Overcoming digital divide slowed down the atrophy of middle frontal gyrus in aging adults

Yumeng Li, Xin Li, Xinyue Zhang, Jiaqing Sun, Junying Zhang, Aiqin Zhu, Zhanjun Zhang

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Abstract

Background: With the essential role of information technology in human life, the use of electronic devices creates a digital divide, particularly among elderly individuals. However, the long-term impact on cognitive aging and brain structural changes remains unclear.

Methods: We examined the role of digital divide in protecting cognition and brain structure in a sample of 1280 elderly participants. The longitudinal data involved 689 individuals. Propensity Score Matching (PSM) was used to match individuals from the Overcoming Digital Divide (ODD) and Digital Divide (DD) groups. A computational framework employing the searchlight technique and cross-validation classification model investigated group differences in structural features and cognitive representation. The aging rate of each voxel's structural feature was calculated to explore the long-term influence of the digital divide.

Results: Following PSM analysis, each group comprised 640 participants. Executive function and processing speed were most affected by DD. Group differences in structural substrates were observed in the fusiform gyrus, hippocampus, parahippocampal gyrus, and superior temporal sulcus. The computational framework identified the key structural substrates related to executive functions and processing speed, excluding the ventro-orbitofrontal lobe. Longitudinal findings highlighted the long-term impact of the digital divide, particularly on the aging rate of the middle frontal gyrus, and its correlation with changes in episodic memory.

Conclusion: The study demonstrated that individuals overcome digital divide exhibit gray matter preservation for intact cognitive performance. Cognitive decline prevention approach though mobile digital devices could be explored further.

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Statement of Authors' Contributions

LYM and LX conceived the study. LYM and ZXY participated in the data collection. LYM carried out the statistical analysis. LYM and LX analyzed and interpreted the data. LYM wrote the manuscript. LX and SJQ revised the manuscript. ZZJ, ZAQ and ZJY supervised and coordinated the study. All authors contributed to the improvement of this manuscript and approved the final version for submission.

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Abstract

Background: With the essential role of information technology in human life, the use of electronic

devices creates a digital divide, particularly among elderly individuals. However, the long-term impact on cognitive aging and brain structural changes remains unclear.

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Conclusion: The study demonstrated that individuals overcome digital divide exhibit gray matter preservation for intact cognitive performance. Cognitive decline prevention approach though mobile digital devices could be explored further.

Keywords: Digital divide; Internet use; Cognitive aging; Neuroplasticity; sMRI; Neural decline

Introduction

Though the mobile devices have become one of the most indispensable technologies in human's modern society, there is still a significant portion of the population that has never utilized it. This gap between individuals who are adept at digital information and communication technologies(ICTs) and those who are not is referred to as the Digital Divide (DD) [1,2]. However, how the absence of this new avenues for connection, information, communication and screen exposure on our brains and cognitive capacities remains unclear. The effect of Digital Divide is notably profound within the older population, who demonstrate considerably lower levels of internet acceptance and utilization [3,4]. Given that rapid growth of the aging population in China, it is conceivable that the digital divide will marginalize older individuals from the swiftly progressing society, potentially impeding their future advancement.

The theory of neural plasticity suggests that the structure of the human brain can undergo long-term changes in response to environmental stimuli and situational triggers [5]. The ubiquitous adoption of the internet and information technology has substantially decreased the costs associated with acquiring new knowledge and participating in social interactions [6]. Consequently, it is contended that the neural modifications induced by the internet are beneficial, especially for the older adults who are experiencing decline. Studies endorsing the theory of neural plasticity propose that smartphone-based online games could potentially alleviate age-related cognitive decline. However, research on smartphone usage inducing neural plasticity effects has been limited to approximately six months, thus inadequately exploring the enduring impacts of ICTs' use on older individuals [7-9].

In contrast, the theory of frontal lobe control and the extended theory of internet addiction suggest that the degenerated prefrontal cortical regions could include the dysfunction of cognitive control and inhibition, which is the potential physiological basis for problematic online behaviors. Thus, older individuals with notable prefrontal atrophy in the course of neural aging not only fail to derive benefits from ICTs' usage in acquiring cognitive enhancement and even face a potential decline in neural flexibility. This decline is also recognized as a clinical precursor to problematic network behaviors in the aging brain [10-12].

In sum, the long-term implications of addressing the digital divide among the elderly population, whether positive or negative, are yet to be substantiated.

To ascertain the long-term implications of addressing the digital divide among the older population, this study, utilizing a large-sample neuroimaging cohort, will investigate the following: (1) The differences in brain structure and cognitive performance between individuals who overcome digital divide and not; (2) the identified brain regions that classify the two groups will also predict their

cognitive performance; (3) the longitudinal alterations of aging rate in cognitive function and brain structure caused by digital divide.

A relationship may exist between the longitudinal changes in cognitive function and brain structure observed in aging populations and the existence of a digital divide.

Method

Study design

The cohort study is based on the registry of communities in Beijing, which tracks age-related changes in cognitive function and neural features (MRI imaging) over years. All of the participants were 50 years or above at the time of baseline enrollment, capable of living independently, without nervous system diseases or psychiatric disorders, with no metal implants or any other contraindications for undergoing MRI within the body, having 6 or more years of formal education. A total of 3380 participants with MRI data were recruited, participants with MMSE score below 24 and without the data to quantify the digital divide were excluded. As a result, only 1400 participants were recruited in the current study. Out of 1400 participants, 1280 of them were included in the current study base on the Propensity Score Matching (PSM). All of the participants who were registered would be revisited every 2 or 3 years. Throughout the follow-up period, factors like bodily metal implants, severe ailments, loss to follow-up, or participant refusal led to 689 individuals undergoing a subsequent MRI scan (See supplementary Figure 1 for precise dropout rates and detailed characterization of the longitudinal sample and data collection framework).

Participants

According to the cross-sectional data, we divided the participants into the digital divide group (DD group) and overcoming digital divide group (ODD group) based on the quantification of the digital divide(See the Measurement). To verify that the cross-group differences of brain structure between two groups were not due to demographic variables (age, gender and education) and some chronic diseases (hypertension, diabetes and hyperlipidemia), we used the Propensity Score Matching (PSM) method[13] to match DD group with the ODD group based on age, education level, gender, hypertension, hyperlipemia and diabetes. Following PSM matching, the initial participants count of 1400 decreased to 1280 (Each group consists 640). The detailed demographic data for both groups can be found in Supplementary Table 1. A total of 689 individuals formed the baseline for tracking data, with 296 in the DD group and 393 in the ODD group, both tracked only once. There were no significant demographic differences between the two groups at baseline. Detailed data can be found in Supplementary Table 2.

The study was conducted in accordance with the institutional review board (IRB) at the Imaging

Center for Brain Research at Beijing Normal University (protocol code ICBIR_A_0041_002_02 and date of approval 03.2015). All participants provided written informed consent for our protocol, which was approved by the ethics committee of the State Key Laboratory of Cognitive Neuroscience and Learning, Beijing Normal University.

Measurements

Quantifying Digital Divide: The quantification indicator of digital divide involves an item about the frequency of using ICT from Leisure Activity Scale (LAS): "How often do you use computer and mobile". We classify individuals with scores of 0(Never), 1(≥Once a year), and 2(≥Once a month) into the DD group, and individuals with scores of 4(≥Once a week) and 5(Everyday) into the ODD group. The DD group means failing to overcome the digital divide while the ODD group means overcoming the digital divide.

In the longitudinal data analysis, participants for whom the use of ICTs could be tracked over time were categorized into either the DD group or the ODD group. We excluded participants who transitioned their status of using the ICTs because crossing the digital divide is a relatively stable state which would not change in the short term. If a transition occurred, it may be due to uncontrollable external factors, which are not the focus of this study.

Cognitive measurements: As described in our previous study, all participants underwent a battery of neuropsychological tests at baseline recruitment [14]. The assessment involved general cognitive ability and cognitive function across five domains including memory, language, attention, spatial processing, and executive function. General cognitive ability was tested using the Chinese version of the MMSE [15]. Memory was tested using the Auditory Verbal Learning Test (AVLT) [16] and the Rey-Osterrich Complex Figure Test (ROCF) [17]. Executive function was tested using the Stroop Color Word Test (SCWT) [18] and the Trail Making Test (TMT-B) [19]. Spatial processing was assessed using the Clock Drawing Test (CDT) [20] and the RO_Copy test [17]. Attention was evaluated using the Symbol Digit Modification Test (SDMT) [21]and the TMT_A test [19]. Language was tested using the Boston Naming Test (BNT) and the Verbal Fluency Test (VFT) [22].

Synthesize the aggregate scores for different cognitive domains

We conducted a confirmatory factor analysis (CFA) analysis for the performance of each cognitive domain (See the Supplementary Figure.1). The path coefficients were used as weights to output the synthesized scores of each cognitive domain. For the reason for this processing is that it facilitates the subsequent modeling with neuroimage data. As a result, all the neuropsychological tests were divided into six domains including memory, visual-spatial, processing speed, executive

function, working memory and language. It should be noted that, due to the fact that only the VFT was included among language-related test, the CFA model in this study did not incorporate it. Therefore, the subsequent scores related to language only used the standardized scores of VFT.

MRI image acquisition and data processing

MRI data were acquired using a SIEMENS PRISMA 3T scanner at the Imaging Center for Brain Research at Beijing Normal University during the baseline recruitment and at follow-up several years later. Participants were in a supine position with their heads snugly fixed by straps and foam pads to minimize head movement. The T1-weighted structural images were acquired using 3D magnetization-prepared rapid gradient echo sequences: 192 sagittal slices, repetition time (TR)=2530 ms, echo time (TE)=2.27 ms, slice thickness=1 mm, flip angle (FOA)=7°, and field of view (FOV)=256 mm×256 mm.

The MATLAB2021b (https://ww2.mathworks.cn/) and SPM12 (https://www.fil.ion.ucl.ac.uk/spm/software/spm12/) toolboxes with default parameters were used to pre-process the structural images. The modulated GM images were smoothed with a Gaussian kernel of 8 mm full width at half maximum (FWHM). We utilized the mean GM map (threshold=0.2) of all the participants to obtain a group brain mask, as well as for subsequent analysis.

High-resolution T1 structural image data were processed using the Cat12 toolbox (http://www.neuro.uni-jena.de/cat/). Apart from using the East Asian brain template for registration, all other parameters were set to default. The specific processing steps are as follows: The raw data were converted to NIFTI format and underwent tissue segmentation within individual space to obtain images of gray matter, white matter, and cerebrospinal fluid. After improving segmentation accuracy through affine processing, the images were spatially normalized using high-dimensional DARTEL and geodesic shooting methods, registering them to the standard MNI brain template after six iterations and resampling the images to a voxel size of 1.5mm^3. Further local adaptive segmentation (LAS) corrected local deviations in individual gray matter tissues. Following the assessment of image quality and tissue segmentation effects, all brain tissue images underwent spatial smoothing using a Gaussian kernel function (FWHM = 8mm).

Statistical analysis

The effect of DD on cognitive function

The intergroup variations between the DD and ODD groups were assessed through independent samples t-test. Cohen’s d was used for the calculation of effect size.

The mixed linear model (MLM) was employed to examine the influence of the DD variable on the rate of cognitive aging at an individual level. Initially, we established the null model and

unconditional growth model. The null model was utilized to determine the hierarchical structure of the longitudinal data for different cognitive functions, which was suitable for MLM analysis. The unconditional growth model was used to identify significant aging patterns in various cognitive functions over time. After selecting these two models, we constructed the full model that encompassed: (1) Level 1: described the individual cognitive level aging patterns, (2) Level 2: investigated the influence of the DD variable on the aging patterns of multiple cognitive abilities in individuals.

Level1:

$$Cognitive\ Score = \pi_0 + \pi_1(Time) + e$$

Level2:

$$\pi_0 = \beta_{00} + \beta_{01}(Age_{baseline}) + \beta_{02}(Gender) + \beta_{03}(Edu) + \beta_{04}(Digital\ Divide) + r_0$$

The Statistical Package for Social Science (SPSS, v25.0) (http://www.spss.com/) was employed for statistical description and difference analysis. The Mplus (v8.3) (http://www.statmodel.com/) software was used to build a MLM for each domain of cognition. Alpha=0.05 was applied to indicate statistical significance.

The effect of DD on brain structural characteristics

Cross-sectional data: We used a two-sample t-test on DD group and ODD group while regressing age, gender, educational level and total intracranial volume (TIV). We employed a significance level of $P<.05$ following false discovery rate (FDR) correction to identify group variances, which were then utilized for subsequent analyses.

A scheme of multi-voxel pattern analysis (MVPA) based on support vector machines (SVM) was used to constrain the brain regions representing the group differences of DD and predicting the individual's cognitive performance. The whole statistical framework was illustrated in Figure 1. First, we used searchlight analysis to generate a neighborhood matrix of voxels using a sliding spherical window centered on a specific voxel with the radius of 2 mm. Subsequently, principal component analysis (PCA) was applied on this matrix to reduce the dimensions of data according to retaining 80% of the variance in order to extract meaningful feature (Figure 1a). Second, SVM was used to classify the different groups in each voxel. The classification accuracy determined through 10-fold cross-validation served as a measure of discriminating capability of the centered voxel. Distinct brain regions exhibiting outstanding classification performance were identified as 3D accuracy map using a specified threshold (greater than 0.6) (Figure 1b). Finally, the dominant regions for classifying different groups were also used searchlight technique to generate a voxel

matrix and extract distinct features. These features were then incorporated in general linear model to predict the behavioral scores of multi-domain cognitive function. The correlations between the predicted and observed scores was calculated to delineate the measure of representing the specific domain of cognition. The statistical significance of the correlation was determined using 10,000 permutations, where predictive scores were shuffled for each permutation, and a correlation coefficient was computed. A null distribution was constructed based on the 10,000 correlation coefficients, and multiple comparisons correction was executed with an FDR threshold of $P<.001$. The brain regions with significant correlation coefficients were characterized as regions associated with the digital divide that represent specific cognitive functions.

Longitudinal data: Based on this, we calculate the annual decline rate of GMV for each participant at the voxel level and region level (AAL template). The maps of decline rate between DD group and ODD group were analyzed using two-sample t-tests with the baseline demographic variables and TIV controlled. Finally, to establish whether changes in cognitive performance were associated with changes in decline rate of GMV, Pearson correlation analysis was conducted.

DPABI was utilized for the analysis. An independent samples t-test was employed to compare GMV between the DD group and the ODD group. The False Discovery Rate (FDR) method for multiple comparison correction analysis method were applied for the extraction of image data. The statistical significance threshold for the voxel size was set at 0.05, whereas for the cluster size it was established at 0.001. All primary Matlab codes supporting the rest findings of this study (mainly in Figure 1) are available online at https://github.com/Rainmon2020/Digital-Divide.git

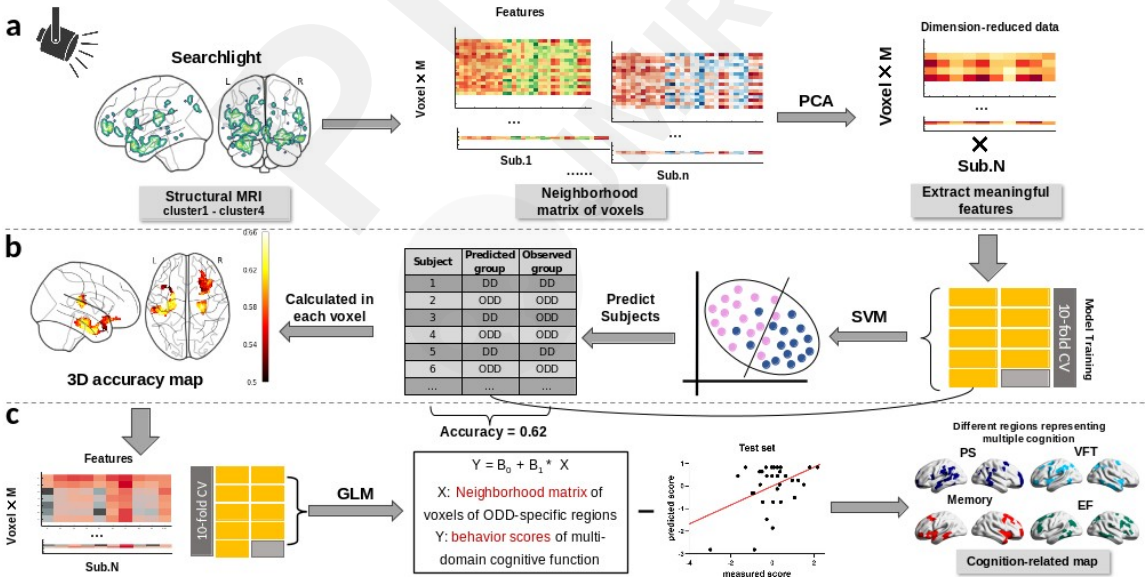

Figure 1. An illustration of the statistical framework using searchlight technique. (a) Searchlight analysis generated a neighborhood voxel matrix using a sliding spherical window. PCA was then applied to reduce data dimensions and extract meaningful features. (b) SVM was used for voxel-

based group classification with 10-fold cross-validation. Distinct brain regions with high classification accuracy were identified in a 3D accuracy map using a specified threshold. (c) The features were added to a general linear model to predict multi-domain cognitive function scores. Correlations between predicted and observed scores were calculated to assess domain-specific representation.

Results

Individual differences in cognitive function of the older population under the Digital Divide

Due to the demographic information have been controlled, independent sample t-test was used to indicate the cognitive differences between two groups. The Supplementary Table 2 presents the differences of multi-domain cognitive function between DD group and ODD group. The cognitive domains with the largest effect size were processing speed (t=4.62, P<.001, *Cohen's d*=0.37) and executive function (t=4.75, P<.001, *Cohen's d*=0.38). The results indicated that the performance of these cognitive function among ODD group were better than the DD group.

The differences of structural substrates between DD and ODD group

Compared with the DD group, the ODD group showed significantly greater GMV in various brain regions in both hemispheres, mainly located in four clusters (Figure 2). The first cluster (Peak label at temporal pole: t = 4.41, P<.001) and second cluster (Peak label at hippocampus: t = 4.19, P<.001) were included fusiform, para-hippocampal gyrus, hippocampus and temporal pole. The third cluster (Peak label at Rolandic Operculum: t = 4.03, P<.001) was included rolandic operculum, superior temporal gyrus, supramarginal gyrus and Heschl gyrus. The last cluster (Peak label at frontal orbital cortex: t = 4.14, P<.001) was included orbital part of inferior frontal gyrus and part of insula. Detailed information for each brain region is listed in Supplementary Table 3. These four clusters were represented the advantageous brain regions for the individuals overcoming the digital divide (ODD group).

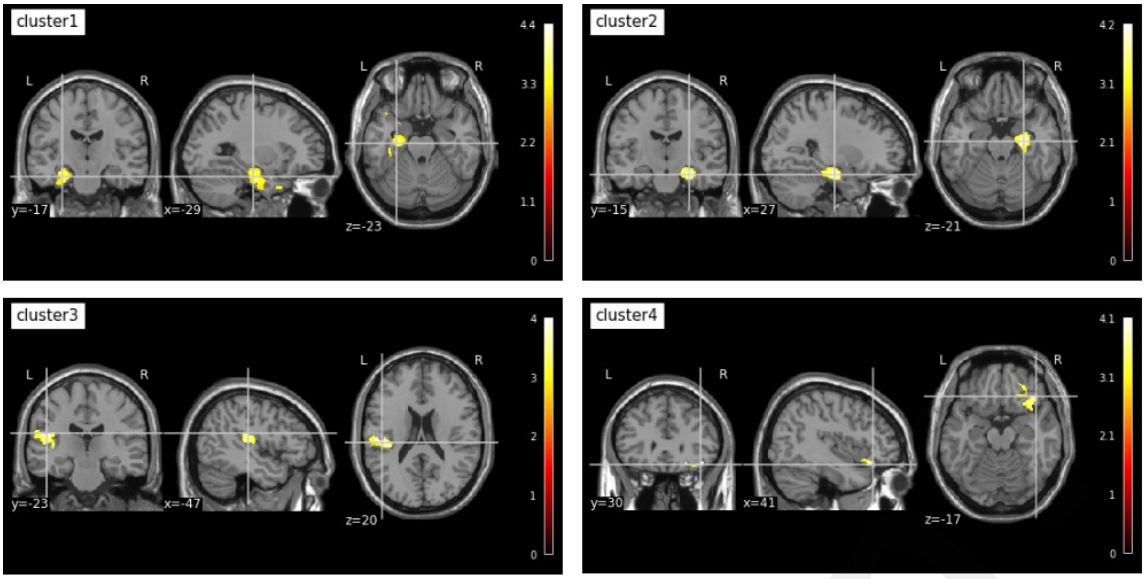

Figure 2. The structural differences between the older adults overcoming the Digital divide and those failed to overcome. The cluster 1 (Peak label at temporal pole: t = 4.41, P<.001) and cluster 2 (Peak label at hippocampus: t = 4.19, P < .001) were included fusiform, para-hippocampal gyrus, hippocampus and temporal pole. The cluster 3 (Peak label at Rolandic Operculum: t = 4.03, P<.001) was included rolandic operculum, superior temporal gyrus, supramarginal gyrus and Heschl gyrus. The cluster 4 (Peak label at frontal orbital cortex: t = 4.14,P <.001) was included orbital part of inferior frontal gyrus and part of insula.

Constrain the brain regions specific for classifying the ODD group and DD group

In order to find out the regions that could effectively represent the features of overcoming the digital divide. We construct a statistical framework (Figure 1a) to constrain the regions to classify the structural substrates specific to the Digital Divide. The statistical framework analyzed the entire brain to extract structural features from the neighborhood matrix of each voxel. Subsequently, SVM model was used to predict the state of the digital divide based on the voxel features. Finally, a 3D accuracy map was generated, the regions where accuracy exceeded a predetermined threshold called constrained regions and the rest regions are excluded regions (Figure 3a). The remaining regions after the output of this framework were recognized as the dominant regions of representing the structural features of overcoming the digital divide. We also we used meta-analytic data from Neurosynth (https://www.neurosynth.org) to decode the constrained and excluded regions (Figure 3b). The decoding result and the subsequent conjunction analysis both indicated that the excluded regions were mainly involved in the ventromedial orbitofrontal area and parts of olfactory and temporal lobes were also excluded (Figure 3c).

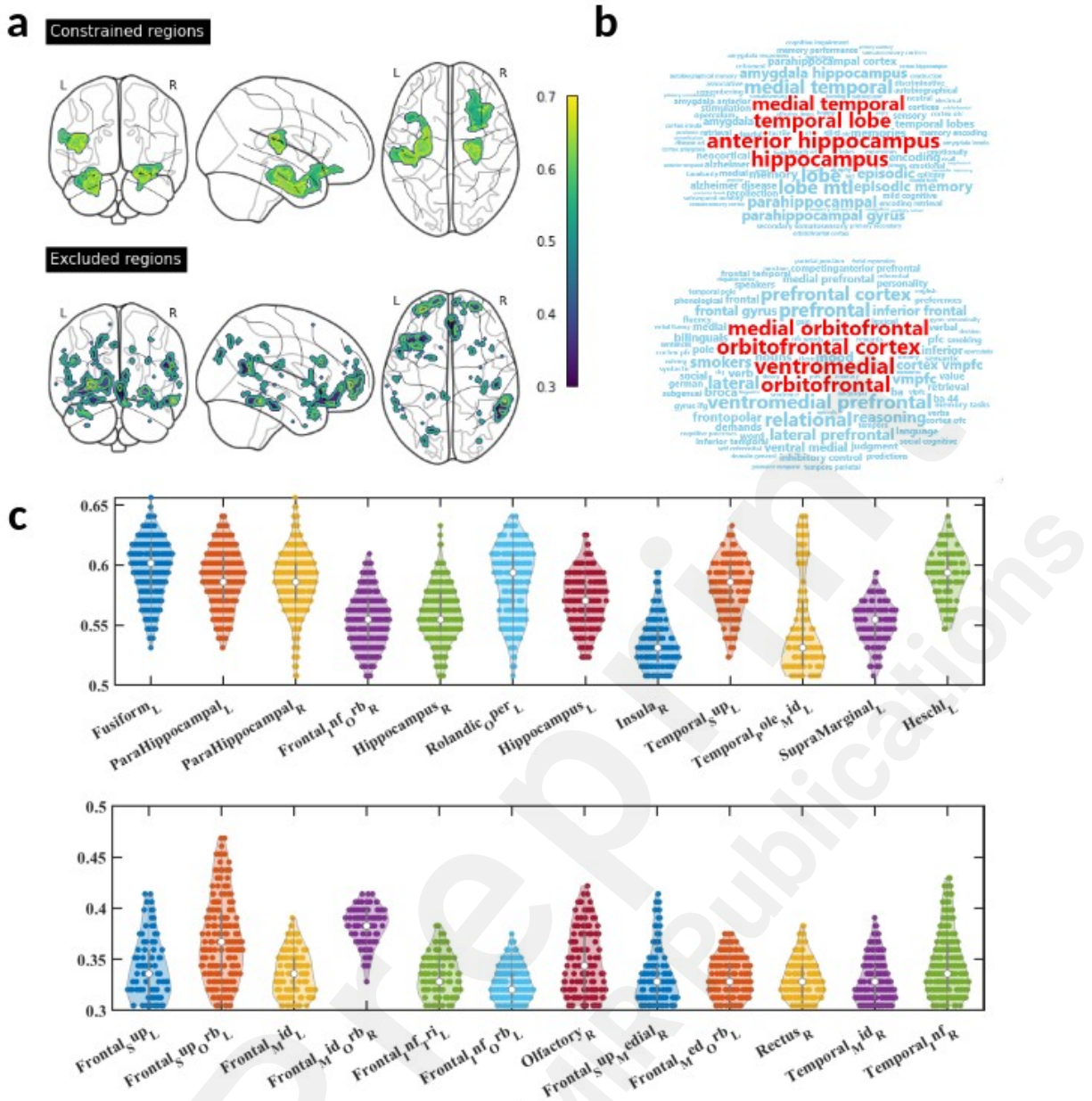

Figure 3. Constrain the brain regions specific for classifying the ODD group and DD group (a) The constrained regions refer to the voxels with classified accuracy above threshold. The excluded regions are the rest regions that display significant GMV difference between two groups, however the classified accuracy is lower than the threshold. Classified accuracy refers to the accuracy of classifying two groups based on voxel-level characteristics through the searchlight statistical framework (see method). (b) The results of constrained and excluded regions decoded through the Neurosynth respectively. The top cloud map represents the decoding of the constrained region, indicating that these brain areas mainly involve the medial temporal lobe and hippocampal regions, while the bottom cloud map represents the decoding of the excluded brain areas, mainly involving the medial orbital frontal regions. (c) The specific distribution and accuracy value of the constrained and excluded regions. The upper map depicts the accuracy distribution of constrained regions,

indicating that the average classification accuracy from high to low is Fusiform, Heschl, Rolandic operculum, Parahippocampus, and hippocampus. The lower map shows the accuracy distribution of the excluded regions, mainly including inferior frontal regions and orbital frontal regions.

Cognitive representation of the constrained regions of digital divide

Based on the aforementioned framework, we also developed a statistical model to analyze the cognitive representation of these regions (Figure 1c). The findings revealed that the constrained regions are most indicative of executive function (EF), with over 80% of the voxels significantly predicting EF scores. Processing speed (PS) ranked as the second most represented cognitive domain, with approximately 50% of the voxels predicting PS scores (Figure 4a). The voxels predict the rest cognitive function such as memory, visual-spatial, working memory and language were no more than 50. This result aligns with behavioral findings that highlight distinct differences between the DD and ODD groups in terms of processing speed and executive function. Notably, the superior temporal pole, hippocampus, and parahippocampus are identified as critical brain regions involved in these differences (Figure 4b). Moreover, the specific brain regions predicting executive function included rolandic operculum, Heschl's gyrus, and superior temporal gyrus. These regions were decoded as tactile and auditory-related cortices (Figure 4c).

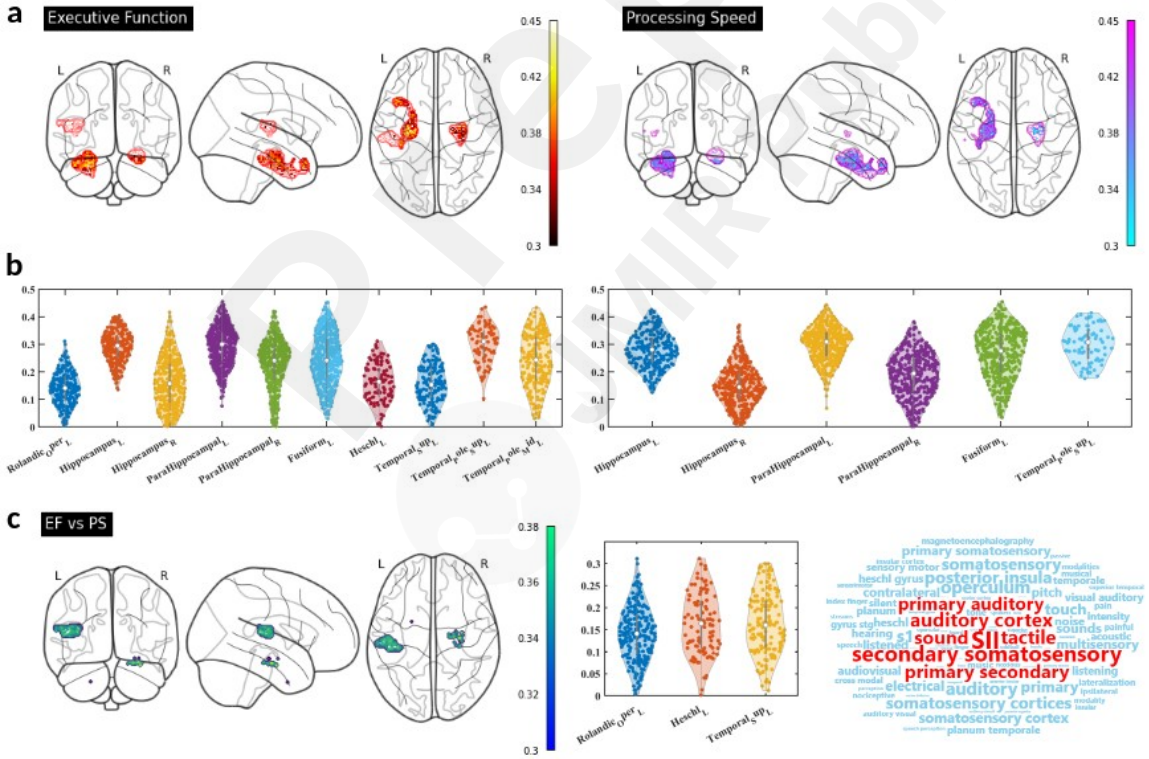

Figure 4. Cognitive representation of the constrained regions of digital divide (a) The distribution of constrained regions predicting executive function (EF) and processing speed (PS). (b) The predictive accuracy(r) of specific brain region distribution of EF and PS. Combining the a & b,

we found that the brain areas in the constrained region representing executive function and processing speed are mainly the hippocampus, parahippocampus, temporal pole, and fusiform. (c) EF regions compared to PS regions: the result indicated the regions specific to EF, including rolandic operculum, Heschl's gyrus, and superior temporal gyrus which were decoded as tactile and auditory-related cortices.

Longitudinal evidence on the digital divide influencing cognitive aging

Significant inter-individual variations were observed for all cognitive abilities in the null model, suggesting the viability of constructing the subsequent mixed linear model (See Supplemental Table 5). However, in the unconditional growth model, the age-related change trend of visual-spatial and working memory did not reach statistical significance, preventing the construction of the full model (also see Supplemental Table 4). Digital divide could significantly influence the aging rate of cognitive function (see Supplemental Table 6). Compared to the ODD group, memory performance of DD group displayed a faster aging rate (B_{14} =2.54, *P*=.011). Moreover, the older participants at the baseline also exhibit a more pronounced rate of memory decline (B_{11} =-2.47, *P*=.014).

The groups did not differ significantly at baseline in terms of demographic variables, as they were matched. Fewer participants were followed up longitudinally. Thus, we did the independent t test for their demographic variables. The result indicated that the longitudinal groups did not differ in terms of these variables (See Supplemental Table 4).

The difference in the decline rate of brain structure between DD and ODD group

To investigate the influence of the digital divide on the structural aging in older adults, the annual aging rate of GMV was calculated for each voxel (See the statistical analysis). We generated brain maps depicting the gray matter volume decline rate for each individual and identified brain regions showing significant group differences in decline rates. The findings reveal that the rate of GMV decline in the middle frontal gyrus (MFG) is notably lower in the ODD group than in the DD group (BA = 46; X = -38, Y =53, Z =11; cluster size =719, Peak t value =3.91) (Figure 5a&b). Moreover, this decline rate in the MFG significantly correlates with individual memory performance (R=0.17, *P*=.02) (Figure 5c), while displaying no significant association with scores in other cognitive domains. Additionally, supplementary materials include a comparison of structural aging rates based on cluster size between the two groups. The results indicate significantly lower GM aging rates in the MFG, orbitofrontal cortex and anterior cingulate gyrus in the ODD group as opposed to the DD group, with these rates also correlating with memory scores (See Supplementary Table 7 and Supplementary Figure 3).

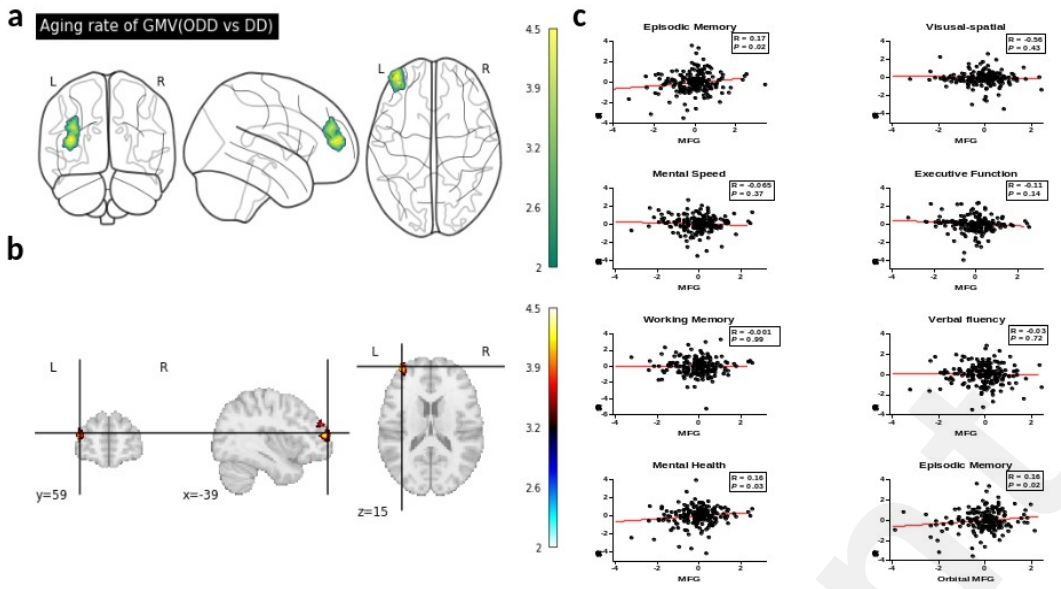

Figure 5. The difference in the decline rate of brain structure between DD and ODD group (a & b) The GMV decline rate in the middle frontal gyrus (MFG) is significantly lower in the ODD group than the DD group. (c) The decline rate in the MFG significantly correlates with individuals' memory performance (R = 0.17, *P*=.02) and shows no significant association with scores in other cognitive domains.

Discussion

Through the utilization of the searchlight technique in cross-sectional data and integrating it with a cross-validation classification prediction model, the study more precisely constrains the distinct brain regions between the DD and ODD groups. The research not only pinpoints the primary brain regions that exhibit the greatest accuracy in discerning differences between the two groups but also delineates how the structural features extracted from these brain regions represent individual cognitive performance. Furthermore, our findings revealed a long-term impact of the digital divide on brain structure. Specifically, the middle frontal gyrus exhibited a faster rate of aging related to the episodic memory alternations attributable to the digital divide.

Through traditional intergroup comparisons, this study observed that the GMV of the ODD group exhibited significant advantages over the DD group in several brain regions, including the fusiform gyrus, hippocampus, parahippocampal gyrus, temporal pole, superior temporal sulcus, and orbito-frontal region. Following the regional screening constraints within the statistical framework of this study, the brain regions capable of more accurately distinguishing between the DD group and ODD group were limited to the fusiform gyrus, hippocampus, parahippocampal gyrus, and a segment of the superior temporal sulcus, while the excluded regions were predominantly concentrated in the ventromedial orbitofrontal region. The ventromedial orbitofrontal (VMOF) area is considered a

component of the reward circuit [23] and is associated with individual self-control [24-26].

The introduction section of the current study mentioned a theory suggesting that elderly individuals may experience reduced self-control due to aging of the frontal lobe, which could impede their cognitive benefits from ICTs. However, based on the above results, we do not support this view because the VMOF brain region related to self-control behavior in the frontal lobe shows a low correlation with ICT usage [27], as demonstrated in this study by the inability to properly distinguish the ODD group from the DD group. Moreover, the rationale behind excluding VMOF in our statistical framework is that previous studies have shown, when controlling for other maladaptive behaviors, specific brain regions associated with internet use excluded the VMOF, retaining the regions of the left temporal cortex [28]. Collectively, our findings imply that there is no significant relationship between self-control behaviors of internet use related to reward circuits in the aging population. In contrast to young people, the older adults are not easily prone to internet addiction, and the elderly who use the internet do not exhibit brain structural damage. Moreover, the key brain regions that differentiate between the two groups are primarily located around the hippocampus and temporal lobe, aligning with prior research exploring the functional activation patterns associated with internet use in older adults. Older individuals engaging in internet activities exhibit heightened activation in regions like the hippocampus and temporal pole, linked to intricate cognitive processes [29]. These results align with the current study, suggesting the potential neural plasticity of these cortical areas associated with advanced cognitive functions in the context of internet utilization. In contrast to prior research, this study did not find a significant contribution of visual cortex in distinguishing internet usage among older individuals [29-31], but tactile and auditory-related cortices showed notable involvement. This indicates that older individuals rely less on visual stimuli in their internet activities. Additionally, as smartphones advance, managing internet use does not always require visual prompts, for example, individuals can utilize voice commands and browse web content using auditory mode. Also, even simple interactions with the internet via touchscreen interface of smartphones could lead to sustained neural cognitive changes [32]. This finding aligns with the outcomes of this research, indicating that specific brain regions associated with sensory and tactile functions can differentiate between groups.

The GMV features of each voxel in the aforementioned brain regions are considered effective in distinguishing structural variances between DD and ODD. The rationale for the discriminative capability of these voxels may stem from cognitive-behavioral distinctions linked to their features and the conditions of DD and ODD. Findings from this research indicate that more than 80% of the voxels in the delineating brain regions can predict executive function, with processing speed

following closely. These results align with behavioral outcomes, highlighting the predictive capacity of gray matter structural traits in differing cognitive functions between the two groups. Notably, brain regions exhibiting relatively strong predictive efficacy encompass the temporal pole, parahippocampal gyrus, and hippocampus. These brain regions are all associated with a range of neurodegenerative diseases and may explain the cognitive impairments found in these diseases.

The temporal pole plays a significant role in the initial pathological progression observed in Alzheimer's disease (AD) [33]. Notable gray matter deterioration in this region was also detected during the initial stage of AD [34]. Furthermore, the degree of temporal pole atrophy is significantly elevated in the Mild Cognitive Impairment (MCI) group compared to the healthy control group, showing a specific correlation with executive function performance [35]. Similarly, the brain structural features of the parahippocampal gyrus and hippocampus are also associated with the preclinical stages of neurodegenerative diseases [36-38]. Although the decline in these regions is commonly believed to be more related to memory impairments. A significant association was observed between reduced volume in the parahippocampal and hippocampal regions and cognitive decline across various domains, such as episodic memory, working memory, processing speed, and executive function [36, 39, 40].

The absence of hippocampus predicting individuals’ memory performance might appear puzzling at first. However, in this study, this result is reasonable because the computational framework of this study distinguishes the DD and ODD groups based on the structural characteristics of each voxel obtained, and memory is not included in characterizing the cognitive performance differences between the two groups. As a result, the prediction of individual cognitive abilities based on brain structure features that differentiate these groups without involving memory aligns with the behavioral findings. Additionally, we adopted the searchlight technique, which is particularly effective for group differentiation [41-43]. Starting from the research question using this method, sacrificing a complete brain region's structural representation is necessary. The correlation between hippocampal gray matter volume (GMV) and memory is strongly influenced by hippocampal subfield segmentation [44]. Hence, the limitation in predicting individual memory without accounting for hippocampal segmentation is justifiable.

Age-related declines in episodic retrieval have been associated with volume reductions in the middle frontal gyrus (MFG) [45-47]. Studies have demonstrated that better structural integrity in the posterior hippocampus and middle frontal gyrus is associated with enhanced within-network connectivity, thus improving associative and source memory performance in older individuals [48]. Therefore, the results of this study show that the slow rate of gray matter decline in the MFG

corresponds to lower memory performance decline. However, in longitudinal studies, the increase in MFG activation associated with individuals' memory decline, which also correspond to the longitudinal decrease in MFG brain structure [49,50]. The structural deterioration of the MFG results in non-benign functional compensation, linked to reduced cognitive performance and potential brain pathology [51-54]. Hence, the preservation of frontal lobe integrity prompted by elderly individuals engaging with the internet can promote a positive brain function pattern without compromising the frontal lobe's behavioral control, thereby partially contradicting the hypothesis that age-related frontal lobe inadequacy gives rise to negative online behaviors.

Our study can be further expanded to an alternative perspective, as mobile-device-based cognitive training has emerged as a crucial strategy to address the challenges posed by dementia to cognitive health [55,56]. Nevertheless, due to constraints in clinical randomized controlled trials, the duration of cognitive training interventions typically falls short of one year. Moreover, the limited sample size resulting from challenges in recruitment and participant attrition diminishes statistical power, potentially yielding adverse outcomes, particularly concerning gray matter neuroplasticity [57-59]. These factors have sparked debates regarding the efficacy of cognitive training [60,61]. Based on a long-term clinical cohort of big data, this study indicate that the aging population can benefit from simple usage of mobile device and internet. Additionally, it revealed consistent gray matter structural variations. Although earlier studies indicated the challenge in reversing gray matter atrophy during aging [62], the rate of gray matter alterations in aging is gradual [63]. Hence, this study proposes a different perspective, suggesting that extended engagement with mobile devices and the internet, leading to increased stimulation and information acquisition for the elderly, may offset the progression of gray matter aging to some extent.

Limitations

Firstly, the ubiquitous adoption of the internet and information technology has substantially decreased the costs associated with participating in social interactions, however, the current study did not use variables measuring the mental health, because only depression scale was included. In the next stage of our cohort study, we propose to collect more variables of mental health in order to investigate the social activity deficiencies caused by the digital divide on the older population. Secondly, concerning the quantification of the digital divide, this study did not differentiate between the specific utilizations of ICTs. Some participants may have only passively received phone calls and messages, lacking active engagement with ICTs for accessing further stimuli. Consequently, there is a potential for misclassification of these individuals into the ODD group.

Conclusion

This study validates the cognitive advantage in older individuals who have overcome the digital divide from the perspective of GM preservation. Our findings demonstrate that individuals overcome the digital divide exhibit significantly higher GMV in brain areas related to Alzheimer's disease than those who have not overcome. Using the computational framework of this study, we can further identify brain regions that can distinguish structural differences between the two groups, as well as predict individual cognitive performance associated with these regions. Furthermore, our longitudinal data reveal a significant decrease in GM aging rate in MFG among individuals overcome the digital divide. In the future, cognitive decline prevention approach through mobile devices could be further explored.

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Conflicts of Interest

None declared.

Data Availability

The data sets analyzed during the study are available from the corresponding author upon reasonable request.

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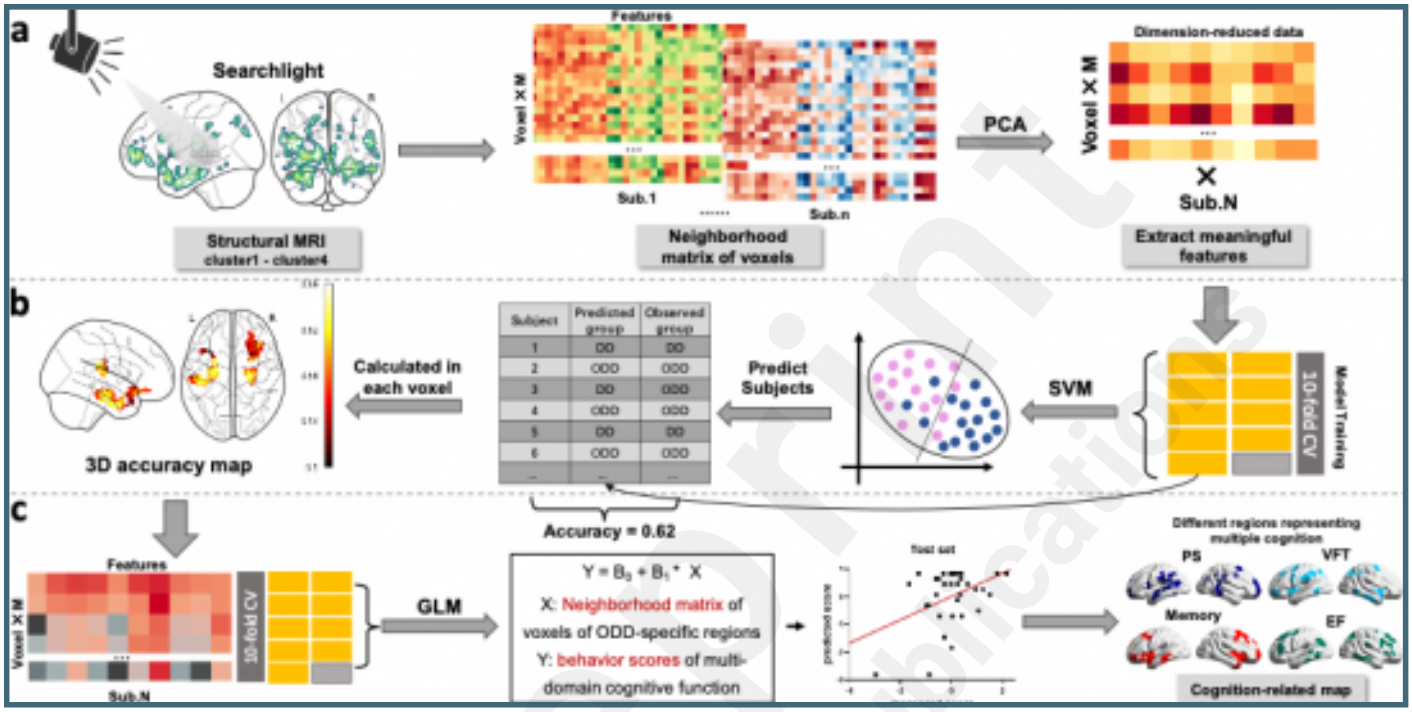
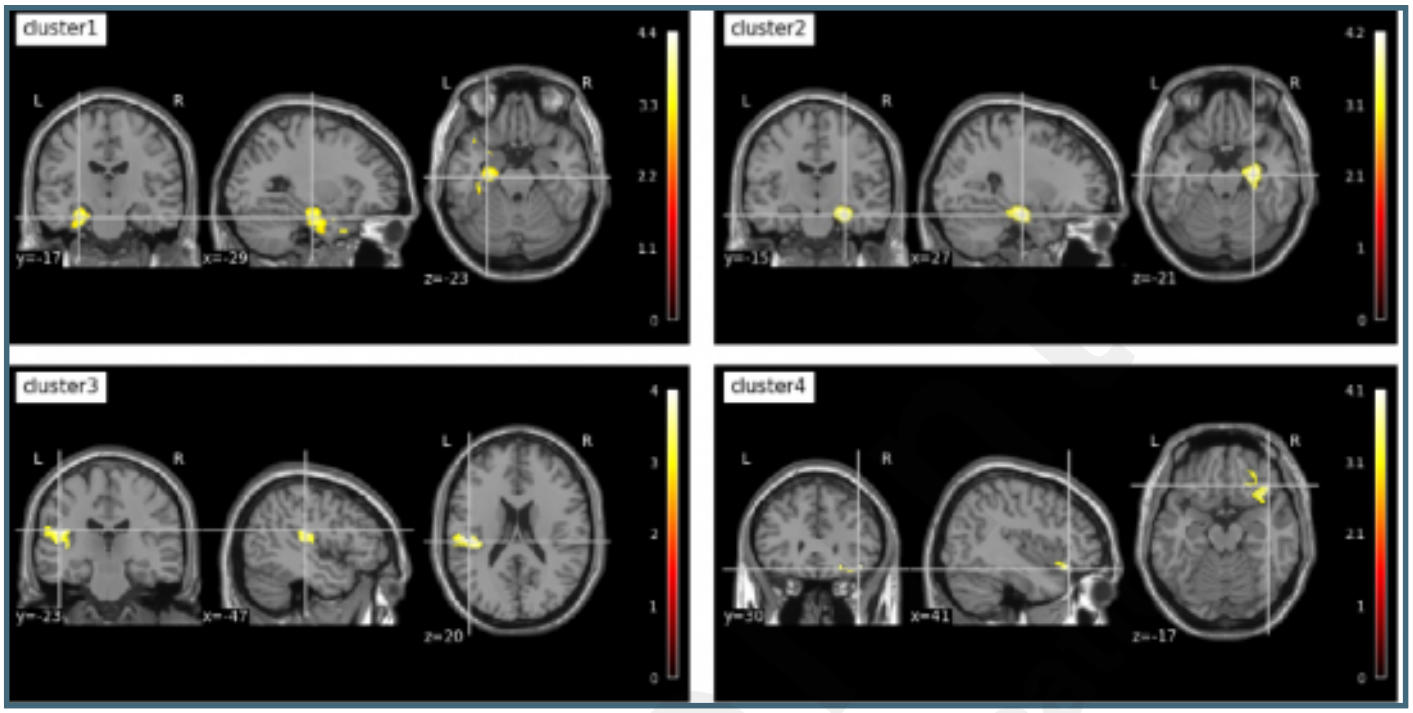
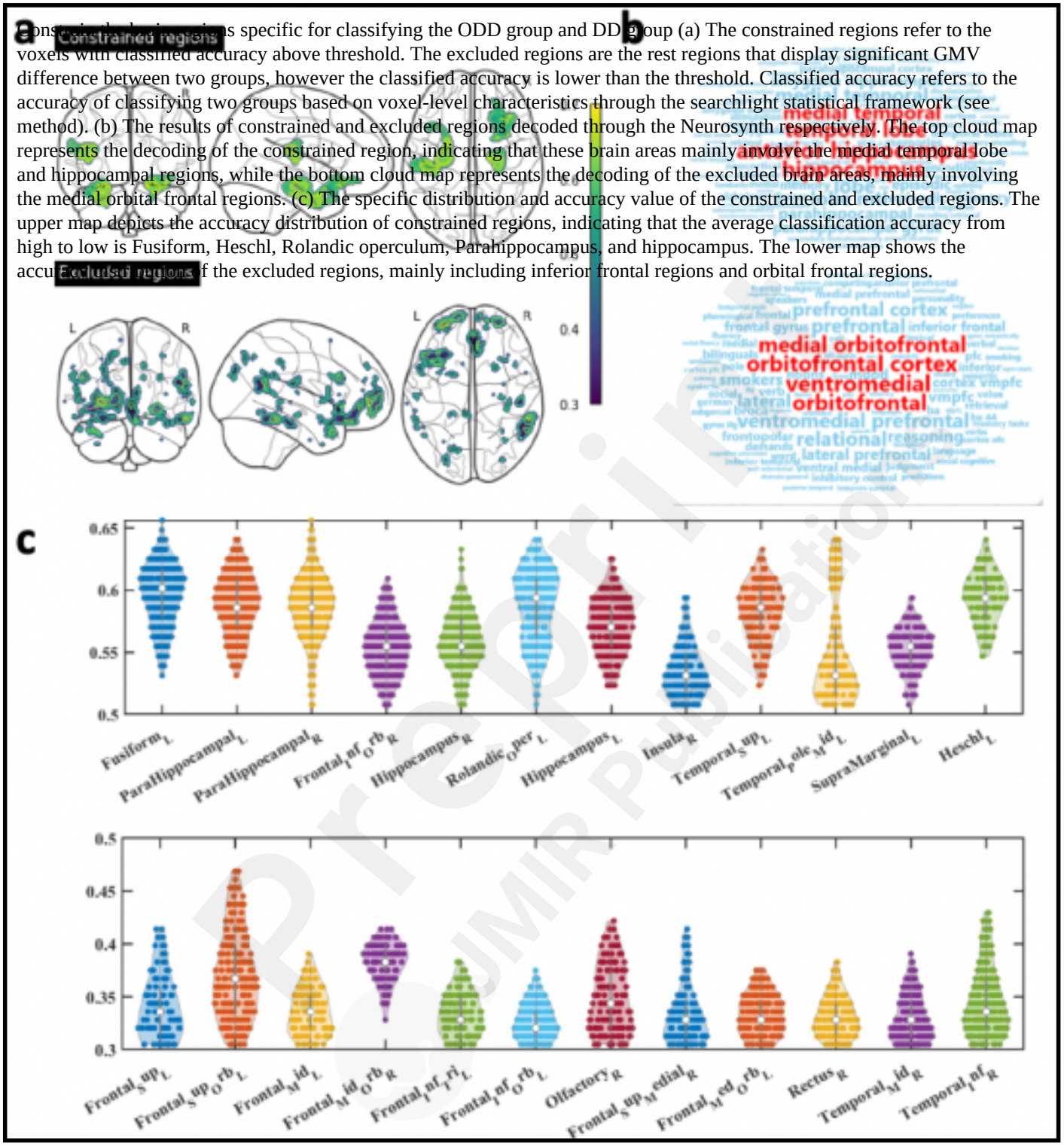
Supplementary Files

Figures

An illustration of the statistical framework using searchlight technique. (a) Searchlight analysis generated a neighborhood voxel matrix using a sliding spherical window. PCA was then applied to reduce data dimensions and extract meaningful features. (b) SVM was used for voxel-based group classification with 10-fold cross-validation. Distinct brain regions with high classification accuracy were identified in a 3D accuracy map using a specified threshold. (c) The features were added to a general linear model to predict multi-domain cognitive function scores. Correlations between predicted and observed scores were calculated to assess domain-specific representation.

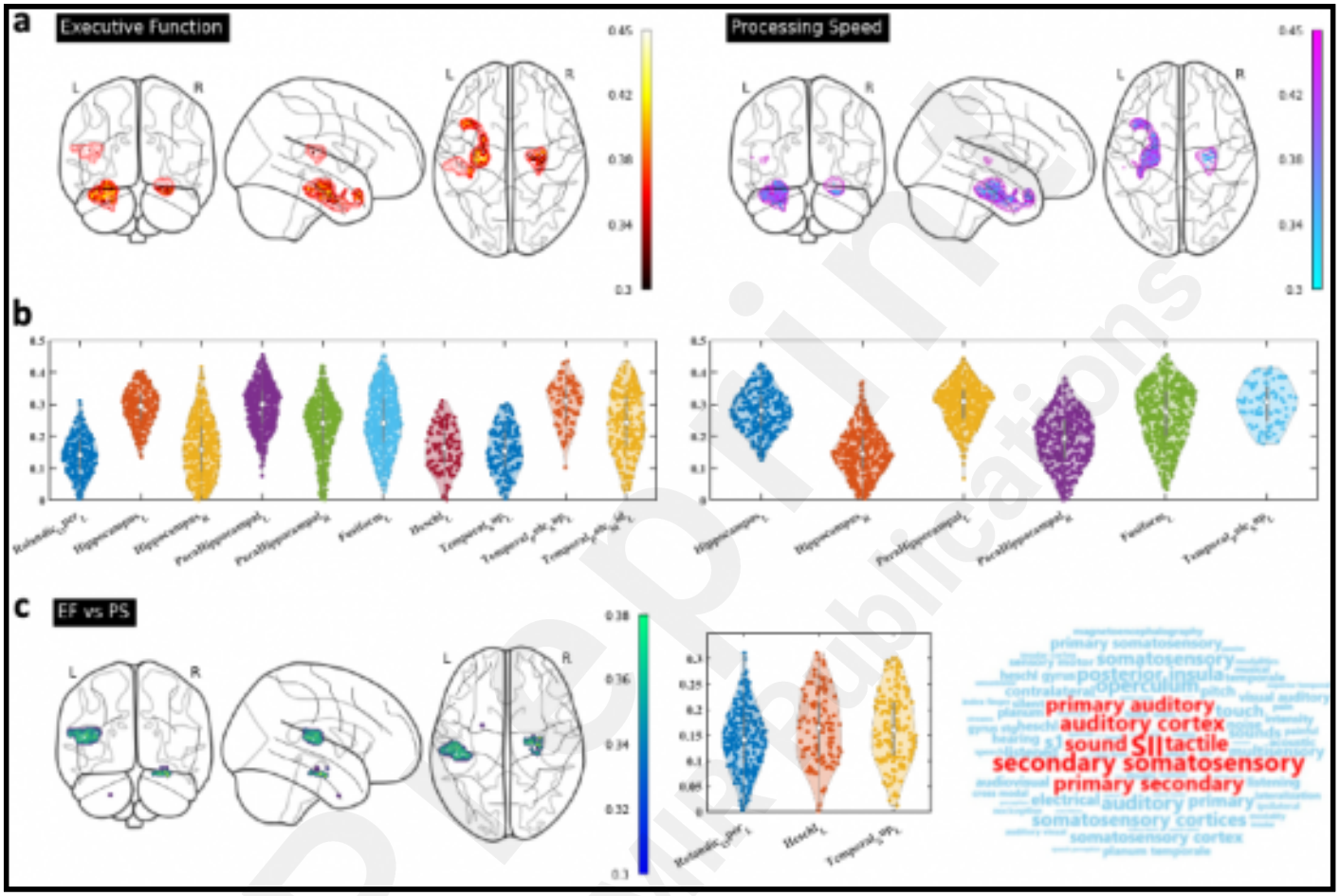




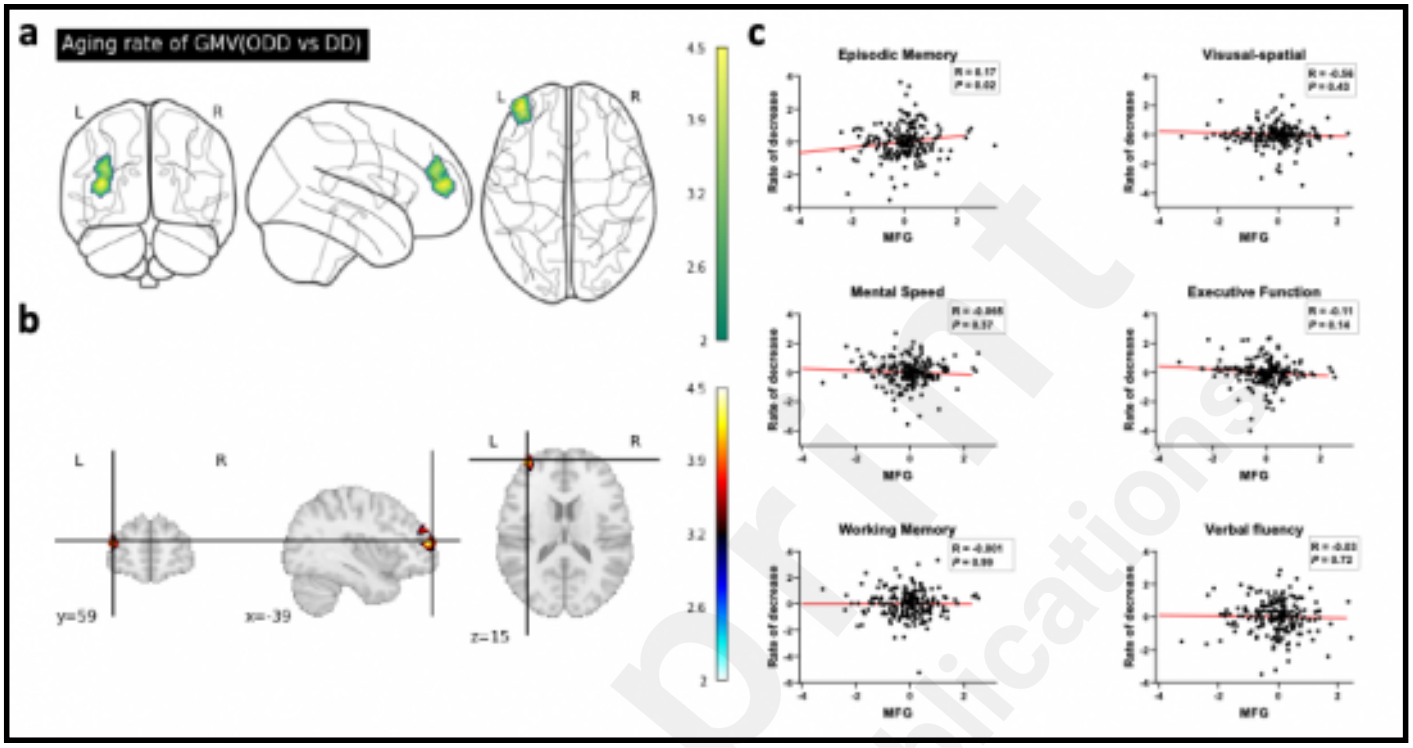


a Constrained brain regions specific for classifying the ODD group and DD group (a) The constrained regions refer to the voxels with classified accuracy above threshold. The excluded regions are the rest regions that display significant GMV difference between two groups, however the classified accuracy is lower than the threshold. Classified accuracy refers to the accuracy of classifying two groups based on voxel-level characteristics through the searchlight statistical framework (see method). (b) The results of constrained and excluded regions decoded through the Neurosynth respectively. The top cloud map represents the decoding of the constrained region, indicating that these brain areas mainly involve the medial temporal lobe and hippocampal regions, while the bottom cloud map represents the decoding of the excluded brain areas, mainly involving the medial orbital frontal regions. (c) The specific distribution and accuracy value of the constrained and excluded regions. The upper map depicts the accuracy distribution of constrained regions, indicating that the average classification accuracy from high to low is Fusiform, Heschl, Rolandic operculum, Parahippocampus, and hippocampus. The lower map shows the accuracy of the excluded regions, mainly including inferior frontal regions and orbital frontal regions.

Cognitive representation of the constrained regions of digital divide (a) The distribution of constrained regions predicting executive function (EF) and processing speed (PS). (b) The predictive accuracy(r) of specific brain region distribution of EF and PS. Combining the a & b, we found that the brain areas in the constrained region representing executive function and processing speed are mainly the hippocampus, parahippocampus, temporal pole, and fusiform. (c) EF regions compared to PS regions: the result indicated the regions specific to EF, including rolandic operculum, Heschl's gyrus, and superior temporal gyrus which were decoded as tactile and auditory-related cortices.



The difference in the decline rate of brain structure between DD and ODD group (a & b) The GMV decline rate in the middle frontal gyrus (MFG) is significantly lower in the ODD group than the DD group. (c) The decline rate in the MFG significantly correlates with individuals' memory performance (R = 0.17, P=.02) and shows no significant association with scores in other cognitive domains.



Multimedia Appendixes

Supplementary figures and tables.

URL: http://asset.jmir.pub/assets/718313cbe28e44784e2cd5507a796169.docx