienced at different life stages, at least in the remote time periods, across the age groups (e.g., recalling childhood birthday parties; first day at a new job). Each narrative was manually scored by two trained individuals for the number of internal and external detail according to the Autobiographical Interview scoring protocol (Levine et al., 2002). These scores are reported in prior studies (Lockrow et al., 2023; Setton, Mwilambwe-Tshilobo, et al., 2022; Setton, Sheldon, et al., 2022) and used in the present analysis.

Content Analysis

Two content analyses were conducted. First, a topic model was constructed to estimate the content diversity or distribution in each of the memories. Second, a similarity analysis was conducted to

Table 1
Demographic Characteristics for the Younger and Older Adults Age Groups

Measure	Younger adults	Older adults
Location		
Ithaca	173 (96 female, 77 male)	121 (66 female, 55 male)
Toronto	28 (18 female, 10 male)	30 (16 female, 14)
Race	53.73% White, 18.91% Asian, 8.46% black or African American, 4.98% mixed race, 5.47% other, 1.99% not provided	90.73% White, 1.32% Asian, 1.32% black or African American, 0.66% mixed race, 1.99% other, 1.32% not provided
Ethnicity	75.62% non-Hispanic or Latino, 10.45% Hispanic or Latino, 7.46% not provided	89.40% non-Hispanic or Latino, 1.32% Hispanic or Latino, 6.62% not provided
Age (years)		
Range	18–34	60–89
M	22.4	68.8
SD	3.33	6.7

estimate the number of shifts between content within each memory, which would speak to narrative coherence. Prior to running these analyses, potential outlier memories were evaluated and removed. Outliers included those that were 2.5 *SD*s above or below the respective age mean. Outlier inclusions did not change the pattern of results reported here.

Topic Modeling

LDA topic modeling was implemented using the Gensim open-source python library (Řehůřek & Sojka, 2011) to examine the overall distribution of content usage in each memory in a "bag-of-words" model (with no temporal aspect). Topic modeling is a data-driven method, which makes it dependent on the amount of data input into to the model. In order to construct topic models with the same amount of data per age group, we randomly selected the largest equivalent number of younger and older adult participants in which all three memories were at least three sentences long, a length recommended by LDA developers (Blei et al., 2003). This approach resulted in 138 participants per group and 414 memories for each topic model. It is recommended to have at least 100 documents (in this case memories) to run LDA topic modeling, and a general guideline is that including over 1,000 documents is ideal (Blei et al., 2003). Future studies implementing LDA topic modeling as we do in this study may wish to follow these guidelines.

First, each autobiographical memory description was parsed using the Natural Language Toolkit (NLTK) sentence tokenizer (Bird et al., 2009). Words in each sentence were then labeled with a parts of speech (POS) tag using the NLTK POS-tagger and tokenized. Examples of POS tags include plural noun, proper noun, adjective, verb, past tense, and adverb. The narratives were then filtered for tokens less than 2 words long (i.e., words that did not contain topic information, e.g., "so," "to") to improve the accuracy of the topic modeling. To account for age-based speech patterns, we modeled the two age groups (younger adults and older adults) independently.

For each model, we ran a hyperparameter grid search to find a suitable number of topics, α, and η estimates (smoothing parameters that reflect the most appropriate number of topics and number of words in a topic, respectively). As a result of this grid search, we identified a topic number of 25, and α and η estimates were set at 1. These parameters were applied to both models to allow comparison of results. Next, for each memory encoded in our models, we calculated the degree to which each topic contributed to explaining the overall distribution of tokens in that memory. We then extracted the maximum topic score for each memory with a higher maximum topic score indicating that a narrative focuses on a singular representation or pool of information and a lower maximum topic score indicating that a particular memory samples from a range of representational topics or sources (e.g., there is more diversity in representational topics). We also calculated entropy from the LDA model, which is inversely related to maximum topic scores, as another metric of the breadth of topics contained in a sample.

Internal Similarity

To calculate internal similarity within a given memory, each memory description was divided into sequential nonoverlapping 15-word segments. Using the Universal Sentence Encoder (Cer et al., 2018), these text segments were embedded into high-dimensional vectors based on the semantic (i.e., shared content) meaning of word sequences in the segments. The meanings used by the Universal Sentence Encoder are from established NLP tasks and are represented in 512-dimensional vectors, which were derived for each input text segment. Content similarity of neighboring text segments is computed using cosine similarity for each of the neighboring embedded vectors (Ladd, 2020). The internal similarity score for a memory is the average of all neighboring segments cosine similarity scores.

Planned Analyses

We used linear mixed modeling, fit with Restricted Maximum Likelihoods, with by-participant random intercepts in all models to account for individual variability and treat it as a nuisance variable. All models included word count and gender as factors of noninterest as both affect text analysis outcome measures (Tausczik & Pennebaker, 2010). Regression coefficients and *p* values were based on Satterthwaite approximations for denominator degrees of freedom, established using the "lme" test via the General Analyses for the Linear Model in Jamovi function in Jamovi (https://www.jamovi.org; Version 0.9.5.12). For each predicted variable, two sets of linear mixed models (LMMs) were constructed. The first LMM was constructed to estimate the predicted variable score from age group, memory time period, and the interaction of these factors. The second set of LMMs were run to test how the variable score related to internal and external details from the Autobiographical Interview in separate models as a function of age group and memory time period.

Results

Topic Modeling Scores

To test our first hypothesis that older adults would tend to have more content diversity within descriptions of autobiographical memories relative to younger adults, we ran separate LMMs estimating maximum topic scores and entropy scores from the LDA models including age group (young, old), memory time period (childhood, teenage, and recent year), and the interaction of these factors (gender and word count included with participant as a random variable, Table 2). The LMM estimating maximum topic score revealed a significant main effect of age group. Regardless of memory time period, older adults had lower maximum topic scores (M = .62, SD = .14) than younger adults (M = .689, SD = .124), suggesting that older adults have memories that span more topics (Figure 2, left panel). This pattern was confirmed by the LMM that estimated entropy scores within the memories. Older adults had greater entropy (i.e., content diversity) in their memories (M = .139, SD = .0.35) than younger adults (M = .12, SD = .32; Figure 2, right panel). There was no time period effect in either of these models.

Internal Similarity Scores

To test our second hypothesis that older adults would have more narrative content shifts relative to younger adults, reflecting lower chronological coherence, we constructed LMMs estimating internal similarity scores including age group (young, old), memory time period (childhood, teenage, and recent year), and the interaction of these factors (Table 3). Word count was included in the model with participant as a random variable. Confirming our hypothesis, there was a significant effect of group such that older adults had lower internal similarity scores (M = .213, SD = .046) than younger adults (M = .224, SD = .040), regardless of memory time period (Figure 3). Following our exploratory investigation of how memory time period affects content, we found a main effect of time period such that memories had higher internal similarity scores for more remote time periods. In other words, memories tended to be more temporally coherent with remoteness (Figure 3).

Table 2

Results of the Linear Mixed Models Estimating Maximum Topic Scores or Entropy Scores of the Autobiographical Memories

Variable	F	Num Df	Den Df	p
Maximum topic scores				
Age group	21.81	1	134	<.001
Time period	0.34	2	285	.714
Word count	54.97	1	398	<.001
Gender	1.86	1	134	.17
Age Group × Time Period	0.19	2	272	.83
Entropy scores				
Age group	18.10	1	134	<.001
Time period	.22	2	285	.80
Word count	276.85	1	398	<.001
Gender	2.51	1	134	.12
Age Group × Time Period	.50	2	272	.61

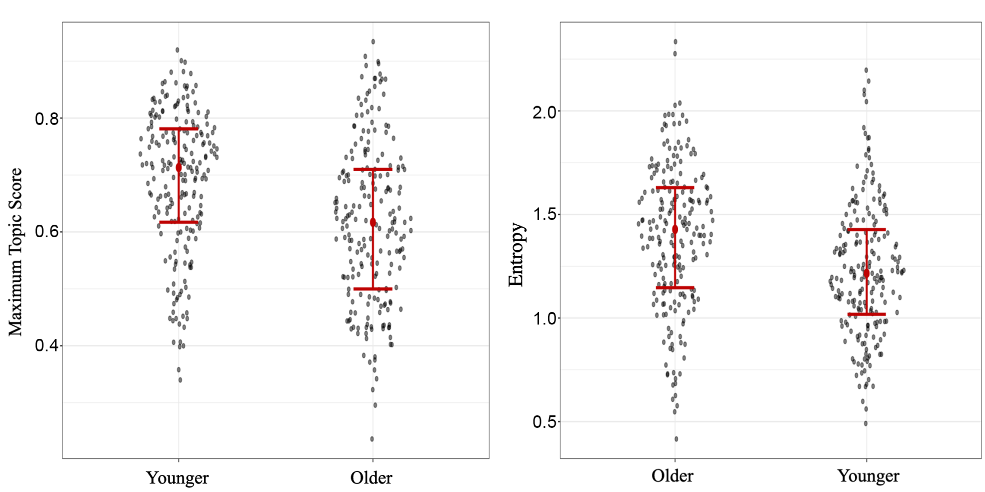
Note. Displayed are the fixed effect omnibus tests for the variables from the models with the formula (max topic score or entropy scores ~ 1 + age group + time period + word count + gender + time period: age group + (1 | participant)). Num Df = numerator degrees of freedom; Den Df = denominator degrees of freedom. Satterthwaite method was used for estimating degrees of freedom.

The Relationship to Detail Generation

As reported elsewhere (Lockrow et al., 2023; Setton, Mwilambwe-Tshilobo, et al., 2022), there were significant differences in internal detail count between younger and older adults across childhood,

Figure 2

Illustrations of the Maximum Topic Scores (Left) and Entropy Scores (Right) for the Autobiographical Memories Described by the Younger and Older Adult Age Groups, Averaged Across Time Period



Note. The central red dot represents the average score, the red error bars represent the standard error, and the grey dots represent individual data points. See the online article for the color version of this figure.

Table 3

Results of the Linear Mixed Model Estimating the Internal Similiarity Scores of the Autobiographical Memories

Variable	*F*	Num Df	Den Df	*p*
Age group	22.35	1	358	<.001
Time period	14.21	2	746	<.001
Word count	196.95	1	954	<.001
Age Group × Time Period	1.85	2	715	.16

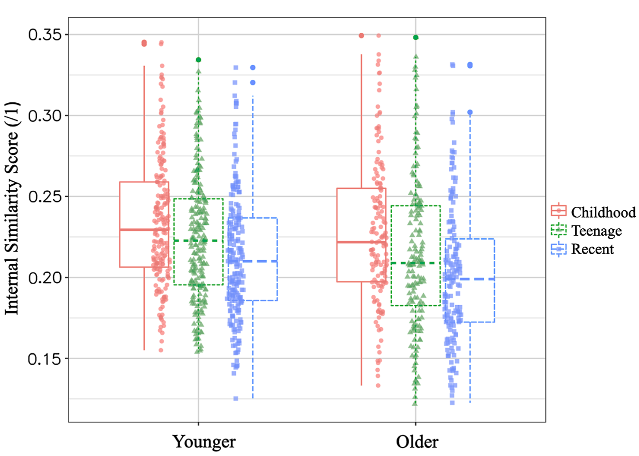
Note. Displayed are the fixed effect omnibus tests for the variables from the model internal similarity scores (~1 + age group + time period + word count + gender + time period: age group + (1 | participant)). Num Df = numerator degrees of freedom; Den Df = denominator degrees of freedom. Satterthwaite method was used for estimating degrees of freedom.

teenage and recent memories, $F(1, 371) = 44.30$, $p < .001$, that was more pronounced with more recent memories, $F(2, 715) = 10.00$, $p < .001$. For external details, there was also an effect of age group such that older adults provided more external details than younger adults across all memories, $F(1, 359) = 15.277$, $p < .001$, and this pattern did not interact with time period, $F(2, 707) = .48$, $p = .62$. These data are plotted in Figure 4.

The detail counts were used to test whether an enhancement in content diversity or narrative content shifts reflected forms of compensation for lower episodic memory among older adults. We constructed separate LMMs to estimate internal and external details from the maximum topic scores, the main measure of content diversity model (Table 4) as well as the similarity scores (Table 5). The LMM estimating external detail generation did not reveal any association to the maximum topic scores (Figure 5, right), yet the LMM predicting internal details from the maximum topic scores and associated factors showed an interaction effect between age group and topic score (Figure 5, left). When we explored this interaction by

Figure 3

Illustrations of the Internal Similarity Scores of the Autobiographical Memories Described by the Younger and Older Adult Age Groups for Each Time Period



Note. The boxplots represent the median score with the interquartile range. Individual data points are plotted next to each boxplot. See the online article for the color version of this figure.

calculating the parameter estimates of maximum topic scores for each age group, we found the relation between topic scores and internal details to be significant for both, but the directionality was different (younger adults: $\beta = 5.411$, $SE = 4.18$, $p = .008$; older adults, $\beta = -10.10$, $SE = 4.16$, $p = .016$). A higher focus on a singular topic—lower content diversity—within a memory was related to more internal details for younger adults, and the reverse pattern was seen for older adults. For older adults, a greater diversity of content topics (lower maximum topic scores) related to a higher number of internal details within a memory. Parallel effects reported with these maximum topic scores were found in LMMs that included entropy scores (Table 6), such that higher entropy scores related to more internal details in older adults' memories but fewer internal details in younger adults' memories. For the internal similarity scores, neither the LMMs to estimate internal nor external details revealed any significant score interactions with age group (Table 5).

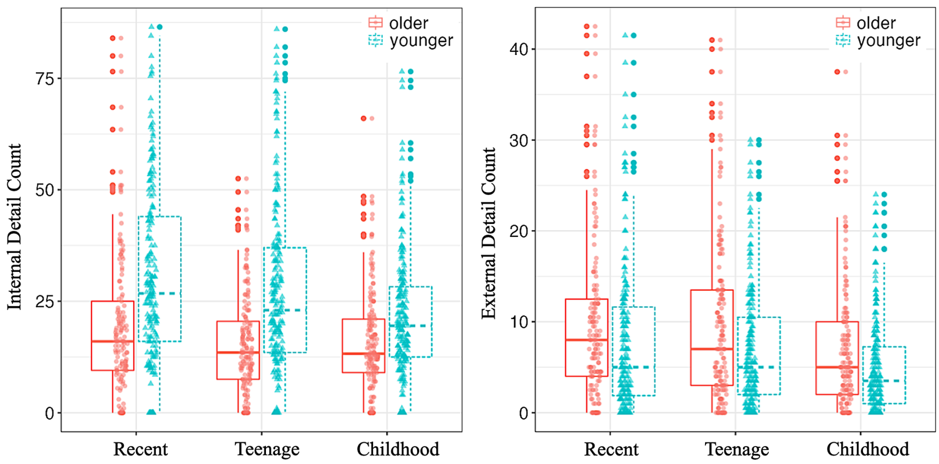
Discussion

Research has focused heavily on illustrating that older age is associated with lower detail specificity of autobiographical memories, such that older adults report fewer specific (episodic) and more general (semantic) details than younger adults (Levine et al., 2002; Sheldon et al., 2018). Much less is known about how the content topics used to represent memories may differ between younger and older adults, or whether there are age differences in how these memories are coherently narrated during recall. In this study, NLP was used to close these gaps in knowledge. Following the understanding that autobiographical memories are the result of integrating a wide variety of content into a coherent personal narrative (Conway, 2009; Conway & Pleydell-Pearce, 2000), we asked whether older adults would include more sources of content, reflecting the formation of generalized or gist-level mnemonic representations. Moreover, we asked whether older adults would tend to provide memory narratives characterized by the use of a broader and potentially more meaning-based form of content coherence, as indicated by more frequent shifts in content over time (Grilli & Sheldon, 2022).

Using a data set in which younger and older adults described autobiographical memories from three time periods (childhood, teenage year, recent year), we first implemented a probabilistic topic model to identify the diversity of content topics used to construct a memory (maximum topic scores and entropy scores). Next, we leveraged an unsupervised internal similarity algorithm to calculate internal similarity scores between text segments within this memory description, calculating the number of content shifts in a memory to estimate narrative coherence. Our analysis revealed that older adults included more content topics in their autobiographical memories than younger adults, indicative of a broader and more generalized way to represent their memories than younger adults. Older adults also described their past experiences with more shifts in content, suggesting that memories are organized with different types of narrative coherence between younger and older adults. We also found that enhanced content diversity within the memories, but not narrative coherence, positively related to the number of specific internal details generated by older adults. In the following sections, we discuss how our results shed new light on younger versus older age differences in remembering.

Figure 4

Illustrations of the Internal and External Detail Counts for the Autobiographical Memories Described by the Younger and Older Adult Age Groups for Each Time Period



Note. The boxplots represent the median score with the interquartile range. Individual data points are plotted next to each boxplot. See the online article for the color version of this figure.

Older Age Is Associated With More Content in the Representations of Autobiographical Memories

In line with our first hypothesis, the topic modeling analysis revealed that older adults draw upon a greater diversity of content topics (lower maximum topic score and higher entropy scores) than younger adults, who tend to focus on one content topic to describe memories. We interpret these findings as evidence of an age-related shift toward representing memories at a gist level, such that older adults are reflecting on the broader meaning of a recalled event and its relation to established knowledge, as opposed to reproducing specific details (Grilli & Sheldon, 2022). One possible explanation for this shift toward gist is that it is the result of impairment in executive control, which is common in older age, leading to memories that are

Table 4

Results of the Linear Mixed Models That Included Maximum Topic Scores to Estimate Internal Details (Top) or External Details (Bottom) in the Autobiographical Memories

Variable	*F*	Num Df	Den Df	*p*
Internal details				
Age group	42.84	1	132	<.001
Time period	1.34	2	261	.27
Gender	.51	1	123	.48
Maximum topic score	.02	1	370	.90
Word count	328.02	1	370	<.001
Age Group × Time Period	3.20	2	252	.04
Age Group × Maximum Topic Score	15.37	1	370	<.001
Time Period × Maximum Topic Score	.11	2	303	.90
Age Group × Time Period × Maximum Topic Score	.33	2	303	.72
External details				
Age group	29.20	1	133	<.001
Time period	.28	2	263	.76
Gender	.02	1	370	.88
Maximum topic score	<.001	1	125	.97
Word count	93.23	1	369	<.001
Age Group × Time Period	1.66	2	254	.19
Age Group × Maximum Topic Score	1.81	1	368	.18
Time Period × Maximum Topic Score	.86	2	309	.43
Age Group × Time Period × Maximum Topic Score	.03	2	309	.97

Note. Displayed are the fixed effect omnibus tests for the variables from the models with the formula (detail count ~ 1 + age group + time period + word count + gender + score + time period: age group + time period: score + score: age group + time period: age group: score + (1 | participant)). Satterthwaite method was used for estimating degrees of freedom. Num Df = numerator degrees of freedom; Den Df = denominator degrees of freedom.

Table 5

Results of the Linear Mixed Models That Included Internal Similarity Scores to Estimate Internal Details (Top) or External Details (Bottom) in the Autobiographical Memories

Variable	*F*	Num Df	Den Df	*p*
Internal details				
Time period	1.01	2	260	.37
Gender	.66	1	124	.42
Word count	327.34	1	368	<.001
Internal similarity score	1.88	1	365	.17
Age group	45.48	1	132	<.001
Age Group × Time Period	4.74	2	254	.01
Time Period × Internal Similarity Score	.15	2	321	.86
Age Group × Internal Similarity Score	1.49	1	367	.22
Age Group × Time Period × Internal Similarity Score	.86	2	319	.42
External details				
Time period	.19	2	260	.83
Gender	.02	1	123	.90
Word count	83.70	1	366	<.001
Internal similarity score	1.37	1	367	.24
Age group	27.36	1	131	<.00
Age Group × Time Period	1.80	2	253	.17
Time Period × Internal Similarity Score	.71	2	324	.49
Age Group × Internal Similarity Score	.36	1	369	.55
Age Group × Time Period × Internal Similarity Score	.13	2	322	.88

Note. Displayed are the fixed effect omnibus tests for the variables from the models with the formula (detail count ~ 1 + age group + time period + word count + gender + internal similarity score + time period: age group + time period: internal similarity score + internal similarity score: age group + time period: age group: internal similarity score + (1 | participant)). Num Df = numerator degrees of freedom; Den Df = denominator degrees of freedom. Satterthwaite method was used for estimating degrees of freedom.

"cluttered" with distally related information (Amer et al., 2022). Impairments in executive control are thought to weaken some older adults' ability to inhibit the so-called irrelevant or off-topic knowledge cued during retrieval ("That reminds me of"), leading to less focused descriptions of the past (Amer et al., 2022; Campbell et al., 2010; Gazzaley et al., 2005; Healey et al., 2013). However, we found that among older adults, higher content diversity, reflected by lower maximum topic scores and higher entropy scores, was positively associated with the ability to provide detail-rich autobiographical memories. This pattern suggests that representing memories with more content, that is at a gist level, may be a strategy to compensate for lower episodic memory processes among older adults. This suggestion fits with theories that propose that semantic memory, a relatively preserved knowledge system with age, can act as a scaffold to retrieve episodic content form our memories (Irish, 2016; Irish & Piguet, 2013). As well, this suggestion fits with evidence of a reorganization of the neural circuits that support autobiographical memory with older age such that there is a stronger reliance on semantic memory neural circuitry (Setton, Mwilambwe-Tshilobo, et al., 2022; Spreng & Turner, 2019).

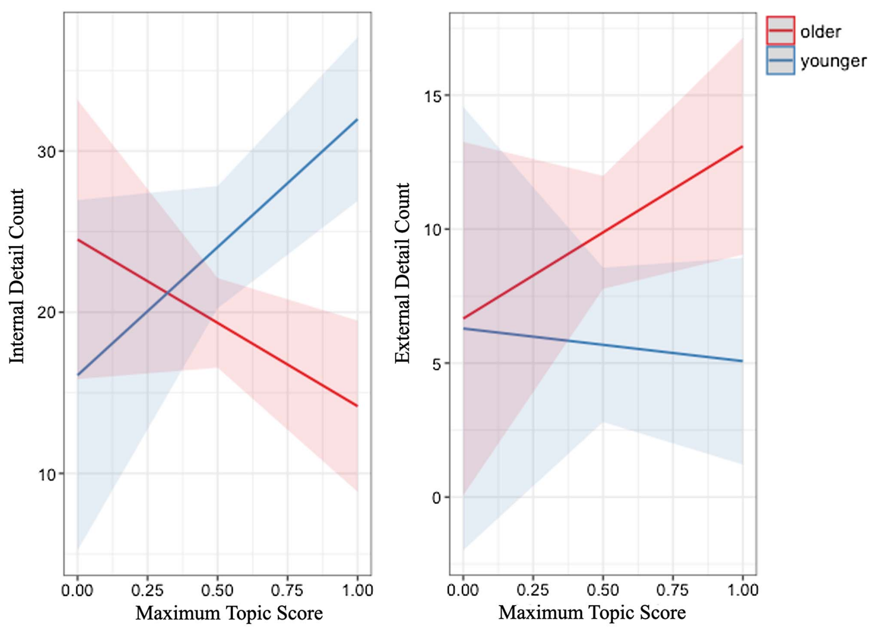
Although we interpret enhanced content with the representations of memories in older adults as beneficial for promoting episodic memory, it is important to consider how relying on a wider array of content to represent memories in a less focused and more gist manner could be detrimental. Several studies have reported that older adults are more susceptible to false memories, endorsing new information that shares features with encoded events as old, which is thought to be due to their tendency to use gist-based memory representations (Balota et al., 1999; Kensinger & Schacter, 1999; Koutstaal & Schacter, 1997). Thus, older adults' tendency to reflect on autobiographical memories at a gist level could lead to confusing occurrences among related autobiographical memories and ultimately misremembering the past. Future research will be necessary to clearly define when gist memory representations help versus hinder older adults.

Older Age Is Associated With Less Chronological Coherence of Narrated Memories

Two effects emerged from the similarity analysis. We first found an effect of the time period from which a memory was recalled for younger and older adults. Memories from remote time periods were described with more similarity among the texts, meaning fewer content shifts, than recent memories. This time period effect is consistent with theories of memory suggesting that over time, memories become consolidated as highly structured representations (Cohn-Sheehy et al., 2022) that do not require organizing details into a narrative upon retrieval (Gilboa & Moscovitch, 2021). Confirming our hypothesis, the second main finding was that older age was associated with more content topic shifts within the memory narratives. In other words, older adults more often shifted between topics as their narratives unfolded, possibly reflecting that their recollections contain more indirect information and "story asides" (Bluck et al., 2016; Boudreau, 2008). This shift may reflect age group differences in the motives for memory sharing, such that in older age, there is less emphasis on providing a chronologically ordered account of the past and more of a priority placed on meaning and value (Hess, 2005; Reese et al., 2011), which may enhance the

Figure 5

Plot Depicting the Relation Between the Number of Internal Details (Right) and External Details (Left) and the Maximum Topic Scores for the Autobiographical Memories Described by the Older and Younger Adult Age Groups



Note. The bold lines represent the average predicted relationship and the error band represents a 95% confidence interval. See the online article for the color version of this figure.

quality of memories (Carstensen & Turk-Charles, 1994; Grilli & Sheldon, 2022; Samanez-Larkin & Carstensen, 2011). According to this motivational account, the differences in internal similarity scores may not reflect lower cognition in older age. This would explain why we did not find a positive relation between internal similarity scores and internal (episodic) details in the autobiographical memories for older adults.

Open Questions

In the present study, we applied a novel text analysis approach to study age effects in the content used to retrieve and describe autobiographical memories. Older adults were more likely to draw content from a broader array of content than younger adults, consistent with gist-based theories of aging and autobiographical memory (Amer et al., 2022; Grilli & Sheldon, 2022). Our results suggest that this may be a compensatory strategy for lower episodic memory in older age. We also found that older adults showed more narrative shifts on average relative to younger adults, indicating a change in coherence of memory narratives that we interpret as reflecting differences in motivation, as opposed to lower cognitive functioning in older age.

From these results, there are some interesting avenues for future work. One research direction to pursue is the role of task demands on autobiographical memory content across the lifespan. In the analyzed data set, participants were asked to simply describe their memories in as much detail as possible. It could be that older adults interpreted this instruction as a request to include background knowledge and related information (details) to a greater degree than younger adults (Pansky et al., 2009). Or, older adults may have tailored their speech to provide background knowledge in service of the person to whom they were talking to, which may reflect a sign of improved communication of memories that accompanies older age. It would be interesting to test whether the content diversity and narrative coherence measures would be more similar between younger and older adults with different retrieval expectations, or whether older adults are unable to engage in flexible forms of remembering, consistently recalling gist-level memories regardless of the retrieval demands (Aizpurua & Koutstaal, 2015).

Another open question is how individual differences in the acceleration of cognitive aging (Tucker-Drob & Salthouse, 2013) impact autobiographical memory recall. In particular, it is not known if differences in working memory capacity, particularly in older adults, (Pansky et al., 2009; Spreng & Turner, 2019) would relate to the inclusion of more content topics or the potentially compensatory relationship between content topics and the recall of episodic details among older adults. Finally, as NLP is an exciting and rapidly growing approach to mine text (Yeung & Fernandes, 2021), further work leveraging these techniques could inform our understanding of autobiographical memory and cognitive aging. For instance, it will be important to further clarify the sample size needed for certain NLP approaches. Although time period interactions were not central to the hypotheses of the present study, we cannot rule out that some nonsignificant age group by time period interactions in the present study reflect a power issue. That said, our sample was relatively large for a study of autobiographical memory and aging focused on group differences. Missed time period interactions, therefore, may be rather subtle in magnitude and could have minimal

Table 6
Results of the Linear Mixed Models That Included Entropy Scores to Estimate Internal Details (Top) or External Details (Bottom) in the Autobiographical Memories

Entropy scores	*F*	Num Df	Den Df	*p*
Internal details				
Age group	49.12	1	134	<.001
Time period	1.41	2	259	.25
Gender	.84	1	124	.36
Word count	219.75	1	370	<.001
Entropy score	.06	1	365	.81
Age Group × Time Period	2.01	2	254	.14
Age Group × Entropy Score	18.81	1	362	<.001
Time Period × Entropy Score	.31	2	297	.74
Age Group × Time Period × Entropy Score	.26	2	297	.77
External details				
Age group	29.93	1	136	<.001
Time period	.27	2	261	.76
Gender	<.001	1	125	1.00
Word count	53.41	1	368	<.001
Entropy score	.62	1	362	.44
Age Group × Time Period	1.09	2	256	.34
Age Group × Entropy Score	.48	1	302	.62
Time Period × Entropy Score	3.24	2	357	.07
Age Group × Time Period × Entropy Score	.05	2	302	.95

Note. Displayed are the fixed effect omnibus tests for the variables from the models with the formula (detail count ~ 1 + age group + time period + word count + gender + score + time period: age group + time period: score + score: age group + time period: age group: score + (1 | participant)). Num Df = numerator degrees of freedom; Den Df = denominator degrees of freedom. Satterthwaite method was used for estimating degrees of freedom.

impact on the more pronounced differences in content and coherence that seem to arise between younger and older adults.

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Received September 16, 2022
Revision received June 6, 2023
Accepted June 7, 2023 ■