The effect of physical and psychological distances in everyday memory retrieval across older and young adults

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Abstract

This study examined how episodic memory performance in young and older adults is influenced by both the physical and psychological representations of locations in everyday life. Over five weeks, participants' GPS location data were collected via a smartphone app and later used in a memory recall test and post-survey. Results showed that both physical and psychological sparsity (i.e., the degree to which a location was spatially or psychologically distinct from others) positively affected memory performance in both age groups. However, only young adults exhibited an interaction effect between physical and psychological sparsity on response accuracy. This difference may stem from older adults' narrower GPS sparsity distribution and fewer location points, suggesting that their narrower range of visited locations was insufficient to reveal this interaction. Our study offers a novel contribution by quantitatively utilizing a psychological measure of memory representation through personalized data and analyzing its relationship with a physical indicator.

Keywords: episodic memory; memory aging; sparsity; psychological distance; experience sampling;

Introduction

A successful episodic memory retrieval in everyday life is shaped by various factors. Particularly, the unique characteristics of the event such as where it took place and what activity was involved influence how memories are stored and, consequently, how well they are later retrieved.

Several studies have shown that physical characteristics, such as the frequency and recency of the event, significantly shape memory performance. The frequency effect refers to how the frequency of memory traces influences memory retrieval, where low-frequency items being more easily recognized than high-frequency ones in a recognition task (Popov & Reder, 2024). As the effect is shaped by pre-experimental experience, individual prior experience has a great impact on the effect (Chalmers, Humphreys, & Dennis, 1997). The recency effect describes how memory strength decreases over time (Friedman & Wilkins, 1985), where the duration between the time of the event and the time of retrieval impacts memory performance.

Despite extensive research on how physical indicators influence episodic memory performance, significantly less attention has been given to the psychological aspects that shape memory performance. Studies examining psychological factors have primarily focused on the encoding and retrieval stages rather than on storage representation itself. For example, Eich (1995) expanded the concept of place-dependent memory by emphasizing that how similar the environments feel play a crucial role in memory performance rather than how similar they look. Additionally, Smith (1995) introduced the mental context hypothesis, proposing that elements such as mood, ambient environments, mental set, and physiological states serve as contextual cues that facilitate memory retrieval. Further studies have demonstrated that imagining a mental context during encoding can enhance later recall (Chu, Handley, & Cooper, 2003; Masicampo & Sahakyan, 2014). However, little is known about how the psychological characteristics of the remembered events affect episodic memory retrieval. Moreover, to our knowledge, no studies have systematically compared the impact of both physical and psychological factors on memory retrieval, as well as the interaction between the two factors.

Additionally, the influences of physical and psychological factors may manifest differently in older adults, whose episodic memory performance often declines with age. Memory impairments in aging populations are frequently linked to difficulties in binding different pieces of information, leading to frequent source monitoring errors (Chen & Naveh-Benjamin, 2012; Boywitt, Kuhlmann, & Meiser, 2012). Studies attribute these deficits to reduced information-binding capacity and impaired inhibitory control, resulting in greater susceptibility to interference from prior experiences caused by cognitive decline (Wang & Cabeza, 2017).

In the current study, therefore, we examined how episodic memory of everyday locations is shaped by both physical and psychological indicators in young and older adults. Unlike physical characteristics of a place, the evaluation of its psychological attributes is highly personal and heavily influenced by an individual's prior knowledge or pre-experimental experience. Therefore, rather than using artificially controlled stimuli in a laboratory setting, it is much more effective to personalize the stimuli by using locations that participants were already familiar with.

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Therefore, we utilized an experience sampling method to extract personalized episodic memories and used them in a subsequent memory test.

Experiment

To investigate how physical and psychological aspects of the memory traces influence episodic memory performance in young and older adults, we passively collected participants' GPS location data using a smartphone app over a five-week period. After completing the data collection, participants underwent a memory test in the laboratory and were asked to recall where they were given a specific date and time. In a subsequent post-survey, participants took part in several tasks such as identifying the locations by labeling them, reporting the frequency and recency of their visits, and providing psychological evaluations of the locations through adjective ratings.

Methods

Participants Fifty young adult participants (23 females, M = 20.98yrs, SD = 1.73yrs) were recruited through flyers around Hanyang University (Seoul, Republic of Korea) and fifty older adult participants (25 females, M = 64.23yrs, SD = 2.45yrs) were recruited through Gallup Korea. Young adults received 100,000 KRW (approximately 68 USD) as a compensation, while older adults were compensated with 200,000 KRW (approximately 136 USD). The research was approved by the Institutional Review Board at Hanyang University.

Design & Procedure

The experiment was within a multi-experiment project, which consisted of two visits, with a five-week GPS data collection period between them. The first visit included pupil size measurement using an eye tracker, two memory tasks, and several attention control tasks. This was followed by a five-week data collection period during which participants' GPS location data was collected via a smartphone app. The second visit began with the same memory tasks and was followed by a memory test based on the collected location data, a post-survey (including location identification, psychological evaluations using adjective ratings, and frequency and recency surveys), and a life satisfaction and demographic survey. In this study, our primary focus is on the GPS location data collection, the corresponding memory test, and the post-survey data (see Figure 1). The pupil size measurements, memory tasks, attention tasks, and a life satisfaction and demographic survey were part of separate research projects, which will be reported elsewhere.

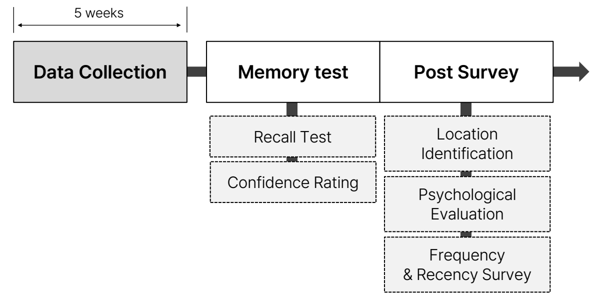

Figure 1: Overview of the main experimental design

Data Collection Before starting the GPS data collection period, participants visited the laboratory and were guided to install a smartphone app for tracking their GPS location (i.e., Traccar). The app was configured to collect GPS data every 60 seconds, and participants were told to keep the app active throughout the entire data collection period. The five-week data collection began on the first Monday after the first visit and ended on the fifth Sunday. The GPS location data was uploaded to the server in real time through Wi-Fi or mobile data connection. To ensure continuous data collection at 60-second intervals, the experimenter monitored the app's data log every morning.

Memory Test After the five-week data collection period, participants re-visited the laboratory within a week to complete a memory test and post-survey. The memory test was based on the GPS location data collected, and only the first four weeks of data were used for the test trials. The fifth week of data was excluded to allow for a one-week retention interval before the memory test. The maximum number of test trials was limited to 50 per participant, with the number of trials per location balanced to include up to three trials for each location.

During each test trial, a specific date and time was displayed on the screen, and participants were asked to indicate their location at that date and time by selecting a location marker on a map (e.g., "Where were you at the time specified below?"; see Figure 2A). The map interface allowed participants to zoom in and out. The location markers where extracted from location points that the participants visited during the data collection period (the definition of location points will be explained below). Then, participants were asked to rate their confidence on a scale from 1 (not confident at all) to 5 (very confident) (see Figure 2B). Participants were instructed not to use calendars or diaries, but to rely solely on the provided date and time information for their recall.

Each test trial included a certain time and date for each stationary point, which was extracted from the raw GPS data, sampled every 60 seconds. Stationary points were defined when the participant stayed within a 50-meter radius for at least 15 minutes. Consequently, all analyzed events in this study represent the events when the participant was not moving. Dynamic events, such as taking the subway to school, were not considered due to the technical challenges of accurately defining such movements (i.e., path of movement) without directly verifying them through the participant's memories. As multiple stationary points could occur at a certain location point, we derived "location points" by clustering stationary points. This was achieved using the DBSCAN clustering algorithm from the scikit-mobility Python package (Pappalardo, Simini, Barlacchi, & Pellungrini, 2022) with the epsilon parameter set to 35 meters. The median value from the GPS coordinates was used for both stationary and location points.

Post Survey Following the memory test phase, a post-survey was conducted to assess the location points that the participants visited during the five-week data collection period. The post-survey consisted of three sub-tasks which included (1) measuring the participants' psychological representation of the location points through adjective ratings, (2) examining the frequency, and (3) recency of visits of these locations.

In the location identification task, participants were presented with location points pinned on a map, one at a time. To include a broader range of location points, data from the entire five-week collection period was used for this task. Then, participants were asked to identify each location point and given an opportunity to label it. Two versions of the map with different zoom levels were provided. Additionally, participants also had the option to indicate that they do not remember the location. Unidentified locations were excluded from subsequent tasks. This task was performed to retrieve memories before carrying out following tasks.

In the psychological evaluation task, participants rated each location point through adjectives on a scale from 1 (not at all) to 5 (very much) to measure the psychological representation of each location point. Thirteen adjectives were displayed next to each location point pinned on the map, and participants were instructed to evaluate the locations based on their initial impressions without overthinking (see Figure 2C). The thirteen adjectives were selected based on a pilot study and previous literature (Joo & Im, 2003): 편안한 (Comfortable), 조용한 (Quiet), 넓은 (Spacious), 아름다운 (Beautiful), 쾌적한 (Pleasant), 정감있는 (Friendly), 자유로운 (Free), 새로운 (New), 복잡한 (Complex), 지루한 (Boring), 불안한 (Anxious), 고된 (Tough), and 그리운 (Nostalgic).

Finally, in the location frequency and recency survey, three questions related to each location point were presented with a pin on the map: (1) the date that they first visited the location, (2) how frequently they visited the location, and (3) whether they visited the location regularly.

Results

Seven older adults whose memory test accuracy was below chance level (calculated as 1 divided by the total number of

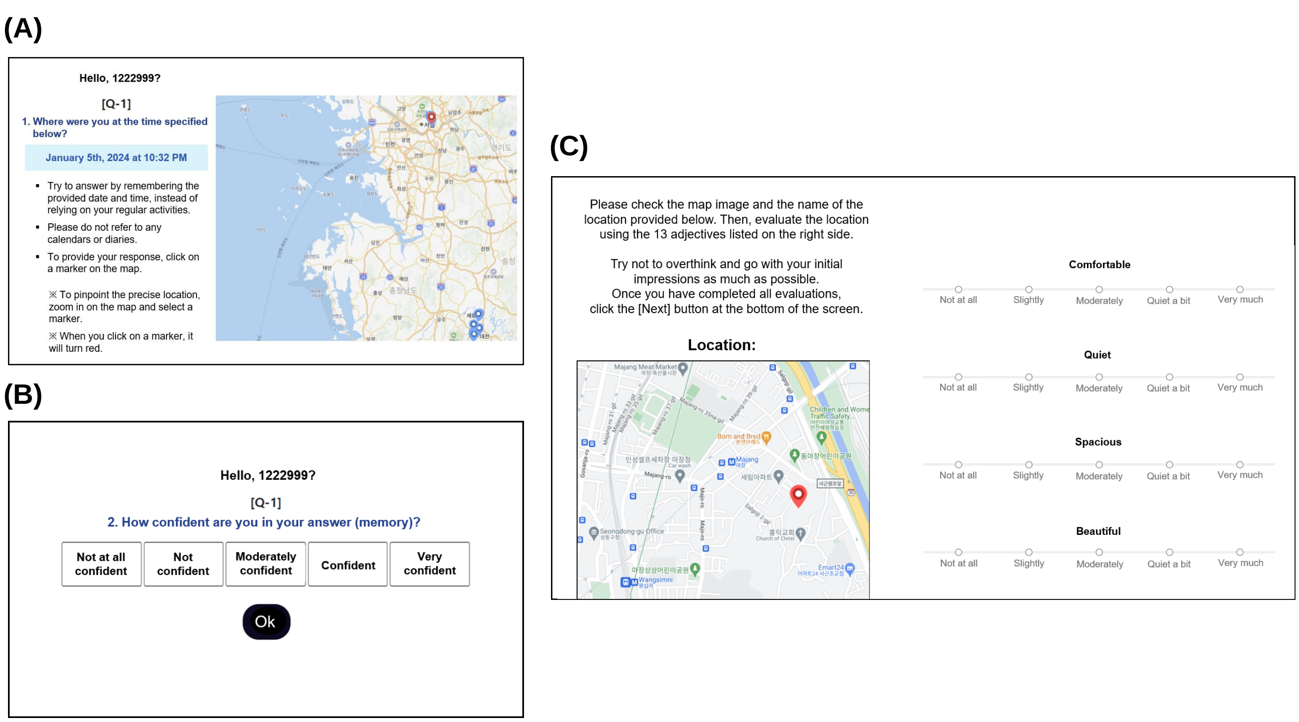

Figure 2: Example of tasks used in the memory test and post-survey. (A) Memory test page showing a single test trial, (B) Memory test page showing a confidence rating for the response, (C) Post-survey: psychological evaluation of locations using adjectives.

location pins on the map) were excluded, resulting in 43 older adult participants for the final analyses. The final memory test data included a total of 2,405 responses for the young adult group ($M = 48.1, SD = 4.38$) and 1,773 responses for the older adult group ($M = 41.23, SD = 11.31$). The average proportion of correct responses across participants was .28 ($SD = .18$) for young adults and .18 ($SD = .14$) for older adults.

To examine how the physical density and psychological similarity of locations influence memory performance, we compared the impact of both the spatial distribution of physical GPS location points and the corresponding psychological adjective ratings on the accuracy of the memory test. We introduced the concept of "location sparsity" to quantify the density of a specific location relative to others. The location sparsity measure would provided how close a location is to other locations, where we expect that more sparser location would have less interference from other memory traces at retrieval. Location sparsity was calculated as the average distance across all pairwise distance between a given location (e.g., A) and all other locations for a participant (e.g., B, C, D, etc.) (see Figure 3). For physical GPS location points, location sparsity was computed using the city block distance between pairwise GPS coordinates. The results were similar when using the Euclidean distance. For psychological adjective ratings, sparsity was calculated using the city block distance in a thirteen-dimensional space based on the adjective rating vectors.

Difference Between Physical and Psychological Sparsity Metrics

To ensure that the location sparsity metric calculated by the physical GPS locations and the psychological ratings provide different information, we analyzed the correlation between the two for each participant. Pairwise distances were calculated for each participant based on GPS coordinates and the thirteen-adjective rating vectors, using the city block metric. The upper triangular elements of the resulting distance matrices were extracted for Pearson correlation analysis. A one-sample t-test revealed that the mean of correlation coefficient across participants was significantly different from 0 ($t(92) = 6.52, p < .001$). However, the mean value was $r = .09$, suggesting that the overall pattern showed a weak or negligible relationship between physical GPS sparsity and psychological sparsity.

Location Sparsity

To examine the impact of location sparsity (both physical and psychological) on memory performance, a logistic mixed-effects analysis was conducted for both young and older adults using the lme4 package (Bates, Mächler, Bolker, & Walker, 2015) in R (R Core Team, 2023). We used the location sparsity of the specific cued location in each memory test trial as the predictor variable.

For physical sparsity, the model included GPS sparsity as a fixed effect and random intercepts for participants,

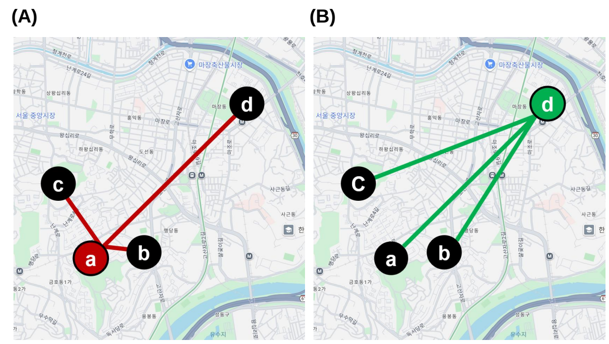

Figure 3: Examples of different location sparsity (physical). (A) Low Sparsity, (B) High Sparsity.

with memory test response accuracy modeled as a binomial outcome. The results showed that GPS sparsity had a significant positive effect on response accuracy for both young adults ($\beta = .26, SE = .07, z = 3.91, p < .001$) and older adults ($\beta = .20, SE = .08, z = 2.54, p < .05$). A similar analysis was conducted for psychological sparsity, where the model included psychological sparsity as a fixed effect and random intercepts for participants, with response accuracy as a binomial outcome. The analysis revealed that psychological sparsity also had a significant positive effect on response accuracy for both young adults ($\beta = .32, SE = .07, z = 4.57, p < .001$) and older adults ($\beta = .45, SE = .09, z = 5.24, p < .001$). These results suggest that locations that are more dispersed, whether physically or psychologically, are more likely to be remembered by participants.

Frequency Although location sparsity affected memory performance, this effect may have been mediated by the frequency of visits to the location points. Therefore, we extended the previous analysis by including location frequency (i.e., how often the participant visited a location from the start of the data collection to the memory test date) for both young and older adults. A logistic mixed-effects model was employed, where we included the location sparsity, location frequency, and the interactions into the model. We had participants as intercepts for a random effect, and response accuracy from the memory test as a binomial outcome.

For physical sparsity, the results for young adults again demonstrated statistically significant effects for GPS sparsity ($\beta = .32, SE = .07, z = 4.54, p < .001$) and location frequency ($\beta = .43, SE = .06, z = 7.82, p < .001$). However, the interaction between GPS sparsity and location frequency was not significant ($\beta = .03, SE = .08, z = .38, p = .71$). Similar results were shown from older adults, with statistically significant effects for GPS sparsity ($\beta = .29, SE = .10, z = 3.01, p < .005$) and location frequency ($\beta = .60, SE = .08, z = 7.22, p < .001$), but no significant interaction ($\beta = .12, SE = .19, z = .66, p = .51$). The same analysis was conducted for psychological sparsity, with the model including psychological sparsity, location frequency, and their interaction as fixed effects. For young adults, there were statistically significant effects for psychological sparsity ($\beta = .23, SE = .07, z = 3.14, p < .005$) and location frequency ($\beta = .43, SE = .06, z = 6.84, p < .001$), but not for interaction ($\beta = -.10, SE = .06, z = -1.63, p = .10$). Similarly, for older adults, significant effects were observed for psychological sparsity ($\beta = .30, SE = .09, z = 3.31, p < .001$) and location frequency ($\beta = .47, SE = .07, z = 6.51, p < .001$), but the interaction was not significant ($\beta = .09, SE = .06, z = 1.55, p = .12$). The lack of significant interactions between location sparsity for both GPS and psychological and location frequency suggests that the effect of location sparsity on memory performance was not mediated by location frequency.

Physical and Psychological Sparsity Interaction

To further explore the relationship between physical and psychological sparsity, we employed a logistic mixed-effects model including GPS sparsity, psychological sparsity, and their interaction as fixed effects, with random intercepts for participants. Response accuracy from the memory test was modeled as a binomial outcome.

Unlike the previous analyses, there were different results between young and older adults with regard to the interaction effect. For the young adult group, the analysis revealed statistically significant effects for GPS sparsity ($\beta = .26, SE = .07, z = 3.67, p < .001$), psychological sparsity ($\beta = .35, SE = .07, z = 4.87, p < .001$), and their interaction ($\beta = -.17, SE = .05, z = -3.24, p < .005$), indicating a significant interaction between physical and psychological sparsity in this group. In contrast, for the older adult group, while GPS sparsity ($\beta = .23, SE = .09, z = 2.49, p < .05$) and psychological sparsity ($\beta = .44, SE = .08, z = 5.24, p < .001$) both showed significant main effects, whereas the interaction between the two was not statistically significant ($\beta = -.10, SE = .07, z = -1.41, p = .16$). These findings suggest that the interplay between physical and psychological sparsity affects memory performance in young adults but not in older adults.

Figure 4A illustrates the interaction between GPS sparsity and psychological sparsity in young adults. The result can be interpreted as follows: when psychological sparsity is high (i.e., a location point elicits a distinct psychological evaluation compared to others), the physical sparsity of that location (i.e., how spatially isolated the location is from others locations) plays a less significant role in influencing memory performance. However, when psychological sparsity is low (i.e., many other location points evoke similar psychological evaluations as the given location point), the physical sparsity of that location becomes more important in its impact on memory performance.

To further investigate why this effect was observed only in the young adult group and not in the older adult group, we compared the distribution pattern of the GPS sparsity and psychological sparsity for both groups (see Figure 4B). This revealed that the GPS sparsity distributions were more dispersed in young adults compared to older adults. To examine distinct patterns in GPS location data for both groups, we applied a K-Means clustering analysis to the GPS coordinates of each participant's location points, with the optimal number of clusters determined using both the elbow method and silhouette analysis. An independent samples t-test showed no statistically significant difference in the number of clusters obtained through silhouette analysis between the two groups ($t(91) = -0.84, p = .41$). Similarly, the number of clusters determined by the elbow method did not statistically differ between the groups ($t(91) = -1.73, p = .09$). While these results did not clarify the observed group differences, we conducted an additional independent samples t-test to examine the difference in the number of location points between young and older adults. Results demonstrated a significant difference ($t(91) = 2.26, p < .05$), with older adults showing a lower mean value (M = 40.79, SD = 18.91) compared to young adults (M = 48.80, SD = 15.27). These findings suggest that the interaction effect between physical and psychological sparsity observed in young adults may not have emerged in older adults due to their more limited range of visited locations. This may have prevented sufficient interaction between GPS sparsity and psychological sparsity, thereby diminishing their combined impact on memory performance.

Discussion

The present study explored how episodic memory performance in young and older adults is influenced by both the physical and psychological representations of locations, as well as how the two factors interact. To effectively assess psychological evaluation, we collected participants' GPS location data over five weeks through an experience sampling method. These data were then used in a memory recall test, in which participants were asked, "Where were you?" as well as in a post-survey where they rated each visited location point using thirteen adjectives. To quantitatively compare physical (GPS coordinates) and psychological (thirteen adjective-based rating vectors) indicators, we introduced location sparsity as a key measure. There was a weak or negligible relationship between these two metrics.

We demonstrated that in both young and older adults, physical GPS sparsity and psychological sparsity—that is, the degree to which a location was spatially or psychologically distinct from other locations—had a positive effect on response accuracy in the memory recall test. In other words, participants tended to show better memory performance when it is physically or psychologically isolated from other locations. Notably, these effects were not confounded with location frequency, confirming that the observed memory benefits were not simply driven by how frequently a location was visited. The results resemble the frequency effect

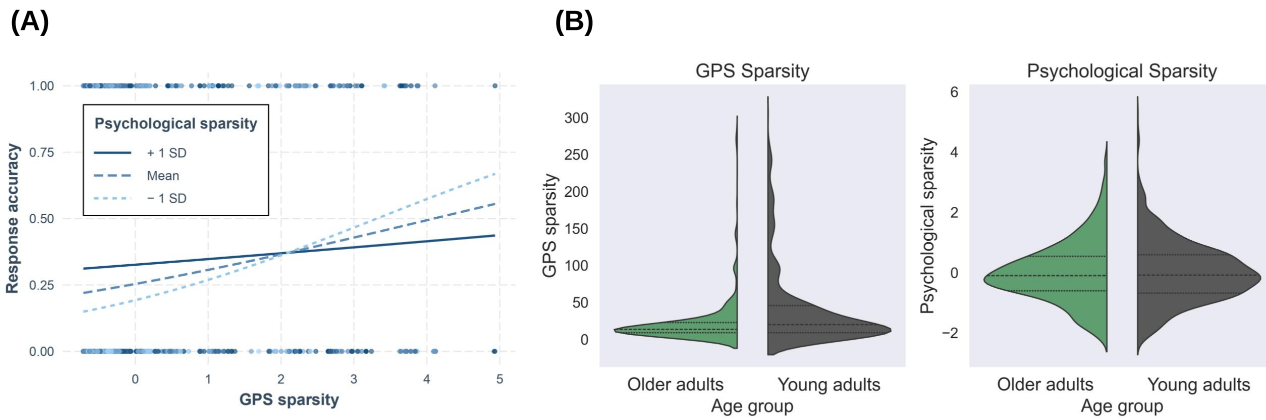

Figure 4: Analyzed plots of physical and psychological sparsity. (A) Interaction between GPS sparsity and psychological sparsity in the young adult group, (B) Distributions of GPS sparsity and psychological sparsity in both young and older adult groups.

in recognition memory (Popov & Reder, 2024), where low-frequency items show better memory performance due to less contexts interfering. Similarly, the current results can be explained by sparser locations having less interference from other locations. However, unlike the classical frequency effect, the interference does not stem from the frequency of the locations experienced but from the distances (either physical or psychological) from other locations.

Importantly, we found that GPS sparsity and psychological sparsity interacted to influence memory performance only in young adults. This interaction suggests that when a location is psychologically sparse (i.e., when it is perceived as distinct from other locations), its physical distribution (i.e., how it is spatially positioned relative to other locations) plays a relatively minor role in memory performance. This finding implies that a psychologically isolated location already serves as a strong enough retrieval cue on its own. However, when a location is psychologically dense (i.e., when it is perceived as psychologically similar to other locations), the impact of GPS sparsity on memory recall becomes more salient. In such cases, the physical distribution of locations may help distinguish between psychologically similar alternatives. Interestingly, this interaction effect was absent in older adults. Additional analyses revealed that compared to young adults, older adults exhibited a narrower GPS sparsity distribution and a fewer number of location points. This suggests that as older adults may be less mobile and have less visited locations, their limited range of visited locations may not have provided enough variation for a meaningful interaction effect to emerge between physical and psychological sparsity.

Our study provides a novel contribution by quantitatively defining a psychological indicator in memory storage representation through personalized data collection and directly comparing it with a physical factor. Importantly, by analyzing the interaction between physical and psychological indicators in young and older adults, we identified distinct patterns in memory process between the two groups. This provides valuable insight into how the differences observed in older adults may stem from their more constrained mobility in daily life compared to young adults.

Given that we defined psychological sparsity through adjective-based ratings of locations, future research could further investigate the properties of these adjective ratings. Prior studies on emotion and memory have shown that pleasant items are remembered more accurately than unpleasant ones (Tait, 1913; Griffitts, 1920; Thomson, 1930). Building on this, future analyses could investigate how valence, pleasantness, and other attributes of adjective ratings impact memory performance. This line of research could provide deeper insights into how psychological representations of real-world environments shape episodic memory recall.

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