Age differences in functional connectivity track dedifferentiation of category representations

Claire Pauley[a,b], Dagmar Zeithamova[c], & Myriam C. Sander[a]

[a] *Center for Lifespan Psychology, Max Planck Institute for Human Development, 14195 Berlin, Germany*

[b] *Faculty of Life Sciences, Humboldt-Universität zu Berlin, 10115 Berlin, Germany*

[c] *Department of Psychology, University of Oregon, 97403 Eugene, Oregon, USA*

Correspondence should be addressed to Claire Pauley at pauley@mpib-berlin.mpg.de.

Abstract

With advancing age, the distinctiveness of neural representations of information declines. While the finding of this so-called ‘age-related neural dedifferentiation’ in category-selective neural regions is well-described, the contribution of age-related changes in network organization to dedifferentiation is unknown. Here, we asked whether age differences in a) functional connectivity to category-selective neural regions and b) segregation of the visual network (i.e., network dedifferentiation) contribute to regional dedifferentiation of categorical representations. Younger and older adults viewed blocks of face and house stimuli in the fMRI scanner. We found an age-related decline in neural distinctiveness for faces in the fusiform gyrus (FG) and for houses in the parahippocampal gyrus (PHG). Functional connectivity analyses revealed age differences in connectivity between the FG and visual network as well as age-related dedifferentiation of the visual network. Interindividual correlations demonstrated that regional distinctiveness was related to connectivity of category-selective regions to the visual network as well as network segregation. Thus, dedifferentiation of categorical representations may be linked to age-related reorganization of functional networks.

Words: 166/170

Keywords: aging, fMRI, dedifferentiation, connectivity

1 Introduction

Aging often results in declines in various cognitive functions, including episodic memory. Age differences in episodic memory performance have been related to the way information is neurally represented, suggesting that neural responses are less distinctive in older adults as compared to younger adults – a phenomenon called “age-related dedifferentiation” (for reviews, see Koen et al., 2020; Koen & Rugg, 2019; Sommer & Sander, 2022). However, little is known about why neural distinctiveness is impaired in older individuals. This may stem from the limited research focused on characterizing neural distinctiveness within individual neural regions rather than considering how these regions communicate with other areas of the brain. Nonetheless, the prospect of a link between neural dedifferentiation and age differences in functional network connectivity has previously been suggested (Goh, 2011), but lacks empirical validation. Here, we seek to understand whether age-related differences in functional long-range connectivity patterns (i.e., network dedifferentiation) helps explain reduced distinctiveness of category-selective regions (i.e., regional dedifferentiation) in older age.

Compared to younger adults, older adults tend to exhibit a reduction in the efficiency of neural processing. At the level of processing within individual regions-of-interest (ROIs), this reduction in efficiency is often investigated in terms of an age-related decline in the selectivity of high-level visual cortices for particular stimulus categories. Senescent declines in neural distinctiveness have been reported in the parahippocampal gyrus (PHG) during scene processing (Koen, 2022; Koen et al., 2019; Srokova et al., 2020), in the fusiform gyrus (FG) for faces (Park et al., 2004, 2012; Pauley et al., 2023), in lateral occipital cortex for objects (Chee et al., 2006; Koen, 2022), and in the visual word form area for words (Park et al., 2004; but, see Koen et al., 2019; Payer et al., 2006 for null age effects). Age differences in neural distinctiveness have been found both as attenuated responses to the stimulus category preferred by a particular region (i.e., neural attenuation) as well as enhanced responses to non-preferred stimuli (Park et al., 2012). However, the neural mechanisms behind these age-related declines in distinctiveness are largely unknown.

This knowledge gap is at least partially attributable to the lack of understanding of the components promoting distinctiveness in high-level visual cortices.

One line of research attempting to understand mechanisms potentially driving categorical distinctiveness examined the connectivity of category-selective ROIs. Connectivity patterns to category-selective ROIs have been used to decode the preferred stimulus category (Chen et al., 2017; Wang et al., 2016) and have been shown to flexibly adapt to the attended stimulus category (Córdova et al., 2016; Keller et al., 2022; Norman-Haignere et al., 2012; Silson et al., 2019). For example, Norman-Haignere and colleagues (2012) found that connectivity between the early visual cortex and ventral temporal cortices varied depending on whether participants were directing their attention to scenes or faces. Specifically, when individuals paid attention to scenes, the connectivity between the PHG and calcarine cortex increased, whereas when they were attending faces, the connectivity between the FG and calcarine cortex increased. Thus, connectivity patterns to category-selective ROIs may support category representations within these regions. Despite these findings, age differences in connectivity to category-selective ROIs and whether this relates to age-related declines in neural distinctiveness has not been investigated.

Studies assessing age differences in functional connectivity frequently report less segregated network structures in older adults, characterized by a reduction in within-network connectivity as well as an increase in between-network connectivity both in pre-defined networks and in networks derived through a graph-theoretical framework (Betzel et al., 2014; Cao et al., 2014; Chan et al., 2017, 2014; Geerligs et al., 2015; Iordan et al., 2017; King et al., 2018). These age-related reductions in neural processing efficiency across large-scale functional brain networks are also referred to as network-level dedifferentiation (Koen et al., 2020). One of the most consistent findings across studies is the negative impact of age on the efficiency of the default mode (DM) network with several findings of reduced within-DM network communication in older adults (Andrews-Hanna et al., 2007; Betzel et al., 2014; Geerligs et al., 2015; Mak et al., 2017; Song et al., 2014). In contrast, age-related effects in some other core networks, including the visual network, are not so clear. Some studies have uncovered age differences in connectivity within the visual network

(Betzel et al., 2014; Varangis et al., 2021), yet others found absent age effects (Geerligs et al., 2015; Iordan et al., 2017; Varangis et al., 2019). Interestingly, Geerligs and colleagues (2015) did not see age differences in within-network connectivity in the visual network, but found an age-related increase in connectivity between the visual and somatomotor networks and between the visual and cingulo-opercular networks. In sum, aging is associated with a decline in the specificity of functional network architecture, manifesting both as attenuated within-network connectivity as well as increased between-network connectivity.

The evidence suggesting that both isolated ROIs and distributed networks exhibit age-related dedifferentiation begs the question as to whether regional and network dedifferentiation are related to one another. Although age-related reductions in both regional activation specialization and specificity of functional network architecture have been described under the term “dedifferentiation” (Koen et al., 2020), their relationship has seldom been tested. In one study, Cassady and colleagues (2020) demonstrated that higher distinctiveness of sensorimotor cortices was associated with more segregation of the sensorimotor network. Thus, their findings provide preliminary evidence suggesting that age-related neural dedifferentiation manifests similarly across regional and global representations. However, whether this relationship extends to the visual network remains to be seen.

In this study, we ask two key questions: (1) are age differences in neural distinctiveness of category-selective regions related to the connectivity of these regions to the visual network and (2) are age differences in neural distinctiveness of category-selective regions related to segregation of the visual network? Using a paradigm in which younger and older adults were presented with blocks of face and house stimuli, we measured age differences in neural distinctiveness of face and house processing in category-selective visual cortices (FG and PHG) with multi-voxel pattern analysis (i.e., regional dedifferentiation). We further assessed age differences in background connectivity of category-selective regions to the visual network as well as age differences in segregation of the visual network (i.e., network dedifferentiation). Using correlation analyses, we investigated the

relationship between regional dedifferentiation and the connectivity patterns to these regions as well as the link between regional and network dedifferentiation.

2 Materials and Methods

Data from this project were previously reported in Pauley et al. (2023) as well as in 2 papers (Kobelt et al., 2021; Pauley et al., 2022) that were later retracted by the authors due to a preprocessing error. The retracted papers (and corrected findings) can be found at https://osf.io/t8dpv/ and https://osf.io/7n3mz/.

2.1 Participants

Data were collected from a total of 76 healthy adults. Participants were recruited within 2 age groups: younger adults (18–27 years, N = 39) and older adults (64–76 years, N = 37). Two participants were excluded due to excessive motion in the scanner (1 younger adult and 1 older adult; see Section 2.5 for details), 3 were excluded due to memory performance below chance level (2 younger adults and 1 older adult), and 2 were excluded due to poor MRI data quality (1 younger adult and 1 older adult). The final sample consisted of 35 younger adults (M (SD)age = 22.3 (2.7) years, 16 females, 19 males) and 34 older adults (M (SD) age = 70.7 (2.4) years, 18 females, 16 males). Participants were screened via telephone for mental and physical illness, metal implants, and current medications. Additionally, all older adults were screened using the Mini-Mental State Examination (Folstein et al., 1975) and all exceeded the threshold of 26 points. The study was approved by the ethics committee of the German Society for Psychological Research (DGPs) and written informed consent was obtained from each participant at the time of the study.

2.2 Stimuli

Stimuli were comprised of 300 grayscale images belonging to 3 different categories: 120 neutral faces (adapted from the FACES database; Ebner et al., 2010), 120 houses (some obtained online and some adapted from Park et al., 2004), and 60 phase-scrambled images (30 faces and 30

houses, constructed from randomly selected face and house images) serving as control stimuli. An additional image from each category was selected to serve as target stimuli for the encoding target-detection task. All nontarget face and house images were randomly divided into 2 sets of 120 images (60 faces and 60 houses). One stimulus set was presented during both encoding and recognition (old images) and the other set was presented only during recognition (new images). The same stimulus sets were used for all participants.

2.3 Experimental design

The following paradigm was part of a larger study spanning 2 days of data collection. This study focuses only on the face-house task, which comprised an incidental encoding phase and a surprise recognition test, both conducted inside the fMRI scanner on the same day with a delay of approximately 30 min (see Figure 1). The encoding phase consisted of 2 identical runs each with 9 stimulus blocks. In order to ensure the participants were paying attention to the stimuli, they were asked to perform a target-detection task in which they pressed a button when 1 of 3 pre-learned target images was presented. Stimuli were randomly distributed into the blocks such that each block contained 20 images of a single category (faces, houses, or phase-scrambled) as well as a category-matched target image. The block order was alternating and counterbalanced across participants, always starting with either a face or house block. The stimulus order within each block was pseudo-randomized with the condition that the target image was not presented in either the first 4 or last 4 trials of a block. Due to a technical problem, the same stimulus order was used for all participants who started with a face block and for 36 of the participants starting with a house block. Prior to the encoding phase, participants completed 5 practice trials of each stimulus category, including each of the target stimuli, to verify that they understood the target-detection task. The non-target training stimuli were excluded from the main experiment. Since the 2 encoding runs were identical, participants were exposed to each stimulus twice during the encoding phase. Phase-scrambled images were not used in any subsequent analyses in this project. Stimuli were presented

for 1200 ms and separated by a fixation cross with a jittered duration between 500 and 8000 ms. In total, the encoding phase lasted approximately 22 min.

Following encoding, participants remained in the scanner briefly while structural scans were collected (see below). Then, they had a short break outside the scanner while they received instructions for the recognition test. They then returned to the scanner to complete the recognition test. The recognition test consisted of 6 blocks (3 face and 3 house) presented across 2 functional runs (3 blocks per run), alternating between face and house blocks. Instructions explaining the task were presented for 7 s at the beginning of each scanning run. Each block contained 20 old images (seen during encoding) and 20 new images of the same stimulus category. For each trial, participants were asked whether the image was old or new, which they indicated via button press. The stimulus order was pseudorandomized such that no more than 3 old or new images were presented consecutively. Due to a technical problem, the same stimulus order was used for 13 participants who started with a face block and 14 participants who started with a house block. Stimuli were presented for 1200 ms and followed by a gray screen for 3000 ms in which participants could give their response. Fixation crosses separated the trials with jittered durations between 500 and 8000 ms. In total, the recognition task lasted approximately 26 min.

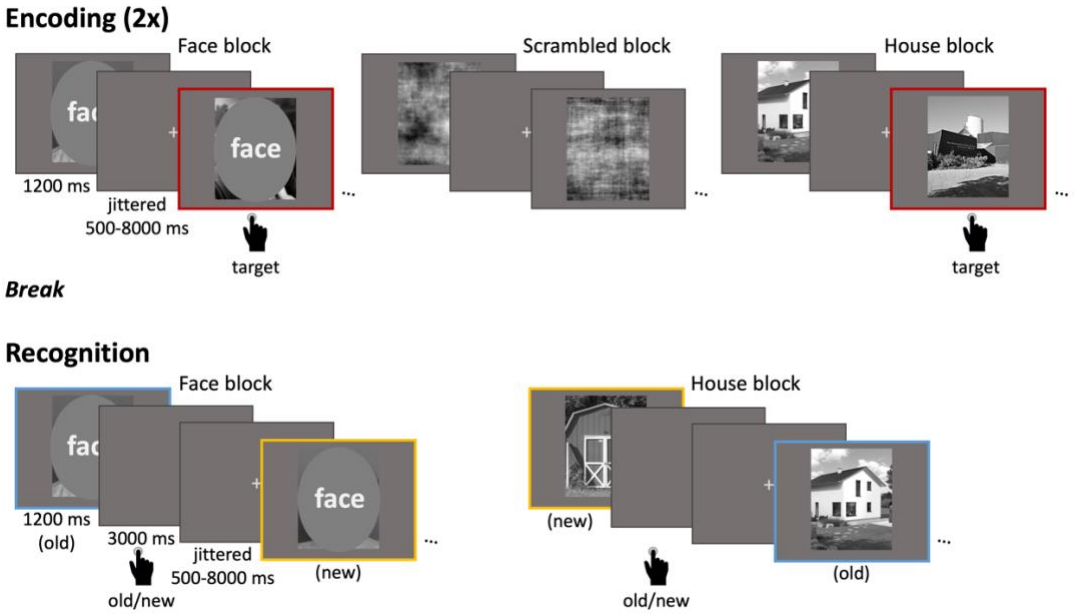

Figure 1. Face-house task design. This fMRI paradigm comprised an incidental encoding phase (top) and a surprise recognition test (bottom). During encoding, two identical runs of face, house, and phase-scrambled images (not assessed here) were presented in a block design with 9 stimulus blocks each (3 alternating blocks from each stimulus category). Each block had 21 trials (20 exemplars of the respective category and 1 pre-learned target stimulus). Participants were instructed to press a button when a target stimulus appeared. During the recognition test, six alternating face and house blocks were presented with 40 trials each (20 old trials from encoding and 20 new trials). Participants indicated via button press whether each image was old or new. Figure reproduced from Pauley et al. (2023).

2.4 Behavioral data analyses

Recognition memory performance was assessed as the difference between the hit rate (proportion of correctly identified old stimuli) and the false alarm rate (proportion of new stimuli incorrectly identified as old stimuli; (Snodgrass and Corwin, 1988). Participants with *Pr* less than zero, indicating a higher probability of responding “old” to new stimuli as opposed to old stimuli, were excluded from subsequent analyses (see also Section 2.1). Dependent-samples *t*-tests were used to determine whether memory performance exceeded chance level. A two-way mixed factorial analysis of variance (ANOVA) was used to assess age differences in recognition memory performance as well as differences related to stimulus type (face vs. house).

2.5 fMRI data acquisition and preprocessing

Brain imaging was acquired with a Siemens Magnetom TrioTim 3T MRI scanner with a 32-channel head-coil. Functional images were collected using an echo planar imaging sequence during both the encoding and recognition phases in 2 runs each. Each encoding run consisted of 270 volumes and each recognition run consisted of 372 volumes (voxel size = 3 × 3 × 3 mm^3; slice gap = 0.3 mm; TR = 2 s; TE = 30 ms). The first 3 volumes of each run were dummy volumes and were excluded prior to preprocessing. Following the encoding phase, a T1-weighted (T1w) magnetization prepared rapid

acquisition gradient echo (MPRAGE) pulse sequence image was acquired (voxel size = 1 × 1 × 1 mm^3; TR = 2.5 ms; TE = 4.77 ms; flip angle = 7°; TI = 1.1 ms). Additionally, turbo spin-echo proton density images, diffusion tensor images, and fluid attenuation inversion recovery images were collected, but not included in the following analyses. Experimental stimuli, which participants viewed via a mirror mounted on the head-coil, were projected using the Psychtoolbox (Psychophysics Toolbox) for MATLAB (Mathworks Inc., Natick, MA).

MRI data were organized according to the Brain Imaging Data Structure (BIDS) specification (Gorgolewski et al., 2016) and preprocessed using fMRIPrep (version 1.4.0; Esteban et al., 2019) with the default settings. The T1w image was corrected for intensity nonuniformity, skull-stripped, and spatially normalized to the ICBM 152 Nonlinear Asymmetrical template version 2009c through nonlinear registration. Functional images were motion-corrected, slice-time corrected, and co-registered to the normalized T1w reference image. As mentioned in Section 2.1, 2 participants were excluded due to excessive motion in the scanner. Excessive motion was defined as having multiple motion artifacts within a given scanner run resulting in framewise displacements greater than the size of the voxel (3 mm; see Power et al., 2012). Finally, functional images were resampled to 2 mm isotropic voxels in order to enhance the signal-to-noise ratio.

2.6 ROIs

Individual regions were defined according to the Automated Anatomical Labeling (AAL) atlas (Version 2; Tzourio-Mazoyer et al., 2002). We isolated the FG and PHG because of their functional roles in face and house processing, respectively (Epstein and Kanwisher, 1998; Kanwisher et al., 1997). Since the anterior FG and PHG have been shown to respond to stimulus categories other than faces and houses (Barense et al., 2010), the FG and PHG were manually segmented to include only the posterior portions of these regions. We further isolated regions belonging to 2 brain networks: visual and default mode (DM). We were particularly interested in the visual network based on findings that connectivity between the visual network and category-selective regions might support category processing (e.g., Norman-Haignere et al., 2012) as well as its obvious role in visual

processing. In order to measure segregation of the visual network, we selected the DM network as the 'between-network' control (see Section 2.10 for details). The visual network comprised 6 regions: calcarine cortex, cuneus, lingual gyrus, inferior occipital cortex (infOCC), middle occipital cortex (midOCC), superior occipital cortex (supOCC). The DM network consisted of 6 regions: medial prefrontal cortex (mPFC), posterior cingulate cortex (PCC), precuneus, left angular gyrus (leftAG), middle temporal gyrus (MTG), and hippocampus. Unless otherwise mentioned, ROIs were bilateral.

2.7 Multi-voxel pattern analysis to assess age differences in neural distinctiveness in category-selective ROIs

We were particularly interested in age differences in neural distinctiveness in regions particularly selective for our visual categories (i.e., faces and houses). Therefore, we measured neural specialization for faces in the posterior FG and for houses in the posterior PHG. First, event-related generalized linear models (GLMs) were performed separately for encoding and recognition. For encoding, four event types were modeled: houses, faces, phase-scrambled images, and target images. For recognition, three event types were modeled: houses, faces, and the instructional period at the beginning of each run. All trials were modeled using finite impulse response (FIR) basis sets, beginning at trial onset and lasting for 20 s post-trial onset for encoding trials and 24 s for recognition trials (for similar methodology, see Wolosin et al., 2012). In each model, 6 motion regressors were additionally included. The beta maps corresponding to 2-8 s post-stimulus onset from the event-related GLMs (described above) were averaged for each stimulus. Regional distinctiveness was initially measured separately for encoding and recognition and was defined as the difference between within-category similarity and between-category similarity. Within-category similarity was defined as the across-voxel correlation of a particular stimulus category in the first run (or either encoding or recognition) to the same stimulus category in the second run (e.g., face-face similarity). Between-category similarity was defined as the across-voxel correlation of a particular stimulus category in the first run to the other stimulus category in the second run (i.e., face-house similarity). In the FG, within-category similarity was considered face-face similarity, whereas in the PHG, within-

category similarity was considered house-house similarity. Regional distinctiveness was then averaged across encoding and recognition for each participant and within each ROI. Correlation coefficients were Fisher-*z* transformed. We first checked that regional distinctiveness values in the FG and PHG were reliably above zero using dependent-samples *t*-tests. Age differences in regional distinctiveness were evaluated using a 2 (age group) x 2 (ROI: FG/PHG) mixed factorial ANOVA on distinctiveness values (i.e., within-category – between-category similarity). Significant interactions were further evaluated using pairwise comparisons. In order to understand whether age differences in neural distinctiveness were driven by age-related attenuation or broadening (Park et al., 2012), we additionally ran a series of independent-samples *t*-tests assessing age differences in within-category similarity and between-category similarity within each ROI (4 tests in total).

2.8 Functional connectivity analysis

In order to utilize our task-based functional data to derive connectivity as well as distinctiveness measures, we employed "background" connectivity, in which task-related responses are modeled and the residual time series is used to examine connectivity. Background connectivity can be used analogously to resting state connectivity (Fair et al., 2007; Frank and Zeithamova, 2023) and, in this case, enabled us to avoid circularity problems, which could have arisen if the same functional data were used for both the connectivity and distinctiveness metrics. The resulting residual timeseries from encoding and recognition were concatenated within each participant. Then, the timeseries were averaged across all voxels within each ROI and correlated using Pearson correlation coefficient. Correlation coefficients were than standardized using Fisher's *r*-to-*z* transform.

2.9 Assessing age differences in connectivity to category-selective ROIs

In order to assess age differences in the mean connectivity of category-selective ROIs to the visual network (e.g., connectivity of FG to the visual network, averaged across all visual network ROIs), we used a 2 (age group) x 2 (ROI: FG/PHG) mixed factorial ANOVA on connectivity scores. Significant interactions were followed up using mean comparisons. With the aim of delineating which specific

regions within the visual network were driving the observed age differences, we additionally conducted a series of independent-samples *t*-tests to check for age differences in connectivity between each category-selective ROI and each ROI within the visual network. Significance was determined by FDR-corrected *p*-values.

2.10 Assessing age differences in the segregation of the visual network

Next, we were interested in whether age-related neural dedifferentiation disrupted the functional organization of the visual network. We measured age differences in the segregation of the visual network by taking the difference in mean connectivity of all ROIs within the visual network (i.e., within-network connectivity) and mean connectivity between the visual and DM networks (i.e., between-network connectivity). We conducted a 2 (age group) x 2 (level: within/between) ANOVA on these mean network-level connectivity scores. Significant interactions were further evaluated using independent-samples *t*-tests. To illustrate the specific ROI-ROI connections underlying age differences in network-level segregation, we additionally used a series of independent-samples *t*-tests to test for age differences in the connectivity between all ROIs. Significance was determined by FDR-corrected *p* values.

2.11 Relating neural distinctiveness to connectivity metrics

Crucially, we were interested in the interindividual relationship between regional distinctiveness and connectivity in order to understand whether the observed interindividual differences in both measures are associated.

To this end, we examined whether connectivity to category-selective regions was related to the magnitude of neural distinctiveness we found in these regions (as measured by multi-voxel pattern analysis). To this end, we used Pearson correlations across all participants (as well as within each age group) in order to relate the distinctiveness of each category-selective region to its average connectivity to the visual network. Age differences in correlation coefficients were evaluated using *z* tests on the within-group correlation coefficients for significant relationships. In order to understand

which specific ROI-ROI connections drove these relationships, we again used the same correlation procedure to relate distinctiveness to individual connectivity scores between category-selective regions and each ROI within the visual network. The significance threshold was adjusted using FDR correction for multiple comparisons.

Then, in order to assess whether neural dedifferentiation manifests similarly across regions and networks, we used Pearson correlations to evaluate the relationships between distinctiveness in each category-selective region and segregation of the visual network.

2.12 Relating distinctiveness and connectivity to memory performance

Finally, we assessed how interindividual differences in neural distinctiveness and connectivity (both between FG/PHG and visual network as well as visual network segregation) relate to memory performance (see Figure 2 for diagram of all analyses). We implemented partial least squares correlation (PLSC) analyses in order to understand the shared impact of age differences in distinctiveness and connectivity on memory performance as well as to delineate the weights of the individual contributions of each measure (Krishnan et al., 2011). We used PLSC because it offers the unique advantage of evaluating multiple interrelated measures in a single model without introducing multicollinearity artifacts (as with multiple regression; Gregorich et al., 2021). First, a between-person correlation matrix was calculated between a vector containing memory performance (*Pr*) and a *n* x 5 matrix comprised of neural distinctiveness in the FG and PHG, mean connectivity between FG/PHG and the visual network, and mean network segregation. This correlation matrix then underwent singular value decomposition, producing a single estimate latent variable (LV) that optimally represents the association between the neural measures and memory performance. The significance of the LV was tested using 10,000 permutation tests of the singular value corresponding to the LV. Robustness estimates were measured using a bootstrapping procedure across 10,000 resamples of the data. Bootstrap ratios (BSRs; normalized robustness estimates) were then calculated by dividing the neural weights from the singular value decomposition by the standard errors of their robustness estimates. Similar to *z* values, BSRs are considered reliably robust with

values above or below ±1.96, which we used to delineate which neural measures were reliably associated with memory performance.

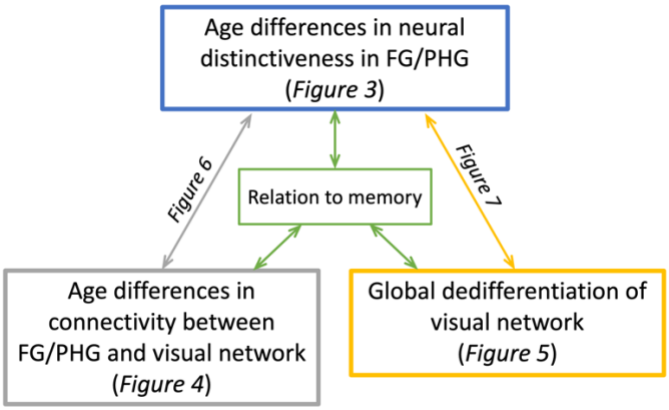

Figure 2. Diagram showing analysis pipeline and where to find the corresponding results.

3 Results

3.1 Behavioral results

Recognition performance (hit rate – false alarm rate) exceeded chance level in both younger ($t(34) = 11.88$, $p < 0.001$, $d = 1.96$) and older adults ($t(33) = 9.37$, $p < 0.001$, $d = 1.57$). We used a mixed factorial ANOVA to test for age and stimulus differences in memory outcomes. This analysis revealed no main effect of age ($F(1,67) = 2.69$, $p = 0.11$, partial-$\eta^2 = 0.03$), indicating that memory performance did not differ between younger ($M \pm SD = 0.24 \pm 0.12$) and older adults ($M \pm SD = 0.19 \pm 0.12$). Furtheremore, neither main effect of stimulus type ($F(1,67) = 2.94$, $p = 0.09$, partial-$\eta^2 = 0.01$) nor interaction ($F(1,67) = 0.12$, $p = 0.73$, partial-$\eta^2 = 0.00$) was identified. These findings corroborate our prior analyses of this data (Pauley et al., 2023).

3.2 Age differences in regional distinctiveness

Using *t*-tests, we first verified that regional distinctiveness values were greater than zero in the FG ($t(68) = 10.85$, $p < 0.001$, $d = 1.29$) and PHG ($t(68) = 9.95$, $p < 0.001$, $d = 1.19$). Then, we performed a 2 (age group) x 2 (ROI) ANOVA to examine age differences in regional distinctiveness values. We

found a main effect of age group ($F(1,67) = 16.15$, $p < 0.001$, partial-$\eta^2 = 0.13$), indicating that younger adults ($M \pm SD = 0.22 \pm 0.14$) had higher regional distinctiveness than older adults ($M \pm SD = 0.12 \pm 0.12$; see Figure 3A). Furthermore, we found a main effect of ROI ($F(1,67) = 11.55$, $p = 0.001$, partial-$\eta^2 = 0.06$), suggesting that distinctiveness was higher in the FG ($M \pm SD = 0.20 \pm 0.16$) than the PHG ($M \pm SD = 0.14 \pm 0.12$). The interaction between age group and ROI was not significant ($F(1,67) = 1.80$, $p = 0.18$, partial-$\eta^2 = 0.01$).

We were additionally interested in whether the observed age differences in regional distinctiveness could be attributed to either neural attenuation, neural broadening, or a combination of both. To this end, we performed *t*-tests to assess age differences in within- and between-category similarity in each ROI. Age differences in within-category similarity in the FG were identified ($t(67) = 3.13$, $p = 0.003$, $d = 0.74$), suggesting that the age-related reduction in regional distinctiveness in the FG could be attributed to neural attenuation (see Figure 3B). Age differences for within-category similarity in the PHG did not reach significance ($t(67) = 1.59$, $p = 0.12$, $d = 0.38$). Furthermore, no age differences in between-category similarity were found in either the FG ($t(67) = -0.85$, $p = 0.40$, $d = 0.20$) or PHG ($t(67) = -0.88$, $p = 0.38$, $d = 0.21$; see Figure 3C).

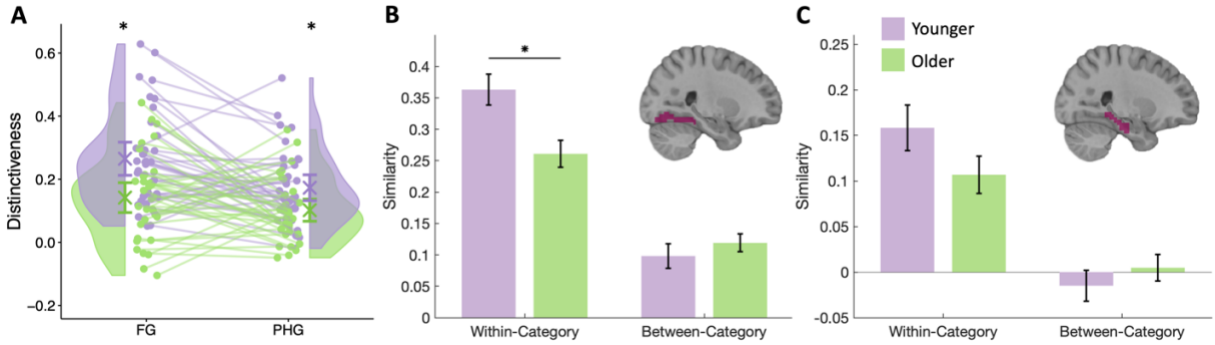

Figure 3. Age differences in regional distinctiveness of category-selective ROIs. Younger adults (purple) demonstrated higher regional distinctiveness (the difference between within-category and between-category similarity) than older adults (green) in both the FG and PHG as defined by multi-voxel pattern analysis (A). Half-violin plots illustrate the sample density of distinctiveness within each ROI and lines connect individual participants. These age differences were driven by reduced within-

category similarity in older adults compared with younger adults in the FG (B). The pattern of age differences in the PHG was similar but was not statistically reliable (C).

3.3 Age differences in functional connectivity to category-selective ROIs

We were interested in whether there were age differences in the mean connectivity of category-selective ROIs to the visual network. To explore this, we used a 2 (age group) x 2 (ROI: FG/PHG) ANOVA on mean connectivity scores (averaged across connectivity to all ROIs within the visual network). The ANOVA revealed a main effect of ROI ($F(1,67) = 1275.40$, $p < 0.001$, partial-$\eta^2 = 0.74$), suggesting that the FG was more strongly connected to the visual network ($M \pm SD = 1.01 \pm 0.17$) compared to the PHG ($M \pm SD = 0.49 \pm 0.15$; see Figure 4A). No main effect of age was identified ($F(1,67) = 2.70$, $p = 0.11$, partial-$\eta^2 = 0.03$), but we found an age by ROI interaction ($F(1,67) = 22.57$, $p < 0.001$, partial-$\eta^2 = 0.05$). Follow-up *t*-tests indicated that younger adults had greater connectivity between the FG and visual network than older adults ($t(67) = 3.24$, $p = 0.002$, $d = 0.77$), but revealed no age differences in the connectivity between the PHG and visual network ($t(67) = -0.34$, $p = 0.73$, $d = 0.08$).

In order to understand the specific regions of the visual network driving the effects observed in the ANOVA, we additionally tested for age differences in connectivity between the category-selective ROIs and each of the ROIs belonging to the visual network using a series of independent-samples *t*-tests. Results of these tests are shown in Figure 4B-C. Younger adults demonstrated greater connectivity between the FG and middle ($t(67) = 5.25$, $p < 0.001$, $d = 1.25$) and superior occipital gyri ($t(67) = 5.59$, $p < 0.001$, $d = 1.33$) as well as the cuneus ($t(67) = 4.14$, $p < 0.001$, $d = 0.99$), suggesting that these regions underly the age difference in connectivity between the FG and the visual network. No age differences in connectivity between the PHG and other ROIs were found (*p*s > 0.10), in line with the lack of age differences observed in the ANOVA, suggesting that connectivity between the visual network regions and PHG does not vary between older and younger adults.

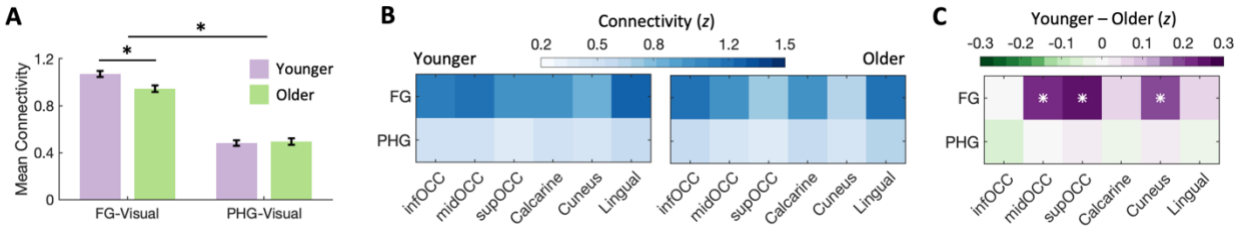

Figure 4. Younger adults (purple) demonstrated greater connectivity between the FG and visual network than older adults (green). Error bars indicate standard error of the mean. Asterisks indicate significant age effects after FDR correction.

3.4 Age-related dedifferentiation of the visual network

Prior studies have reported that older adults demonstrate less segregated global networks characterized by a decrease in within-network connectivity and an increase in between-network connectivity (Geerligs et al., 2015). To understand whether our sample demonstrates analogous age effects, we performed a 2 (age group) x 2 (level: within/between) ANOVA on mean connectivity values within the visual network and between the visual and DM networks. We found a significant main effect of level ($F(1,67) = 2425.00$, $p < 0.001$, partial-$\eta^2 = 0.61$; see Figure 5A-B), indicating that connectivity across regions within the visual network ($M \pm SD = 1.09 \pm 0.21$) was greater compared to connectivity between the visual and DM networks ($M \pm SD = 0.61 \pm 0.21$). A significant interaction between age group and level was found ($F(1,67) = 33.19$, $p < 0.001$, partial-$\eta^2 = 0.02$), suggesting that older adults demonstrated less segregated network structures than younger adults, in line with the age-related dedifferentiation hypothesis. Follow-up *t*-tests revealed that this interaction could not clearly be attributed to either an age-related decrease in connectivity within the visual network ($t(67) = 0.38$, $p = 0.71$, $d = 0.26$) or an age-related increase in connectivity between the networks ($t(67) = -1.14$, $p = 0.26$, $d = 0.31$). No main effect of age was found ($F(1,67) = 0.02$, $p = 0.89$, partial-$\eta^2 = 0.00$).

In order to disentangle which specific ROI-ROI connections drove the network-level effects, we further conducted independent-samples *t*-tests to investigate age differences in connectivity

between each individual ROI within each of the functional networks. See Figure 5C-D for the complete results.

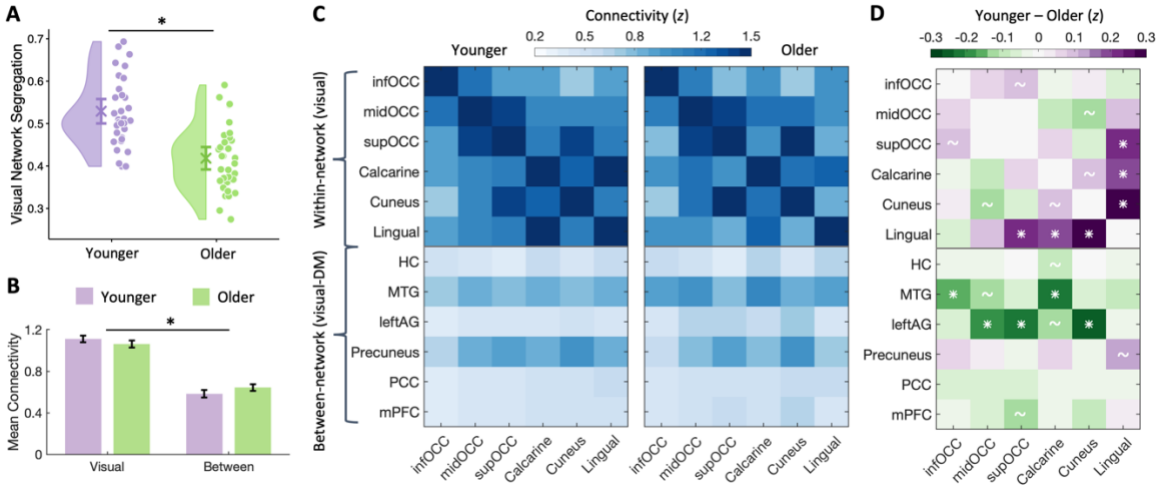

Figure 5. Younger adults (purple) demonstrated greater segregation of the visual network than older adults (green; A-B). Half-violin plots illustrate the sample density of network segregation (the difference in within- minus between-network connectivity). Error bars indicate standard error of the mean. Age differences between individual ROIs within the visual and DM networks (C-D). Asterisks indicate FDR-corrected age effects and tildes indicate uncorrected age effects.

3.5 Regional distinctiveness associated with connectivity to category-selective ROIs

In order to understand whether the magnitude of distinctiveness in category-selective ROIs was related to how connected they were to the visual network, we correlated the distinctiveness of the FG and PHG (separately) to their mean coactivation with the visual network using Pearson correlations. Older adults demonstrated a negative relationship between distinctiveness in the PHG and connectivity between the PHG and visual network (r = -0.43, p = 0.01), suggesting that older individuals with more distinctive house representations tended to have lower connectivity between the PHG and visual network (see Figure 6A-B). Furthermore, we found age differences in the correlation between distinctiveness in the PHG and connectivity between the PHG and visual network ($r_{younger}$ = 0.14; z = 2.39, p = 0.02). No other relationships reached significance (ps > 0.11). Then, we assessed for which particular regions within the visual network the connectivity with

category-selective regions tracked interindividual variability in neural distinctiveness. Correlation coefficients are plotted in Figure 6C-D. Briefly, the results indicate that the negative relationship observed in older adults was driven by connectivity between the PHG and occipital cortices, calcarine cortex, and cuneus. Furthermore, a positive relationship was found between distinctiveness in the FG and connectivity between the FG and midOCC (and supOCC, though not after correcting for multiple comparisons), suggesting that individuals with more distinctive face representations also tended to have greater connectivity between the FG and midOCC.

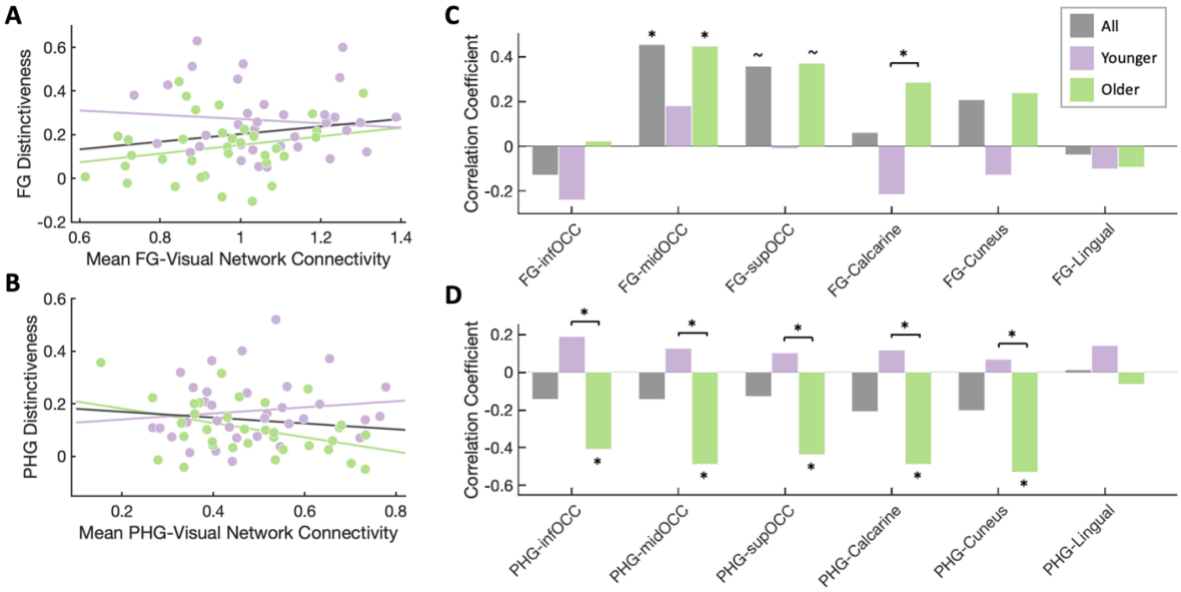

Figure 6. Scatter plots show the relationships between connectivity to the visual network and distinctiveness in the FG (A) and PHG (B). Younger adults are shown in purple, older adults in green, and the whole sample in gray. Coefficients of Pearson correlations between connectivity to the visual network and distinctiveness in the FG (C) and PHG (D) as well as age differences in the coefficients (indicated by lines with asterisks). Asterisks indicate significant age effects after FDR correction and tildes indicate uncorrected age effects.

3.6 Regional dedifferentiation associated with network dedifferentiation

We were further interested in whether the magnitude of neural distinctiveness in each category-selective ROI was related to interindividual variation in the segregation of the visual network.

Correlations of the whole sample revealed relationships between segregation of the visual network and the magnitude of distinctiveness in the FG (r = 0.29, p = 0.02) and in the PHG (r = 0.24, p = 0.05; see Figure 7). No within-group relationships reached significance. To summarize, these results indicate a positive relationship between regional and network dedifferentiation, suggesting that individuals with higher neural distinctiveness in the FG and PHG also tend to have greater segregation of the visual network.

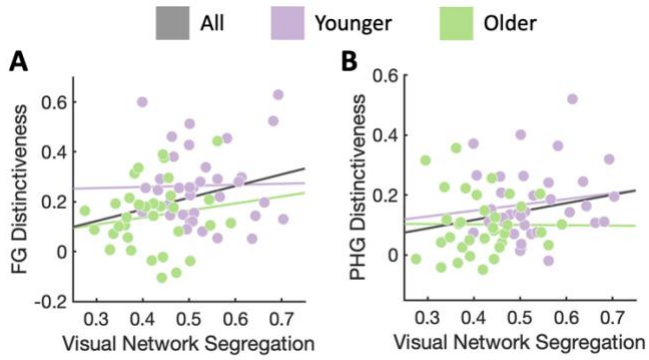

Figure 7. Segregation of the visual network was associated with regional distinctiveness in the FG (A) and PHG (B). Younger adults are shown in purple, older adults in green, and the whole sample in gray.

3.7 Interindividual variability in memory performance linked to regional distinctiveness

In order to understand whether age differences in distinctiveness and connectivity were associated with memory, we performed a PLSC analysis relating memory performance to regional distinctiveness in the FG and PHG, mean connectivity between the FG/PHG and the visual network, and mean network segregation of the visual network. This PLSC analysis revealed a single reliable latent variable (LV; p = 0.03) that optimally represents the relationship between the neural measures and memory. Younger and older adults demonstrated modest latent correlations (r = 0.38 and 0.39, respectively). Bootstrap ratios (BSRs) revealed neural distinctiveness in the FG and PHG as the stable components of the LV explaining the largest amount of information common to memory performance and the neural measures (BSRs = 2.11 and 2.50, respectively). The positive

relationship indicates that higher neural distinctiveness in both the FG and PHG is associated with better memory performance across individuals.

4 Discussion

Age-related neural dedifferentiation has garnered increasing attention over the last two decades as a potential underlying source of senescent cognitive decline (Li et al., 2001; for reviews, see Koen et al., 2020; Koen & Rugg, 2019; Sommer & Sander, 2022). Studies have reported evidence for neural dedifferentiation for individual stimuli (Koen, 2022; St-Laurent et al., 2014; Trelle et al., 2019), stimulus categories (Koen et al., 2019; Park et al., 2004; Pauley et al., 2023; Srokova et al., 2020), and global networks (Betzel et al., 2014; Chan et al., 2014; Geerligs et al., 2015; Varangis et al., 2019). Thus far, few studies have investigated network dedifferentiation and looked for a link between network and regional dedifferentiation. Furthermore, whether aging targets the functional relationships of categorically-selective regions has yet to be explored. Here, in a sample of younger and older adults, we assessed age-related neural dedifferentiation across both the global network and categorical levels, their relation to one another, as well as the possibility that age differences in connectivity patterns to categorically-selective regions may be related to the observed regional dedifferentiation of categorical representations.

The present results show that the neural distinctiveness of visual categories is reduced in older adults compared with younger adults. Specifically, we demonstrate that older adults exhibited lower representational specificity in the FG and PHG for faces and houses, respectively. This attenuation of distinctiveness was driven by less representational similarity within the region's preferred stimulus category in older adults, suggesting that the representational components reflecting category inclusion are altered in aging. Previous studies have reported so-called "neural attenuation" in the extended face network for faces (Park et al., 2012) as well as in the PHG for scenes (Koen et al., 2019). However, Park and colleagues (2012) reported neural broadening rather than neural attenuation in the FG for faces, contradicting the present findings. This discrepancy could be attributed to methodological differences between the two studies in that Park et al. (2012)

assessed distinctiveness based on mean activation values whereas we used multi-voxel pattern analyses. Altogether, our findings support the age-related neural dedifferentiation hypothesis and suggest that these age differences in neural distinctiveness are due to deteriorated category-selective representations.

Despite growing research focused on connectivity patterns to categorically-selective regions (Córdova et al., 2016; Furl, 2015; Keller et al., 2022; Norman-Haignere et al., 2012), the impact of age on these functional relationships has been so far overlooked. Here, we found greater connectivity between the FG and visual network compared to the PHG. Furthermore, we observed age-related declines in the coupling of the FG to regions within the visual network. Specifically, connectivity between the FG and the superior and middle occipital gyri as well as between the FG and the cuneus was reduced in older adults compared with younger adults. Together, these findings may suggest that task-relevant communication between occipital cortices and the FG is impaired in older age.

Goh (2011) proposed that age-related reductions in distinctiveness of category-selective regions might be a byproduct of impaired interregional communication. In line with this hypothesis, we identified relationships between distinctive category processing in the FG and PHG and their connectivity to other visual regions. Specifically, higher distinctiveness in the FG was associated with greater connectivity between the FG and middle occipital gyrus, suggesting that greater communication with early visual cortices might support the specificity with which the FG can process faces. In general, visual cortices were well-connected to the FG in younger and older adults, but these specific connections demonstrated age-related declines in connectivity. Thus, apparently, the senescent decline in connectivity between the FG and occipital cortices and the senescent decline in distinctiveness of the FG go hand in hand, linking age-related neural dedifferentiation in category-selective regions to disruptions in their communication with other brain regions. We additionally observed (negative) relationships between distinctive house processing in the PHG and connectivity between the PHG and various regions of the visual network in older adults. Compared to the FG, the PHG was not especially well-connected to the visual network, even in younger adults, indicating that

it does not typically communicate with visual regions. Therefore, these negative associations between distinctiveness and connectivity in the PHG suggest that reduced distinctiveness occurs alongside uncharacteristically greater connectivity between the PHG and the visual network. In other words, increased communication of the PHG and visual regions may introduce noise into the local signal, thus impairing the quality of house-specific representations in older adults (Antonenko and Flöel, 2013). In sum, we provide evidence pointing to a potential link between age-related neural dedifferentiation of categorical representations and age differences in connectivity to category-selective regions, albeit with dissociative implications between the FG and PHG. In the FG, distinctiveness and connectivity appear mutually supportive, whereas in the PHG, increasing connectivity is evidently maladaptive for distinctiveness.

We found evidence for an age-related disruption in intrinsic network organization in the visual network, indicative of network dedifferentiation. The observed age differences were not explicitly driven by either reduced within-network connectivity or increased between-network connectivity in older adults compared with younger adults, but rather characterized by a combination of both. Our individual ROI-based analyses revealed age-related declines in connectivity between regions within the visual network. In contrast, prior studies reported no differences in connectivity between younger and older adults among visual regions during resting-state assessments (Geerligs et al., 2015; Varangis et al., 2019), but age differences during tasks (Varangis et al., 2021). In our study, age differences in the connectivity between the visual and DM networks were particularly salient. These findings mirror work from Pruitt and colleagues (2022) who also showed age-related modulation of DM network connectivity with other networks (see also, King et al., 2018). Reports of greater coupling between the visual network and other networks in older adults are rather rare (Geerligs et al., 2015). However, age-related increases in connectivity of the DM network with other networks have been reported often (Chong et al., 2019). In sum, our results indicate degraded neural network segregation in aging, particularly impacting the visual network by disrupting within-network coupling as well as inter-network communication.

Regional dedifferentiation in the FG and PHG was associated with dedifferentiation of the visual network. Hence, individuals with more distinctive local functional processing also tend to exhibit more segregated large-scale network organization. These results are in line with those from Cassady and colleagues (2020), who found a comparable relationship between distinctiveness of sensorimotor processing and network segregation. Together, these findings suggest that the age-related decline in distinctive neural processing appears to be a wide-ranging phenomenon that manifests similarly in both inter- and intraregional signaling, potentially as a result of an age-dependent physiological mechanism (Baltes and Lindenberger, 1997). For example, age-related dopaminergic dysregulation has been proposed to impair the fidelity of neural signaling and thus reducing distinctiveness in cortical representations (Li et al., 2000). In line with this proposal, dedifferentiation of neural representations has been linked to age differences in dopamine receptor concentrations (Abdulrahman et al., 2017). Additionally, blocking dopaminergic (D2) receptors reportedly mimicks age differences in functional network organization, albeit to a lesser extent (Achard and Bullmore, 2007). Thus, age differences in the dopaminergic system could potentially account for the related senescent declines in both regional distinctiveness and network segregation in the current study, though more work is needed to validate this theory.

Finally, interindividual variability in neural distinctiveness in the FG and PHG tracked memory performance. This finding aligns with prior studies (including previous analyses on this dataset; see Pauley et al., 2023) underlining the importance of highly detailed representations to support memory processing (for reviews, see Koen et al., 2020; Koen and Rugg, 2019; Sommer and Sander, 2022).

All in all, we find that older adults demonstrate declines in distinctiveness in categorical representations, connectivity to category-selective regions, and segregation of large-scale brain networks compared with younger adults. Crucially, our findings point to a possible link between the impaired regional processing and age differences in connectivity to these regions as well as between impaired regional processing and deficits in interregional communication. Due to the modest sample size, we feel it is important to note that our findings should be interpreted as preliminary evidence, aiming to stimulate future research into the association between age-related neural dedifferentiation

and age differences in functional network organization. Ultimately, understanding how functional neural representations differ between younger and older adults may be helpful to elucidate cognitive trajectories in older adulthood.

Disclosure

The authors declare no competing financial interests.

Author statement

Claire Pauley: Formal analysis, Software, Writing - Original Draft. **Dagmar Zeithamova:** Methodology, Writing – Review & Editing. **Myriam C. Sander:** Conceptualization, Project administration, Supervision, Writing – Review & Editing.

Acknowledgments

This work was conducted within the projects “Lifespan Age Differences in Memory Representations (LIME)” (PI: M.C.S.) and Lifespan Rhythms of Memory and Cognition (RHYME) (PI: Markus Werkle-Bergner) at the Max Planck Institute for Human Development. C.P. was a fellow of the International Max Planck Research School on the Life Course. D.Z. was supported by the National Institute of Neurological Disorders and Stroke (R01-NS-112366). M.C.S. was supported by the MINERVA program of the Max Planck Society. We thank all student assistants who helped with data collection, Gabriele Faust and members of the LIME and RHYME projects for helpful feedback, Julia Delius for editorial assistance, and all study participants for their time.

References

Abdulrahman, H., Fletcher, P.C., Bullmore, E., Morcom, A.M., 2017. Dopamine and memory dedifferentiation in aging. NeuroImage 153, 211–220. https://doi.org/10.1016/j.neuroimage.2015.03.031

Achard, S., Bullmore, E., 2007. Efficiency and Cost of Economical Brain Functional Networks. PLOS Comput. Biol. 3, e17. https://doi.org/10.1371/journal.pcbi.0030017

Andrews-Hanna, J.R., Snyder, A.Z., Vincent, J.L., Lustig, C., Head, D., Raichle, M.E., Buckner, R.L., 2007. Disruption of large-scale brain systems in advanced aging. Neuron 56, 924–935. https://doi.org/10.1016/j.neuron.2007.10.038

Antonenko, D., Flöel, A., 2013. Healthy Aging by Staying Selectively Connected: A Mini-Review. Gerontology 60, 3–9. https://doi.org/10.1159/000354376

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

Barense, M.D., Henson, R.N.A., Lee, A.C.H., Graham, K.S., 2010. Medial temporal lobe activity during complex discrimination of faces, objects, and scenes: Effects of viewpoint. Hippocampus 20, 389–401. https://doi.org/10.1002/hipo.20641

Betzel, R.F., Byrge, L., He, Y., Goñi, J., Zuo, X.-N., Sporns, O., 2014. Changes in structural and functional connectivity among resting-state networks across the human lifespan. NeuroImage 102 Pt 2, 345–357. https://doi.org/10.1016/j.neuroimage.2014.07.067

Cao, M., Wang, J.-H., Dai, Z.-J., Cao, X.-Y., Jiang, L.-L., Fan, F.-M., Song, X.-W., Xia, M.-R., Shu, N., Dong, Q., Milham, M.P., Castellanos, F.X., Zuo, X.-N., He, Y., 2014. Topological organization of the human brain functional connectome across the lifespan. Dev. Cogn. Neurosci. 7, 76–93. https://doi.org/10.1016/j.dcn.2013.11.004

Cassady, K., Gagnon, H., Freiburger, E., Lalwani, P., Simmonite, M., Park, D.C., Peltier, S.J., Taylor, S.F., Weissman, D.H., Seidler, R.D., Polk, T.A., 2020. Network segregation varies with neural distinctiveness in sensorimotor cortex. NeuroImage 212, 116663. https://doi.org/10.1016/j.neuroimage.2020.116663

Chan, M.Y., Alhazmi, F.H., Park, D.C., Savalia, N.K., Wig, G.S., 2017. Resting-State Network Topology Differentiates Task Signals across the Adult Life Span. J. Neurosci. 37, 2734–2745. https://doi.org/10.1523/JNEUROSCI.2406-16.2017

Chan, M.Y., Park, D.C., Savalia, N.K., Petersen, S.E., Wig, G.S., 2014. Decreased segregation of brain systems across the healthy adult lifespan. Proc. Natl. Acad. Sci. U. S. A. 111, E4997–E5006. https://doi.org/10.1073/pnas.1415122111

Chee, M.W.L., Goh, J.O.S., Venkatraman, V., Jiat, C.T., Gutchess, A., Sutton, B., Hebrank, A., Leshikar, E., Park, D., 2006. Age-related changes in object processing and contextual binding revealed using fMR adaptation. J. Cogn. Neurosci. 18, 495–507. https://doi.org/10.1162/jocn.2006.18.4.495

Chen, Q., Garcea, F.E., Almeida, J., Mahon, B.Z., 2017. Connectivity-based constraints on category-specificity in the ventral object processing pathway. Neuropsychologia 105, 184–196. https://doi.org/10.1016/j.neuropsychologia.2016.11.014

Chong, J.S.X., Ng, K.K., Tandi, J., Wang, C., Poh, J.-H., Lo, J.C., Chee, M.W.L., Zhou, J.H., 2019. Longitudinal Changes in the Cerebral Cortex Functional Organization of Healthy Elderly. J. Neurosci. 39, 5534–5550. https://doi.org/10.1523/JNEUROSCI.1451-18.2019

Córdova, N.I., Tompary, A., Turk-Browne, N.B., 2016. Attentional modulation of background connectivity between ventral visual cortex and the medial temporal lobe. Neurobiol. Learn. Mem. 134, 115–122. https://doi.org/10.1016/j.nlm.2016.06.011

Ebner, N.C., Riediger, M., Lindenberger, U., 2010. FACES-a database of facial expressions in young, middle-aged, and older women and men: Development and validation. Behav. Res. Methods 42, 351–362. https://doi.org/10.3758/BRM.42.1.351

Epstein, R., Kanwisher, N., 1998. A cortical representation the local visual environment. Nature 392, 598–601. https://doi.org/10.1038/33402

Esteban, O., Markiewicz, C.J., Blair, R.W., Moodie, C.A., Isik, A.I., Erramuzpe, A., Kent, J.D., Goncalves, M., DuPre, E., Snyder, M., Oya, H., Ghosh, S.S., Wright, J., Durnez, J., Poldrack, R.A., Gorgolewski, K.J., 2019. fMRIPrep: A robust preprocessing pipeline for functional MRI. Nat. Methods 16, 111–116. https://doi.org/10.1038/s41592-018-0235-4

Fair, D.A., Schlaggar, B.L., Cohen, A.L., Miezin, F.M., Dosenbach, N.U.F., Wenger, K.K., Fox, M.D., Snyder, A.Z., Raichle, M.E., Petersen, S.E., 2007. A method for using blocked and event-related

fMRI data to study “resting state” functional connectivity. NeuroImage 35, 396–405. https://doi.org/10.1016/j.neuroimage.2006.11.051

Folstein, M.F., Folstein, S.E., McHugh, P.R., 1975. “Mini-mental state”. A practical method for grading the cognitive state of patients for the clinician. J. Psychiatr. Res. 12, 189–198. https://doi.org/10.1016/0022-3956(75)90026-6

Frank, L.E., Zeithamova, D., 2023. Evaluating methods for measuring background connectivity in slow event-related functional magnetic resonance imaging designs. Brain Behav. 13, e3015. https://doi.org/10.1002/brb3.3015

Furl, N., 2015. Structural and effective connectivity reveals potential network-based influences on category-sensitive visual areas. Front. Hum. Neurosci. 9, 253. https://doi.org/10.3389/fnhum.2015.00253

Geerligs, L., Renken, R.J., Saliasi, E., Maurits, N.M., Lorist, M.M., 2015. A Brain-Wide Study of Age-Related Changes in Functional Connectivity. Cereb. Cortex 25, 1987–1999. https://doi.org/10.1093/cercor/bhu012

Goh, J.O.S., 2011. Functional dedifferentiation and altered connectivity in older adults: Neural accounts of cognitive aging. Aging Dis. 2, 30–48.

Gorgolewski, K.J., Auer, T., Calhoun, V.D., Craddock, R.C., Das, S., Duff, E.P., Flandin, G., Ghosh, S.S., Glatard, T., Halchenko, Y.O., Handwerker, D.A., Hanke, M., Keator, D., Li, X., Michael, Z., Maumet, C., Nichols, B.N., Nichols, T.E., Pellman, J., Poline, J.B., Rokem, A., Schaefer, G., Sochat, V., Triplett, W., Turner, J.A., Varoquaux, G., Poldrack, R.A., 2016. The brain imaging data structure, a format for organizing and describing outputs of neuroimaging experiments. Sci. Data 3, 1–9. https://doi.org/10.1038/sdata.2016.44

Gregorich, M., Strohmaier, S., Dunkler, D., Heinze, G., 2021. Regression with highly correlated predictors: Variable omission is not the solution. Int. J. Environ. Res. Public. Health 18. https://doi.org/10.3390/ijerph18084259

Iordan, A.D., Cooke, K.A., Moored, K.D., Katz, B., Buschkuehl, M., Jaeggi, S.M., Jonides, J., Peltier, S.J., Polk, T.A., Reuter-Lorenz, P.A., 2017. Aging and Network Properties: Stability Over Time and

Links with Learning during Working Memory Training. Front. Aging Neurosci. 9, 419. https://doi.org/10.3389/fnagi.2017.00419

Kanwisher, N., McDermott, J., Chun, M.M., 1997. The fusiform face area: A module in human extrastriate cortex specialized for face perception. J. Neurosci. 17, 4302–4311. https://doi.org/10.1523/JNEUROSCI.17-11-04302.1997

Keller, A.S., Jagadeesh, A.V., Bugatus, L., Williams, L.M., Grill-Spector, K., 2022. Attention enhances category representations across the brain with strengthened residual correlations to ventral temporal cortex. NeuroImage 249, 118900. https://doi.org/10.1016/j.neuroimage.2022.118900

King, B.R., van Ruitenbeek, P., Leunissen, I., Cuypers, K., Heise, K.-F., Santos Monteiro, T., Hermans, L., Levin, O., Albouy, G., Mantini, D., Swinnen, S.P., 2018. Age-Related Declines in Motor Performance are Associated With Decreased Segregation of Large-Scale Resting State Brain Networks. Cereb. Cortex N. Y. N 1991 28, 4390–4402. https://doi.org/10.1093/cercor/bhx297

Kobelt, M., Sommer, V.R., Keresztes, A., Werkle-Bergner, M., Sander, M.C., 2021. Tracking age differences in neural distinctiveness across representational levels. J. Neurosci. 41, 3499–3511. https://doi.org/10.1523/jneurosci.2038-20.2021

Koen, J.D., 2022. Age-related neural dedifferentiation for individual stimuli: an across-participant pattern similarity analysis. Aging Neuropsychol. Cogn. 29, 552–576. https://doi.org/10.1080/13825585.2022.2040411

Koen, J.D., Hauck, N., Rugg, M.D., 2019. The relationship between age, neural differentiation, and memory performance. J. Neurosci. 39, 149–162. https://doi.org/10.1523/JNEUROSCI.1498-18.2018

Koen, J.D., Rugg, M.D., 2019. Neural dedifferentiation in the aging brain. Trends Cogn. Sci. 23, 547–559. https://doi.org/10.1016/j.tics.2019.04.012

Koen, J.D., Srokova, S., Rugg, M.D., 2020. Age-related neural dedifferentiation and cognition. Curr. Opin. Behav. Sci. 32, 7–14. https://doi.org/10.1016/j.cobeha.2020.01.006

Krishnan, A., Williams, L.J., McIntosh, A.R., Abdi, H., 2011. Partial Least Squares (PLS) methods for neuroimaging: A tutorial and review. NeuroImage 56, 455–475. https://doi.org/10.1016/j.neuroimage.2010.07.034

Li, S.-C., Lindenberger, U., Frensch, P.A., 2000. Unifying cognitive aging: From neuromodulation to representation to cognition. Neurocomputing 32–33, 879–890. https://doi.org/10.1016/S0925-2312(00)00256-3

Li, S.-C., Lindenberger, U., Sikström, S., 2001. Aging cognition: From neuromodulation to representation. Trends Cogn. Sci. 5, 479–486. https://doi.org/10.1016/S1364-6613(00)01769-1

Mak, L.E., Minuzzi, L., MacQueen, G., Hall, G., Kennedy, S.H., Milev, R., 2017. The Default Mode Network in Healthy Individuals: A Systematic Review and Meta-Analysis. Brain Connect. 7, 25–33. https://doi.org/10.1089/brain.2016.0438

Norman-Haignere, S.V., McCarthy, G., Chun, M.M., Turk-Browne, N.B., 2012. Category-Selective Background Connectivity in Ventral Visual Cortex. Cereb. Cortex 22, 391–402. https://doi.org/10.1093/cercor/bhr118

Park, D.C., Polk, T.A., Park, R., Minear, M., Savage, A., Smith, M.R., 2004. Aging reduces neural specialization in ventral visual cortex. Proc. Natl. Acad. Sci. U. S. A. 101, 13091–13095. https://doi.org/10.1073/pnas.0405148101

Park, J., Carp, J., Kennedy, K.M., Rodrigue, K.M., Bischof, G.N., Huang, C.M., Rieck, J.R., Polk, T.A., Park, D.C., 2012. Neural broadening or neural attenuation? Investigating age-related dedifferentiation in the face network in a large lifespan sample. J. Neurosci. 32, 2154–2158. https://doi.org/10.1523/JNEUROSCI.4494-11.2012

Pauley, C., Kobelt, M., Werkle-Bergner, M., Sander, M.C., 2023. Age differences in neural distinctiveness during memory encoding, retrieval, and reinstatement. Cereb. Cortex 33, 9489–9503. https://doi.org/10.1093/cercor/bhad219

Pauley, C., Sommer, V.R., Kobelt, M., Keresztes, A., Werkle-bergner, M., Sander, M.C., 2022. Age-related declines in neural selectivity manifest differentially during encoding and recognition. Neurobiol. Aging.

Payer, D., Marshuetz, C., Sutton, B., Hebrank, A., Welsh, R.C., Park, D.C., 2006. Decreased neural specialization in old adults on a working memory task. Neuroreport 17, 487–491. https://doi.org/10.1097/01.WNR.0000209005.40481.31

Power, J.D., Barnes, K.A., Snyder, A.Z., Schlaggar, B.L., Petersen, S.E., 2012. Spurious but systematic correlations in functional connectivity MRI networks arise from subject motion. NeuroImage 59, 2142–2154. https://doi.org/10.1016/J.NEUROIMAGE.2011.10.018

Pruitt, P.J., Tang, L., Hayes, J.M., Ofen, N., Damoiseaux, J.S., 2022. Lifespan differences in background functional connectivity of core cognitive large-scale brain networks. Neurosci. Res. https://doi.org/10.1016/j.neures.2022.09.005

Silson, E.H., Steel, A., Kidder, A., Gilmore, A.W., Baker, C.I., 2019. Distinct subdivisions of human medial parietal cortex support recollection of people and places. eLife 8, e47391. https://doi.org/10.7554/eLife.47391

Snodgrass, J.G., Corwin, J., 1988. Pragmatics of measuring recognition memory: Applications to dementia and amnesia. J. Exp. Psychol. Gen. 117, 34–50. https://doi.org/10.1037/0096-3445.117.1.34

Sommer, V.R., Sander, M.C., 2022. Contributions of representational distinctiveness and stability to memory performance and age differences. Aging Neuropsychol. Cogn. 29, 443–462. https://doi.org/10.1080/13825585.2021.2019184

Song, J., Birn, R.M., Boly, M., Meier, T.B., Nair, V.A., Meyerand, M.E., Prabhakaran, V., 2014. Age-related reorganizational changes in modularity and functional connectivity of human brain networks. Brain Connect. 4, 662–676. https://doi.org/10.1089/brain.2014.0286

Srokova, S., Hill, P.F., Koen, J.D., King, D.R., Rugg, M.D., 2020. Neural differentiation is moderated by age in scene-selective, but not face-selective, cortical regions. eNeuro 7. https://doi.org/10.1523/ENEURO.0142-20.2020

St-Laurent, M., Abdi, H., Bondad, A., Buchsbaum, B.R., 2014. Memory reactivation in healthy aging: Evidence of stimulus-specific dedifferentiation. J. Neurosci. 34, 4175–4186. https://doi.org/10.1523/JNEUROSCI.3054-13.2014

Trelle, A.N., Henson, R.N., Simons, J.S., 2019. Neural evidence for age-related differences in representational quality and strategic retrieval processes. Neurobiol. Aging 84, 50–60. https://doi.org/10.1016/j.neurobiolaging.2019.07.012

Tzourio-Mazoyer, N., Landeau, B., Papathanassiou, D., Crivello, F., Etard, O., Delcroix, N., Mazoyer, B., Joliot, M., 2002. Automated Anatomical Labeling of activations in SPM using a macroscopic anatomical parcellation of the MNI MRI single-subject brain. NeuroImage 15, 273–289. https://doi.org/10.1006/nimg.2001.0978

Varangis, E., Habeck, C.G., Razlighi, Q.R., Stern, Y., 2019. The Effect of Aging on Resting State Connectivity of Predefined Networks in the Brain. Front. Aging Neurosci. 11. https://doi.org/10.3389/fnagi.2019.00234

Varangis, E., Habeck, C.G., Stern, Y., 2021. Task-based functional connectivity in aging: How task and connectivity methodology affect discovery of age effects. Brain Behav. 11. https://doi.org/10.1002/brb3.1954

Wang, X., Fang, Y., Cui, Z., Xu, Y., He, Y., Guo, Q., Bi, Y., 2016. Representing object categories by connections: Evidence from a mutivariate connectivity pattern classification approach. Hum. Brain Mapp. 37, 3685–3697. https://doi.org/10.1002/hbm.23268

Wolosin, S.M., Zeithamova, D., Preston, A.R., 2012. Reward modulation of hippocampal subfield activation during successful associative encoding and retrieval. J. Cogn. Neurosci. 24, 1532–1547. https://doi.org/10.1162/jocn_a_00237