**Materials and Methods**

*Participants*. One-hundred and twenty adult participants, ages 40-45, were recruited from Florida International University’s (FIU) Psychology and Engineering department (60 females, 60 males). Prior to the start of our experiment, the university’s IRB authorized the study’s procedure. Participants assented to the informed consent and received compensation for their participation in the study. To avoid biologically related task interference and maximization of our effects of interest (i.e., face and scene detection), we screened for (a) major medical conditions (i.e., Alzheimer’s and dementia) using the Alzheimer’s Disease Assessment Scale (Sinner et al., 2012) and Disability Assessment Scale for Dementia (Gauthier et al., 1994); and (b) psychiatric disorders (i.e., anxiety and depression) by means of the Beck Anxiety Inventory (BAI) (Beck & Steer, 1993) and Beck Depression Inventory (BDI) (Steer et al., 1996). BAI and BDI are 21-item questionnaires assessing levels of anxiety and depression symptomatology, respectively, over the past month. Only 1 male participant met eligibility criteria. The remaining 119 volunteers presented moderate to severe levels of Alzheimer’s and/or anxiety. The eligible participant was right-handed and had corrected to normal vision.

*Localizer Task Procedure*. The localizer task consisted of 2 runs. Every trial initiated with a white fixation cross on a black background (0.75 seconds) and the interstimulus interval (ISI) interval was 0.75 seconds. Every run consisted of 7 segments: a 10-second face block, a 5-second math block, a 10-second scene block, and a final 5-second math block. Neutrally valenced water scenes, or, neutrally valenced male or female faces (140 faces total) were shown. Using a MR-compatible 2-button response device, subjects were instructed to indicate, while the image was on the screen, whether scenes contained water or whether faces were male or female. For math trials, participants were presented basic mathematical equations and instructed to indicate whether the result was less than or greater than “5”.

*Perceptual and Visual Conditional Associative Task Procedures.*

The perceptual baseline task consisted of 4 runs with 2.5 second trials. Every trial initiated with a with a white fixation cross on a black background (0.75 seconds). Between each stimulus presentation, there was an interstimulus interval (ISI) of 0.75 seconds showing the same fixation cross. During the perceptual baseline trial, the participant observed a visual static image with a box to the left and another to the right of the white fixation cross (1 second). The boxes varied in brightness. During the response phase, the participant was given 1 second to choose the brighter of the two boxes. For 0.8 seconds, a green “Yes” feedback appeared in the middle of a black screen, if a correct response was provided. A red “No!” and white “?” was shown for incorrect responses and over 1-second delayed responses, respectively.

The visual conditional associative task consisted of 4 runs and trials of 2.5 second duration. Like the perceptual baseline task, every trial initiated with a with a white fixation cross on a black background (0.75 seconds). The ISI had the same duration. The participant was presented a kaleidoscope centered image paired with 2 household objects placed to the right and left (1 second). These were fixed order associations, meaning that each kaleidoscope stimulus was *always* associated with 1 of the 2 objects. The participant was instructed to learn the association between each shape and object by means of trial and error. The position of the objects switched for all the kaleidoscope-object trials. Some of the kaleidoscope shape-object pairings consisted of a water scene and face picture to the right and left of the kaleidoscope-centered stimulus. The participant had to select the water or face stimulus, depending on the shape-object pairing that came *before* it. This trial was referred to as the conditional association trial (i.e., some of the kaleidoscope shape-object pairings were uniquely associated with a face or a scene in the upcoming trial). Once again, the participant had to learn the associations by means of trial and error. For 0.8 seconds, a green “Yes” feedback appeared in the middle of a black screen for correct responses, a red “No!” for incorrect response, and a white “?” for over 1-second delayed responses.

*Neuroimaging Acquisition Parameters*. Neuroimaging data were acquired at the Center for Imaging Science at FIU, using a 3T Siemens MAGNETOM Prisma scanner with a 32-channel head coil. We collected T2\*-weighted EPI sequence (TR = 1.76, TE = 35 ms, flip angle, 52 degrees, FOV = 1800 mm, axial slices = 355, slice acceleration = 3, voxel size = 2 mm isotropic), a T1-weighted magnetization-prepared rapid gradient echo sequence (MPRAGE: TR = 2500 ms, TE = 2.9 ms, flip angle = 8.0, FOV = 256 mm, sagittal slices = 176, voxel size = 1 mm isotropic) and 1420 brain volumes.

*MRI and Anatomical Preprocessing.* Prior to the preprocessing steps, data were converted from DICOM to nifti format utilizing the Brain Imaging Data Structure (BIDS) (Gorgolewski, 2016).

Acquired data were preprocessed using a Nipype (Nipype version 0.12.1; Gorgolewski et al., 2011), Python-based script with a preprocessing pipeline drawn from the following software: Advanced Normalization Tools (ANTS) (Avants et al., 2008); Analysis of Functional NeuroImages (AfNI) (AFNI version 20.1.00; Cox, 1996), FSL 5.0.11 (Smith et al., 2004), artifact detection toolbox (ART – implemented in Nipype), and Freesurfer 7.1 (FS) (Fischl, 2012). Upon completion of the study, preprocessing and data analyses pipelines will be made publicly available via *Github* (www.github.com), using a study specific github repository.

For our anatomical preprocessing, T1-weighted images were skull-stripped and registered MNI-152 template using FSL’s FLIRT, accounting for 6 degrees of freedom rigid body transformation (i.e., 3 rotations (pitch, roll, and yaw) and 3 translations (x, y, z)). To create a study-specific template and thus diminish normalization errors, ANTS software was used. By using a non-linear, symmetric diffeomorphic map, the skull-stripped FS brain was normalized to our study-specific template. The output warps served to transfer contrast parameter estimated into template space preceding fixed-effects modeling for subsequent group-level tests.

The following BOLD neuroimaging data preprocessing steps were followed: first, AfNI’s 3dToutcount permitted the identification of the total number of outliers at each volume. We subsequently searched the first 201 volumes and using FSL’s Extract ROI, extracted the earliest volume of the first run. This served as the basis or reference for our motion correction of functional runs, which were realigned to the first volume of the first run using FSL’s McFlirt and a “linear” interpolation. Motion correction allows us to correct for any individual head motion that occurred during the task. RapidArtDetection then identified the images in the functional series that were considered outliers solely based on intensity or motion deviations (>3 z-normalized SD mean intensity; 0.2 mm frame-wise displacement). Subsequent slice timing correction was performed with AfNI’s 3dTshift command. Functional data were aligned to structural high-resolution anatomical space by means of FS’ BBRegister. The FS parcellation and segmentation file (i.e., aparc+aseg) was binarized, dilated by 1 mm, and warped back into EPI space by utilizing the ApplyVolTransform tool. Data was spatially smoothed using the SUSAN algorithm (Smith & Brady, 1997) from FSL and a 4 mm FWHM. The brightness threshold was set to 75% of the median value of each run and a mask constituting the mean function.

**MRI Data Analysis**

*Anatomical Regions of Interest.* Our study aimed to unravel the contribution of the hippocampus (HPC) and parahippocampal gyrus (PrHPC) in face and scene detection. Previous studies in amnesic patients have reported the role of the posterior PrHPC and posterior HPC in scene detection and the PrHPC and anterior HPC in face discrimination (Mundy et al., 2013). To perform subsequent corresponding analyses, bilateral hippocampal and parahippocampal subfields will be manually delineated on high resolution structural images based on a methodology implementing ITK Snap software (version 3.2.0 Yushkevich et al., 2006) (Dalton et al., 2017). The following regions will be masked: PrHPC, CA1, CA3/2, dentate gyrus (DG)/CA4, subiculum, parasubiculum, and uncus. Then, a novel hippocampal segmentation designed by Dalton and colleagues (2019), will be used based on a medial HPC demarcation to distinguish anterior from posterior divisions. Each hippocampal subregion will be segmented into either 4 sections comprised of the CA1, subiculum, and parasubiculum; 3 segments comprised of the dentate gyrus (DG)/CA4, CA2/CA3; or 2 sections dividing uncus. All segmentations will be done along the longitudinal axis. Our anterior and posterior masks will be defined by the first hippocampal slice and the first DG slice, respectively. The anterior and posterior PrHPC subdivisions will be demarcated by the first slice of the DG.

**Localizer Task Neuroimaging Data Analysis**

A general linear model in FSL will be used to analyze our functional data. Our regressors of no interest included: motion (i.e., x, y, z translations; pitch, roll, and yaw rotations), first and second derivatives, normalized motion, Lagrange polynomials (i.e., first, second, and third) to account for low frequency signal variability, and outlier thresholds for ach time point. Face and scene stimuli, as well as the math tasks were considered our regressors of interest. Scene and face task-based regressors were modeled separately to respectively examine (a) activation differences between the posterior segments of the HPC and PrHPC, and (b) between the anterior subregions of the HPC and PrHPC.

**Task-Based Functional Connectivity Analysis**

A beta-series correlation (Rissman et al., 2004) will assess the concurrent contribution of the posterior HPC and PrHPC in scene identification and anterior HPC and PrHPC in face identification. Each event received a different regressor, all which will be then convolved with the hemodynamic response (HRF). Using a least-square method (LSS) (Mumford et al., 2012), a brain activation beta coefficient for each region will be estimated for each trial. The LSS iterates over every trial to estimate the brain activity of each task. Our regressors of interest and no interest will be included into a general linear model for our trials of interest (i.e., faces and scenes). The contrast parameters for each face and scene trial will be constructed into a beta-series and averaged across all voxels in our HPC and PrHPC. Correlations will be performed between respective anterior and posterior HPC and PrHPC subregions. The correlation coefficient’s arctangent and pair-wise comparisons will be subsequently computed.

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