Received: 28 October 2021 | Revised: 27 December 2021 | Accepted: 8 January 2022
DOI: 10.1002/hbm.25786

RESEARCH ARTICLE

WILEY

Intersubject correlation analysis reveals the plasticity of cerebral functional connectivity in the long-term use of social media

Bo Hu[1] | Ying Yu[1] | Lin-Feng Yan[1] | Guo-Qing Qi[2] | Dong Wu[2] | Yu-Ting Li[1] | An-Ping Shi[1] | Chen-Xi Liu[1] | Yu-Xuan Shang[1] | Ze-Yang Li[1] | Guang-Bin Cui[1] | Wen Wang[1]

[1]Department of Radiology, Functional and Molecular Imaging Key Lab of Shaanxi Province, Tangdu Hospital, Fourth Military Medical University (Air Force Medical University), Xi'an, Shaanxi, China

[2]Institution of Basic Medicine, Fourth Military Medical University (Air Force Medical University), Xi'an, Shaanxi, China

Correspondence
Wen Wang, Department of Radiology, Functional and Molecular Imaging Key Lab of Shaanxi Province, Tangdu Hospital, Fourth Military Medical University (Air Force Medical University), Xi'an.
Email: wangwen@fmmu.edu.cn

Guang-Bin Cui, Department of Radiology, Functional and Molecular Imaging Key Lab of Shaanxi Province, Tangdu Hospital, Fourth Military Medical University (Air Force Medical University), Xi'an.
Email: cuigbtd@fmmu.edu.cn

Funding information
Hovering Program of Fourth Military Medical University, Grant/Award Number: axjhww; National Natural Science Foundation of China, Grant/Award Numbers: 81771815, 81801676; The Talent Foundation of Tangdu Hospital, Grant/Award Numbers: 2018BJ003, 2018MZ012

Abstract

Owing to the limitations of cross-sectional studies, it is unclear whether social media induce brain changes, or if individuals with certain biological traits are more likely to use social media. Functional connectivity (FC) can reflect cerebral functional plasticity, and if social media can influence cerebral FC, then the FC of light social media users should be more similar to that of heavy users after they "heavily" used social media for a long period. We combined longitudinal study design and intersubject correlation (ISC) analysis to investigate this similarity. Thirty-five heavy and 21 light social media users underwent cognitive tests and functional MRIs. The 21 light social media users underwent another functional MRI scan after completing an additional four-week social media task. We conducted the ISC at the group, individual, and brain-region levels to investigate the similarity of FC and locate the brain regions most affected by social media. The FC of light social media users was more similar to that of heavy social media users after they completed the four-week social media task. Then, social media had an impact on half of the brain, involving almost all brain networks. Finally, cerebral FC that mostly affected by social media was associated with selective attention. We concluded that the impact of social media use on cerebral functional connectivity changes is revealed by ISC method and longitudinal design, which may provide guidance for clinical practice. The methods used in the current research could also be applied to similar domains.

KEYWORDS
functional connectivity, functional MRI, intersubject correlation, neuroplasticity, social media

Abbreviations: 3D-BRAVO, three-dimensional brain volume sequence; AAL, automatic anatomy labeling; ANOVA, analysis of variance; BET, brain extraction tool; CPT, continuous performance test; FC, functional connectivity; FC-matrix, functional connectivity matrix; FC-vector, functional connectivity vector; fMRI, functional magnetic resonance imaging; FOV, filed of view; FA, flip angle; FWHM, full-width at half maximum; INS, insula lobe; ISC, intersubject correlation; MNI, Montreal Neurological Institute; ROI, region of interest; RT, reaction time; SCWT, Stroop color word test; TE, time of echo; TR, time of repetition.

Bo Hu, Ying Yu, and Lin-Feng Yan contributed equally to this study.

1 | INTRODUCTION

Daily life is increasingly saturated with social media information, and there is growing interest in the effect of social media use on our brains and minds. Studies have associated social media with decreased attention, memory, and learning abilities (Crone & Konijn, 2018; Firth et al., 2019; Ophir, Nass, & Wagner, 2009) as well as structural (Hutton, Dudley, Horowitz-Kraus, DeWitt, & Holland, 2020) and functional (Moisala et al., 2016) brain changes. Almost all researchers declared that their work was limited in the investigation of causality because of its cross-sectional design (Choi et al., 2021; Firth et al., 2019; Lamblin, Murawski, Whittle, & Fornito, 2017; Loh & Kanai, 2016; Moisala et al., 2016; Uncapher et al., 2017; Uncapher & Wagner, 2018). Hence, it is still unclear whether social media induce changes in the brain, or if individuals with certain biological traits are more likely to use social media (Firth et al., 2019; Madore et al., 2020). Understanding this causality will provide guidance on whether interventions are appropriate, which are helpful, and how to conduct them. Recommendations and guidelines cannot be made without relevant evidence, and longitudinal research can fill this void.

Functional MRI (fMRI)-based functional connectivity (FC) represents important biological features of the brain and alters with the changes in brain states. FC is an ideal noninvasive biomarker to reflect cerebral functional plasticity (Beaty et al., 2018; Finn et al., 2015; Rosenberg & Finn, 2016). For example, FC changes were found to be responsible for short-term neurofeedback training with motor imagery (Marins et al., 2019), and musical training could induce functional auditory-motor network plasticity in young adults (Li et al., 2018). Consequently, if social media can influence cerebral FC, then the FC of light social media users (LSMs) should be more similar to that of heavy users after they "heavily" used social media for a long period.

Intersubject correlation (ISC) is an imaging analysis method that allows us to measure similarity across experimental conditions (Nastase, Gazzola, Hasson, & Keysers, 2019). By using ISC method, Gao et al. (2020) reported a method to draw the reliability map of individual differences in naturalistic imaging. Guo, Hyett, Nguyen, Parker, and Breakspear (2016) found distinct FC in depression subtypes during the viewing of emotionally salient films. Consequently, ISC methods can be used to investigate the similarity of FC among heavy social media users (HSMs), LSMs at baseline state and after they "heavily" using social media for a long period.

Our hypothesis is that social media can lead to cerebral FC alterations. We tested this using ISC methods at both the groups and individual levels to investigate the similarity mentioned above. We then used brain-region ISC to locate brain regions most affected by social media and investigated the relationship between these FCs and cognitive function. To improve the credibility of our research, we validated all of our findings by conducting several sensitive analyses, including head motion, brain atlas, data size, global signal regression (GSR), and statistical methods.

2 | MATERIALS AND METHODS

2.1 | Subjects

Figure 1 shows the procedure of subject recruitment. First, 175 undergraduate students aged 18 to 22 years old were recruited from Fourth Military Medical University. All subjects completed a self-reported questionnaire on demographic information (including age, sex, height, weight, smoking habits, alcohol consumption, color blindness, handedness, history of brain trauma, and family history of mental illness) and smartphone habits (including time per day spent on social media, games, chat, film and TV, and other activities) mainly based on their smartphone time monitors. Social media refers to three of the most

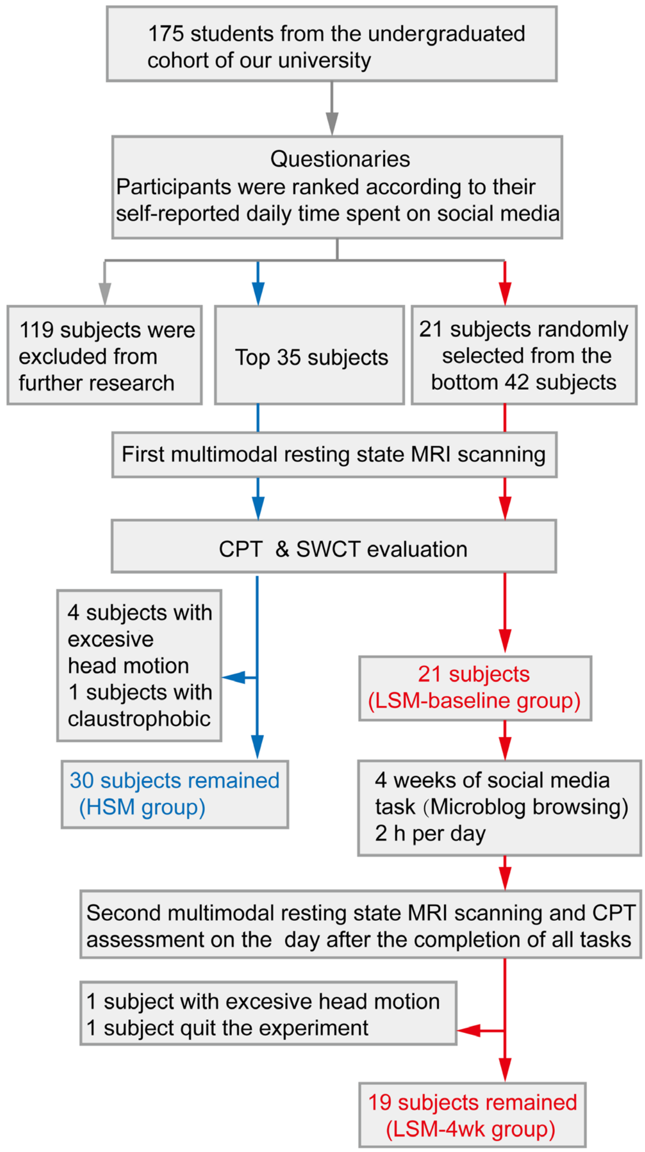

FIGURE 1 Flowchart of subject recruitment. CPT, continuous performance task; HSM, heavy social media user; LSM, light social media user; SWCT, Stroop color word test

common social media apps in China that based on user's relationship and follow mechanism to share short real-time information, which were Microblog, TikTok, and Kwai (https://marketingtochina.com/top-10-social-media-in-china-for-marketing/). Participants with a Body mass index (BMI) greater than 30 or less than 18.5, any use of cigarettes or alcohol, color blindness, or left-handedness were excluded. This study received approval from the institutional review board of Tangdu Hospital, Fourth Military Medical University, and all subjects provided written informed consent.

2.2 | Social media task and experimental design

We aimed to recruit two groups of subjects, which were subjects with heavy social media use and subjects with light social media use. Given that there is currently no definite standard to distinguish between HSM and LSM, we ranked the existing cohort according to the daily time spent on social media, and aimed to recruited similar numbers of subjects (40 subjects for each group) from both ends (top as HSM and bottom as LSM). However, there is a break of the daily time spent on social media between the top-36th subject (1 h) and the top-35th subject (1.8 h), so we only recruited the top-35 subjects to improve the consistency. Besides, the daily time spent on social media of the bottom-40th subject (0.7 h) was the same as both the bottom-41st and bottom-42nd subjects; consequently, we recruited the bottom-42 subjects to improve the consistency. Finally, two groups of subjects were recruited: (1) top-35 subjects with the heaviest daily social media use (HSM group); (2) half of the bottom-42 subjects (21 subjects, randomly selected) (LSM group). The data of the other bottom-21 subjects was not used, because the task of them was reading a sci-fi novel, which is not the topic of the current research. Microblog (weibo.com), whose function is similar to those of Twitter and Facebook, is one of the most used social media apps in China. To prevent biases caused by diverse apps, browsing Microblog on a smartphone was defined as the social media task.

The experiment was designed as follows (Figure 1): (1) all subjects received multimodal MRI scans on the first visit, (2) a long-term social media task was assigned to subjects in the LSM group (2 h/day for four continuous weeks). The time of 2 h/day was based on the average daily time spent on social media by the HSM group, and (3) another multimodal MRI scan was conducted the day after the long-term task.

2.3 | Cognitive test

Previous studies have reported that social media are related to impaired attention because they require users to frequently switch between various information and apps (Ophir et al., 2009; Uncapher & Wagner, 2018). Consequently, we used the continuous performance task (CPT) (Corkum & Siegel, 1993) and Stroop color and word test (SCWT) (Scarpina & Tagini, 2017) to evaluate sustained and selective attention. Detailed information of CPT and SWCT are described in Appendix S1.

2.4 | Neuroimaging data acquisition and preprocessing

All MR images were acquired using a GE Discovery MR750 3.0-T scanner with an eight-channel phased-array head coil. Foam pads were used to limit head movement, and earplugs to silence scanner noise. During the experiment, participants were told to close their eyes but not to fall asleep. T1-wieghted imaging (T1WI) and blood oxygen level-dependent (BOLD) imaging was acquired, and detailed parameters of scanning is provided in Appendix S1. Imaging data preprocessing was conducted on Statistical Parameter Mapping (SPM12, Wellcome, Imaging Neurology Group, London, UK; http://www.fil.ion.ucl.ac.uk/spm) and DPABI toolkit (Chao-Gan & Yu-Feng, 2010; Yan, Wang, Zuo, & Zang, 2016) running on MATLAB 2018a. The preprocessing procedure was the same as that in our previous publications (Hu et al., 2019b; Hu et al., 2019a; Hu, Yu, Wang, & Cui, 2021; Yu et al., 2019). Detailly speaking, the first 10 time points were discarded to ensure magnetization stability and to allow participants to adapt to the scanning environment. Slice timing and head-motion correction were performed, and framewise displacement (FD) was controlled to prevent potential spurious connectivity (Yan et al., 2013). In this procedure, scans with head motion of translation greater than 2.0 mm or rotation greater than 2° were excluded. BOLD images were normalized to the Montreal Neurological Institute (MNI) space according to high-resolution T1-weighted imaging then resampled to $3 \times 3 \times 3$ mm^3. After that, BOLD images were smoothed with an 8-mm full-width at half maximum (FWHM) isotropic Gaussian kernel. Nuisance signals, such as the 24-parameter head motion profile, white matter, and cerebrospinal fluid signals, were regressed from the time series of each voxel to exclude noise from non-neuronal sources. Then, the linear trend was removed from the time series. The Anatomical Automatic Labeling (AAL) atlas with 116 brain regions was used to construct the whole-brain FC-matrix. All codes and FC-matrices were uploaded (https://github.com/hubolll/Social_media_ISRSA) so that researchers can validate our work and apply these methods to their own data.

2.5 | Neuroimaging data augmentation

To overcome the effects of a small sample size, we augmented imaging data two, three, and four times, and repeated all experiments with these data. In brief, the BOLD signal was equally divided into two, three, and four parts, and FC-matrices were calculated from the derived signals. Zhu et al. (2021) used a randomized sliding-window method to augment raw BOLD data dozens of times to improve the efficacy of the FC-based machine learning model; however, we only augmented the data several times to validate the stability of our findings.

2.6 | Theory and procedure of ISC

In theory, if social media lead to brain changes that can be represented by FC, the FC-matrices of the HSM group should be more similar to those of the LSM group after the four-week social media task (LSM-4wk) than the LSM group at the baseline state (LSM-baseline) (Figure 2a). We designed a hierarchical protocol of ISC to comprehensively explore this issue, including group (Figure 2b), individual

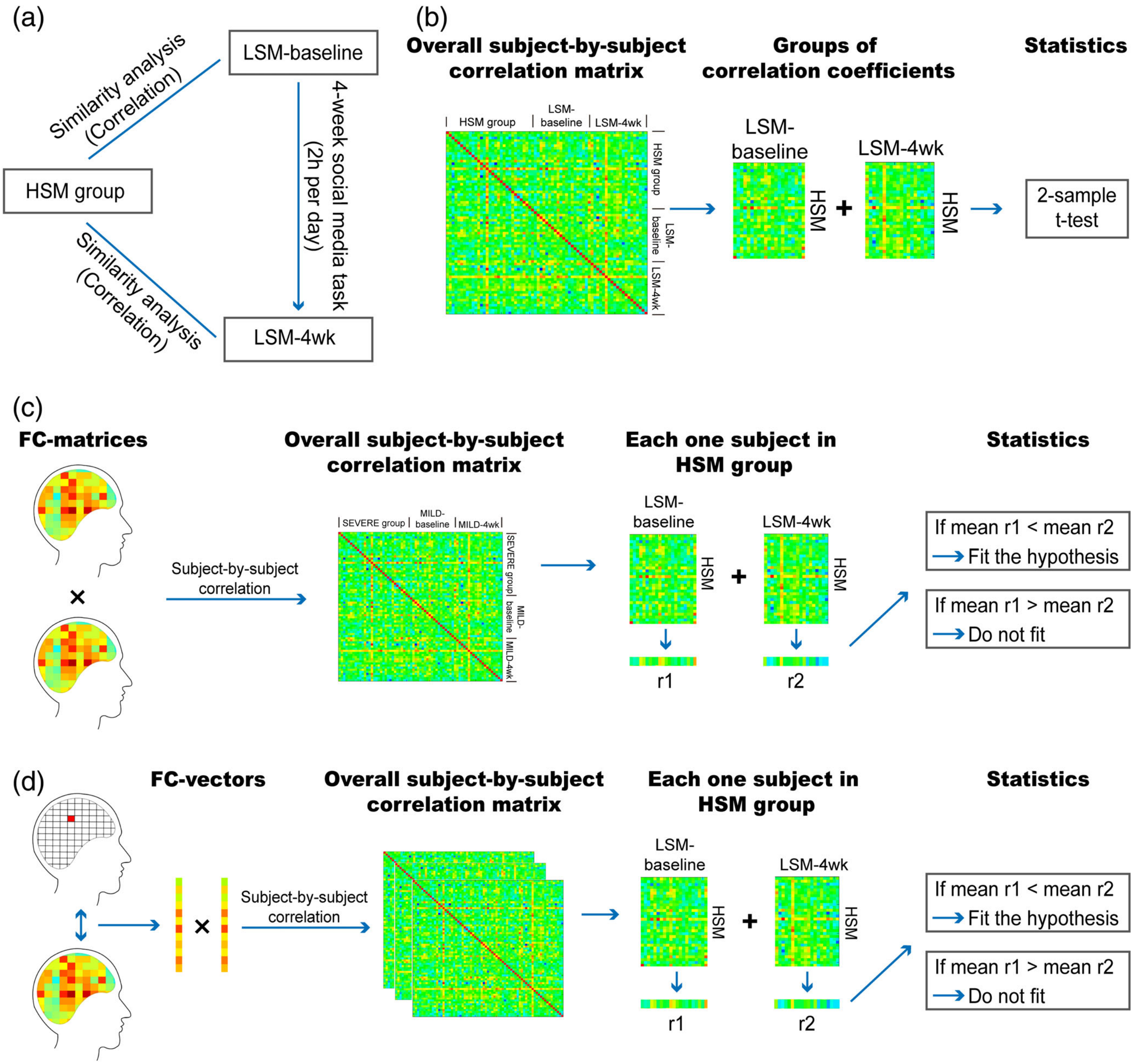

FIGURE 2 Flowcharts of data analysis. (a) General design of intersubject correlation (ISC) procedure. The similarities between HSM and LSM-baseline groups and between HSM and LSM-4wk groups were investigated. (b) Procedure of ISC at group level. FC-matrices of all subjects were correlated with each other to form an overall subject-by-subject correlation matrix. The correlation coefficient between LSM-baseline and HSM groups was compared with that between LSM-4wk and HSM groups. (c) Procedure of ISC at the individual level. For each subject in the HSM group, there were two sets of correlation coefficients: with all subjects in the LSM-baseline group, and with all subjects in the LSM-4wk group. Mean values of these two sets of correlation coefficients were further compared. If the correlation coefficient of a subject in the HSM group was more similar to that of the LSM-4wk group ($r2 > r1$), we regarded it as fitting the hypothesis. (d) Procedure of ISC at brain-region level. An FC-vector represented the gross FC of each brain region (FCs between this region and all other regions), and FC-vectors of all subjects were correlated with each other to form an overall, subject-by-subject correlation matrix. For all brain regions, a set of overall correlation matrices (equal to the number of pre-defined brain regions) represented their inter-subject similarities. Similarly, for each brain region, if the correlation coefficient of a subject in the HSM group was more similar to that of the LSM-4wk group ($r2 > r1$) than that of the LSM-baseline group, it was regarded as fitting the hypothesis. HSM, heavy social media user; LSM, light social media user

(Figure 2c), and brain-region levels (Figure 2d). In all procedures, we avoided correlation between the LSM-baseline and LSM-4wk groups to prevent the potential bias introduced by the intrasubject similarity.

2.6.1 | ISC at group level

The procedure closely followed methods in previous research (Finn et al., 2015). FC-matrices of all subjects were correlated with each other to form an overall subject-by-subject correlation matrix (Figure 2b). To minimize the influence of nuisance signal, subjects with outlier correlation coefficients with all the other subjects (the mean correlation coefficient beyond (mean value ± 2.5 SDs) were excluded, because the subject had conspicuous abnormal correlation with all the others. Each subject had a mean correlation coefficient derived by averaging all the correlation coefficients between this subject and all the other subjects. Two classes of correlation coefficients were selected, which were correlation coefficient between the HSM and LSM-baseline groups as well as between the HSM and LSM-4wk groups. We compared these two groups of correlation coefficients through a 2-sample t-test, and in theory, the second class of correlation coefficients (HSM vs. LSM-4wk) should have been larger than the first (HSM vs. LSM-baseline) (Figure 2b).

2.6.2 | ISC at individual level

We used the overall subject-by-subject correlation matrix mentioned above, but analyzed similarity at the individual level. We calculated the mean correlation coefficients between one subject in the HSM group and all subjects in the LSM-baseline group/LSM-4wk group. In theory, the second correlation coefficient (HSM vs. LSM-4wk) should always be larger than the first (HSM vs. LSM-baseline). We calculated the ratio of subjects who fit the above hypothesis to all subjects in the HSM group as illustrated by the following function:

$$\text{Ratio} = \frac{\sum_{i=1}^{N} X_i = \begin{cases} 1, \dfrac{\sum_{k=1}^{M} Corr(S_i, Mb_k)}{M} < \dfrac{\sum_{j=1}^{L} Corr(S_i, M4wk_j)}{L} \\ 0, \dfrac{\sum_{k=1}^{M} Corr(S_i, Mb_k)}{M} > \dfrac{\sum_{j=1}^{L} Corr(S_i, M4wk_j)}{L} \end{cases}}{N},$$

where N is the number of subjects in the HSM group, M is the number of subjects in the LSM-baseline group, L is the number of subjects in the LSM-4wk group, X_i is each subject in the HSM group, S_i is the FC-matrix of each subject in the HSM group, Mb_k is the FC-matrix of each subject in the LSM-baseline group, $M4wk_j$ is the FC-matrix of each subject in the LSM-4wk group, and *Corr* is the calculation of the Pearson correlation coefficient.

A permutation test (5000 times) was conducted for multiple comparison correction by randomly replacing the labels in the LSM-baseline and LSM-4wk groups, and the statistical significance (p value) was the order of initial ratio calculated before the calculation of all ratios in the permutation test:

$$p\,\text{value} = \frac{\sum_{i=1}^{N} Y_i = \begin{cases} 1, & PR_i > IR \\ 0, & PR_i < IR \end{cases}}{N},$$

where PR_i is the ratio calculated in each permutation, IR is the initial ratio calculated before, N is the permutation time, and Y_i is each permutation.

2.6.3 | ISC at brain-region level

Similar to Section 2.5.2, where we investigated the similarity of whole-brain FC-matrices, we investigate the similarity of FC-vectors for each brain region. An FC-vector for each of the 116 brain regions in this study represents the FCs between it and all the other regions, which is expressed in the following equation:

$$FCV(x) = \{r | r = Corr(B_x, B_y), 0 < y \le A,\ y \ne x,\ y \in N_+\}$$

where *FCV(x)* is the FC-vector of the target brain region x, B_x is the BOLD signal of the target brain region x, B_y is the BOLD signal of all the other brain regions, and A is the number of brain regions.

The FC-vectors of all subjects were correlated with each other to form 116 overall subject-by-subject correlation matrices to represent the inter-subject similarity of all brain regions (Figure 2d). We calculated the number of subjects in the HSM group for each brain region who fit the hypothesis that the similarity of subjects in the HSM group to those in the LSM-4wk group should always be larger than the similarity to the LSM-baseline group. A permutation test (5000 times) was conducted for multiple comparison correction at the brain-region level, and the Benjamini and Hochberg (Benjamini & Hochberg, 1995) false discovery rate (FDR) was used for multiple comparison correction for all brain regions.

2.7 | Impact of 4-week social media on FC and its relationship with cognitive performance

To further validate our findings, we used a conventional 2-sample t-test to investigate the impact of the 4-week social media task on FC. First, we compared the FC-matrices between the HSM and LSM-baseline groups and selected the most affected FCs with a threshold of $p < .001$ (other thresholds were also tested). The selected FCs in the LSM-4wk group were investigated to see whether these differences were attenuated. Finally, FCs with significant differences were associated with SCWT and CPT performances (both FC and cognitive performance were those at baseline state) to investigate their relationship. It should be noted that to investigate the impact of 4-week social media on FC changes, we also directly compared the FC between the baseline and 4-week follow-up in the LSM group by using paired-t test.

2.8 | Statistics

SPSS version 20.0 was used for statistical analysis. To validate the significance of grouping based on social media use, a general linear model was built to compare the intergroup differences of social media use with age; BMI; daily time spent chatting, watching film and TV, playing games, and other activities; and significant interactions as covariates to control. A Kolmogorov–Smirnov analysis was used to check whether the data conformed to a normal distribution. A 2-sample t-test or one-way analysis of variance (ANOVA) was used to compare the inter-group demographic information, cognitive performance, and neuroimaging data that conform to the Gaussian distribution, and a nonparametric test was used otherwise. Cohen's d was calculated to reflect the effect size of intergroup difference (Nakagawa & Cuthill, 2007). A paired-t test was used to compare the FC between the baseline and 4-week follow-up in the LSM group.

3 | RESULTS

3.1 | Demographic information and cognitive performance

The demographics and cognitive performances of the three groups of subjects are listed in Table 1. A significant interaction was found between group and daily watching of film and TV (Figure 3, $F = 5.784$, $p = .020$). This was because, in the HSM group, the association between daily social media use and watching film and TV ($r = .297$, $p = .088$) was stronger than that in the LSM group ($r = -.489$, $p = .034$). However, interactions between groups and other variables (age, BMI, chatting, playing games, and other activities) were not significant (Figure 3, F = .126, .133, .002, .254, and .002; p = .724, .717, .962, .616, and .969, respectively).

Consequently, we built a general linear model, with daily social media use as the dependent variable; group as an independent

TABLE 1 The demographics and behavioral performances

	HSM ($N = 30$)	LSM-baseline ($N = 21$)	LSM-4wk ($N = 19$)	p value
Age (years)	21.13 ± 0.73	20.90 ± 1.04	20.79 ± 1.03	.413
Hight (cm)	175.10 ± 4.32	174.19 ± 6.84	174.21 ± 6.55	.814
Weight (kg)	67.15 ± 6.47	67.12 ± 7.85	67.45 ± 7.63	.987
BMI (kg/m^2)	21.89 ± 1.84	22.07 ± 1.67	22.18 ± 1.70	.841
Smartphone using habits				
Chatting (h)	0.98 ± 0.92	0.91 ± 0.91	0.87 ± 0.95	.914
Game (h)	0.55 ± 0.59	0.60 ± 0.60	0.53 ± 0.59	.932
Film/TV series (h)	0.29 ± 0.53	0.19 ± 0.43	0.21 ± 0.45	.721
Social media (h)	2.05 ± 0.83	0.41 ± 0.35	0.41 ± 0.36	<.001
Other activities (h)	0.96 ± 1.14	0.44 ± 0.78	0.48 ± 0.42	.102
CPT performances				
d'-context	3.59 ± 0.48	3.52 ± 0.52	3.47 ± 0.50	.694
Mean RT (ms)	391.98 ± 87.01	381.95 ± 81.92	369.19 ± 45.06	.673
Instability (ms)	121.81 ± 48.03	107.34 ± 44.90	136.44 ± 33.86	.196
Fatigability	0.35 ± 0.20	0.25 ± 0.26	0.42 ± 0.15	.075
SCWT performances				
Correct number	86.29 ± 19.06	82.67 ± 17.80	–	.512
False number	14.40 ± 8.43	16.11 ± 8.36	–	.493
Omission number	19.77 ± 10.96	21.94 ± 10.30	–	.609
Congruent correct	12.91 ± 4.03	12.83 ± 4.27	–	.947
Incongruent correct	36.51 ± 9.95	35.06 ± 9.17	–	.611
Pronunciation relevant correct	11.54 ± 3.24	10.17 ± 3.69	–	.173
Irrelevant correct	25.54 ± 7.58	24.67 ± 6.02	–	.675
Congruent correct RT (ms)	597.74 ± 193.46	567.94 ± 201.30	–	.609
Incongruent correct RT (ms)	1651.52 ± 488.68	1577.00 ± 435.94	–	.583
Pronunciation relevant RT (ms)	529.91 ± 161.39	466.39 ± 170.27	–	.193
Irrelevant correct RT (ms)	1174.11 ± 354.28	1121.00 ± 273.18	–	.583

Note: Data were reported as mean value ± SD.
Abbreviations: CPT, continuous performance task; HSM, heavy social media user; LSM, light social media user; SCWT, Stroop color and word test.

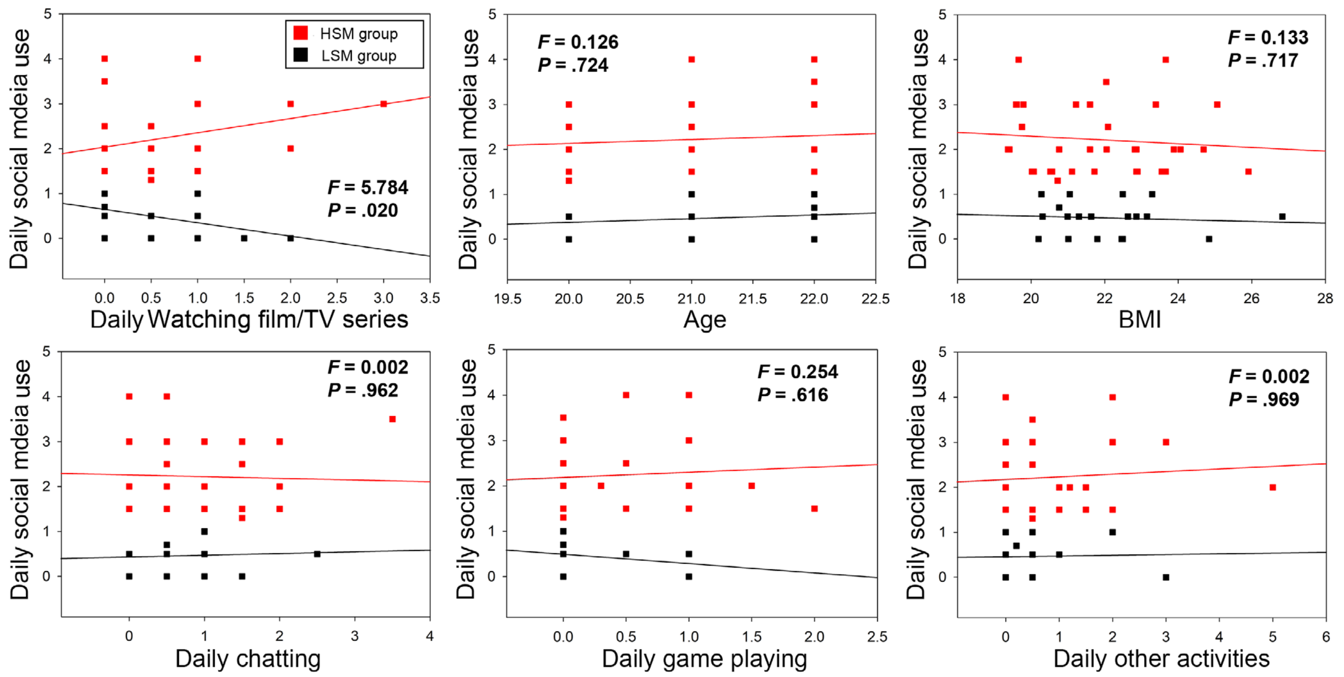

FIGURE 3 Correlation between daily social media use and other variables in HSM and LSM groups. A significant interaction was found between group and daily watching of film and TV due to that in the HSM group, and the association between daily social media use and watching film and TV was stronger than that in the LSM group. HSM, heavy social media user; LSM, light social media user

variable; and age, BMI, daily chatting, watching film and TV, game playing, other activities, and the interaction between group and daily watching of film and TV as covariates to control. We found that different groups significantly predicted daily time spent on social media ($F = 24.914$, $p < .001$), which validated the significance of grouping subjects into HSM and LSM groups. In addition, although we did not observe significant cognitive differences among these three groups, the attentional fatigability of the HSM group tended to be more similar to that of the LSM-4wk group than to that of the LSM-baseline group (HSM $= 0.354 \pm 0.197$, LSM-4wk $= 0.422 \pm 0.154$, LSM-baseline $= 0.250 \pm 0.259$; tested with ANOVA, $p = .075$, $F = 2.714$).

3.2 | Intersubject FC-matrix similarity at group level revealed the effect of social media

One subject in the HSM group and one in the LSM-4wk group with outlier overall correlation coefficients ($r = .420$ and .414, respectively, Figure 4a) were excluded. Their mean correlation coefficient with all the other subjects were less than 2.5 SDs (SD $= .034$) from the mean value (mean $= .529$), which was .444 ($.529–2.5 \times .034$). When we used the BOLD data with GSR in preprocessing, the correlation coefficients between the HSM and LSM-4wk groups ($r = .523 \pm .053$) was higher than between the HSM and LSM-baseline groups (Figure 4b, $r = .508 \pm .064$), and the difference was significant ($p = 8.42 \times 10^{-4}$). We also calculated the effect size (Cohen's d) and found a small to medium effect of inter-group difference (Cohen's $d = .243$) (Becker, 2000). When we used the BOLD data without GSR in preprocessing, the effect size decreased to 0.182 (Figure S1), indicating that the controlling of global artifacts driven by motion and respiration is critical for improving the sensitivity and effectiveness of group-level ISC method.

We repeated this procedure using other brain atlases (Figure S2), and all results were consistent. In addition, considering that ISC may be susceptible to head motion, we investigated the influence of head motion by directly comparing the inter-subject similarity of head motion matrices (FC-matrices were replaced by head motion matrices), but we found no difference (Cohen's $d = .050$, $p = .414$; Figure S3), indicating that the influence of head motion on the results could be ignored. We validated our findings using the augmented data, and we found all results consistent across different augmentations (Figure S4).

In short, after 4-week social media use, the FC characteristics of the LSM group were more similar to those of the HSM group.

3.3 | Intersubject FC-matrix similarity at individual level validated the effect of social media

The similarities between the HSM, LSM-baseline, and LSM-4wk groups were investigated at the individual level. In 29 subjects in the HSM group (excluding one with an outlier correlation coefficient), 25 (ratio $= 0.862$, chance ratio $= 0.500$) had higher correlation coefficients with the LSM-4wk group, which fit our prior hypothesis ($p < .001$, Figure 4c and d). We repeated this procedure using other brain atlases (Figure 4d; Figure S5a,b), and with GSR (Figure 4d;

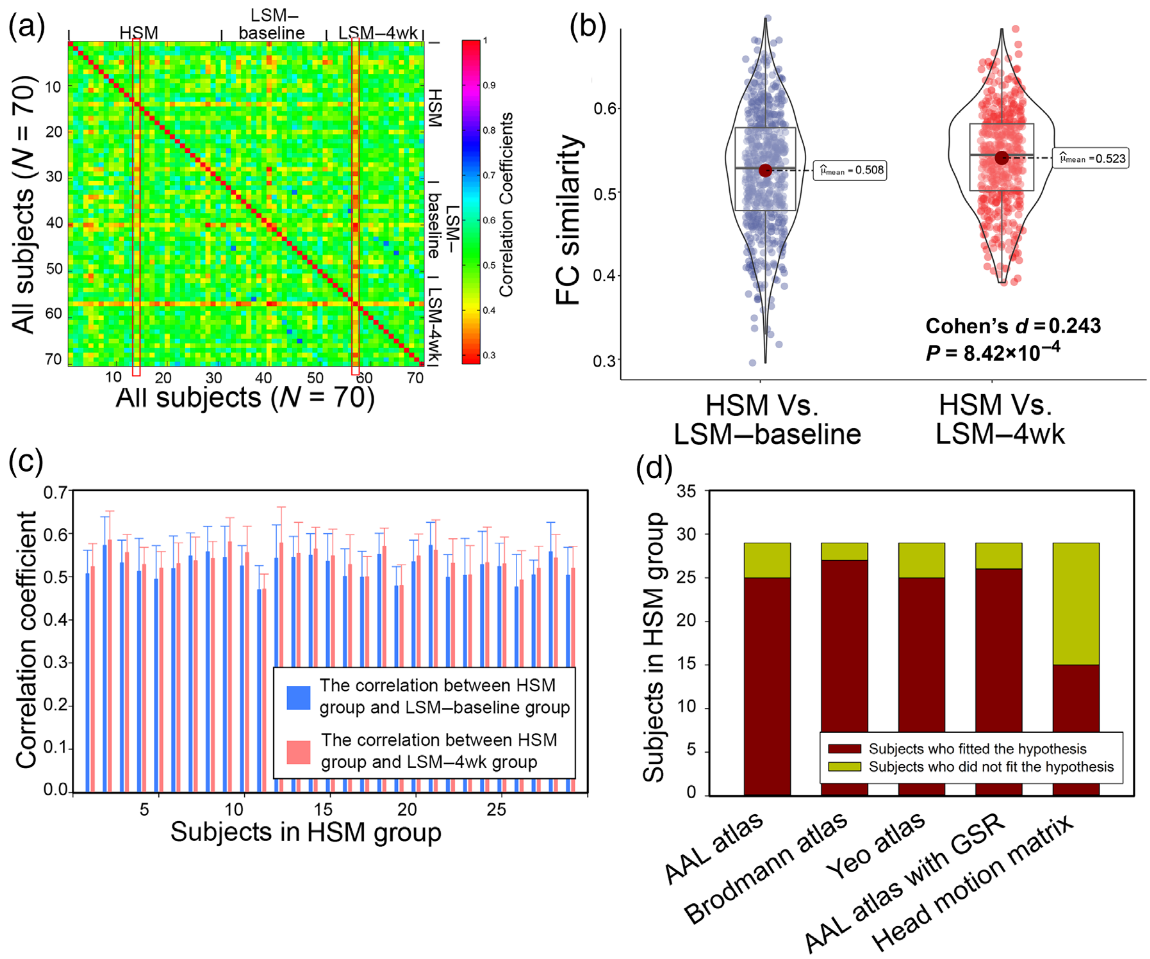

FIGURE 4 Intersubject similarity results at group and individual levels. (a) Two subjects with outlier similarity with all other subjects were excluded (red rectangle). (b) Comparison of intersubject similarity at group level by using BOLD data with global signal regressing (GSR) in preprocessing. Similarity between HSM and LSM-4wk groups was significantly greater than between HSM and LSM-baseline group (Cohen's $d = 0.243$, $p = 8.42 \times 10^{-4}$). (c) Intersubject similarity at individual level. Of 29 subjects in the HSM group, 25 fit our hypothesis (ratio = 0.862, $p < .001$). (d) Validation of intersubject similarity at the individual level. We used two other brain atlases and data with GSR in preprocessing, and all results were consistent ($p < .001$). We repeated this procedure using only a head motion matrix, but only 15 subjects fit our hypothesis (ratio = 0.517, $p = .232$). HSM, heavy social media user; LSM, light social media user

Figure S5c) in preprocessing, and all results were consistent. We repeated this experiment using head motion matrices, but the ratio was only 0.414 ($p = .325$, Figure 4d; Figure S5d), which suggests the influence of head motion can be ignored. We validated our findings using the augmented data, and found all results consistent across different augmentations (Figure S6).

This experiment further validated our hypothesis at the individual level: after 4-week social media use, the FC features in the LSM group were more similar to those of the HSM group.

3.4 | Intersubject FC-vector similarity located brain regions mostly affected by social media

This procedure was similar to that in Section 3.3, using the FC-vector to represent FCs between a predefined brain region and all the other regions, and all brain regions were tested. In 65 brain regions (of 116 in the AAL atlas), the HSM group was more similar to the LSM-4wk group (ratio = 0.655–1.000; $p = .035$–$p < .001$, Figure 5a), and 56 brain regions survived FDR correction (Table S1). However, in 15 brain regions, the HSM group was more similar to the LSM-baseline group (ratio = 0.000–0.345; $p < .001$–$p = .033$, Figure 5a), and 3 survived FDR correction (Table S1).

We repeated this procedure using BOLD images with GSR (Figure 5b), and found the result consistent (Figure 5c). To better explain the results, we classified those brain regions into nine networks, following Schaefer et al. (Schaefer et al., 2018) and AAL atlas, and found that brain regions that fit the hypothesis involved almost all brain networks, and all results were consistent across data augmentations (Figure 5d) and thresholds of significance (Figure S7). However, for brain regions that contrary to the hypothesis, the results derived from BOLD data with and without GSR were not consistent (Figure 5e), which may have resulted from the threshold of significance (Figure S8). That is, if there are very few positive results, the

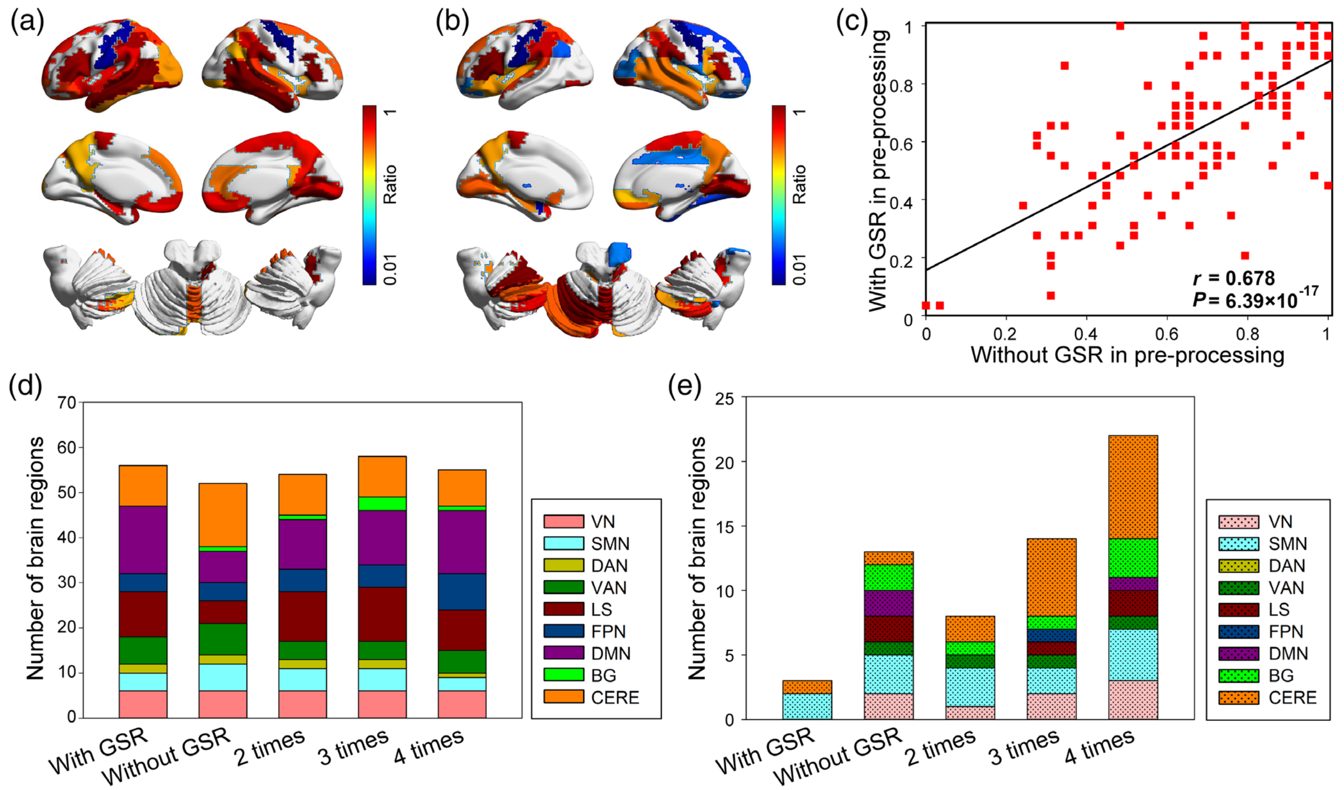

FIGURE 5 Intersubject similarity at brain-region levels. (a) Brain regions of HSM group that were more similar to LSM-4wk group (red yellow) and LSM-baseline group (blue green). Color refers to the ratio of subjects in the HSM group who fit our hypothesis. (b) Validation of previous results using BOLD data with global signal regression (GSR) in preprocessing. (c) Correlation between the results with and without GSR in preprocessing. For all brain regions, there were 116 ratios that represented whether these brain regions were affected by social media, and ratios derived from the BOLD data with and without GSR in preprocessing were highly correlated. (d) Distribution of brain regions that fit our hypothesis among brain networks. These brain regions are mainly located in the VN, SMN, LS, FPN, DMN, and CERE. These results were consistent when we used BOLD data with GSR, and when we augmented all data two, three, and four times. (e) Distribution of brain regions of HSM group that contrary to our hypothesis. We found the results were not consistent between the results with and without GSR, and when we augmented all data two, three, and four times. CERE, cerebellum; DMN, default mode network; FPN, frontoparietal network; HSM, heavy social media user; LS, limbic system; LSM, light social media user; SMN, somatomotor network; VN, visual network

final reported results may be greatly influenced by the threshold of significance and multiple comparison correction methods. When the threshold of significance was loose ($p = .05$, uncorrected), all results were again consistent.

In short, the FC characteristics of over half the brain regions that involve almost all brain networks could be shaped by four-week social media use.

3.5 | Impact of social media on FCs and its relationship to cognitive assessments

In addition to the intersubject similarity analysis, a traditional 2-sample t-test was used to investigate this issue. The FC between the HSM and LSM-baseline groups was compared. No significant results were found after FDR correction, indicating the difference between these two groups may not be great enough to survive FDR correction. Consequently, to detect the difference more sensitively, we arbitrarily defined the threshold of significance as $p = .001$ (other thresholds were also tested, and all results were consistent; Figures S9 and S10), and 18 FCs were finally selected. As expected, almost all these FCs of the LSM-4wk group were between the HSM and LSM-baseline groups (Figure 6a), indicating that after the four-week social media task, the difference of FC between LSM-baseline and HSM was attenuated. These FCs connected the limbic system (LS), somatomotor network (SMN), visual network (VN), cerebellum (CERE), default mode network (DMN), and basal ganglia (BG) (Figure 6b and c). This result was also consistent with the result derived from BOLD data that with GSR (Figure S11). We additionally compared the FC between the baseline and 4-week follow-up in the LSM group by using paired-t test, however, there was no significant result after FDR or network-based statistics (NBS) correction (Figure S12).

We evaluated the selected relationship between FC characteristics and cognitive assessments at the baseline state. According to Figure 6c, the FC between VN and LS was positively correlated with the pronunciation relevant correct number ($r = 0.411$, $p = 0.004$) and reaction time (RT) of SWCT ($r = .430$, $p = .003$). The FC between

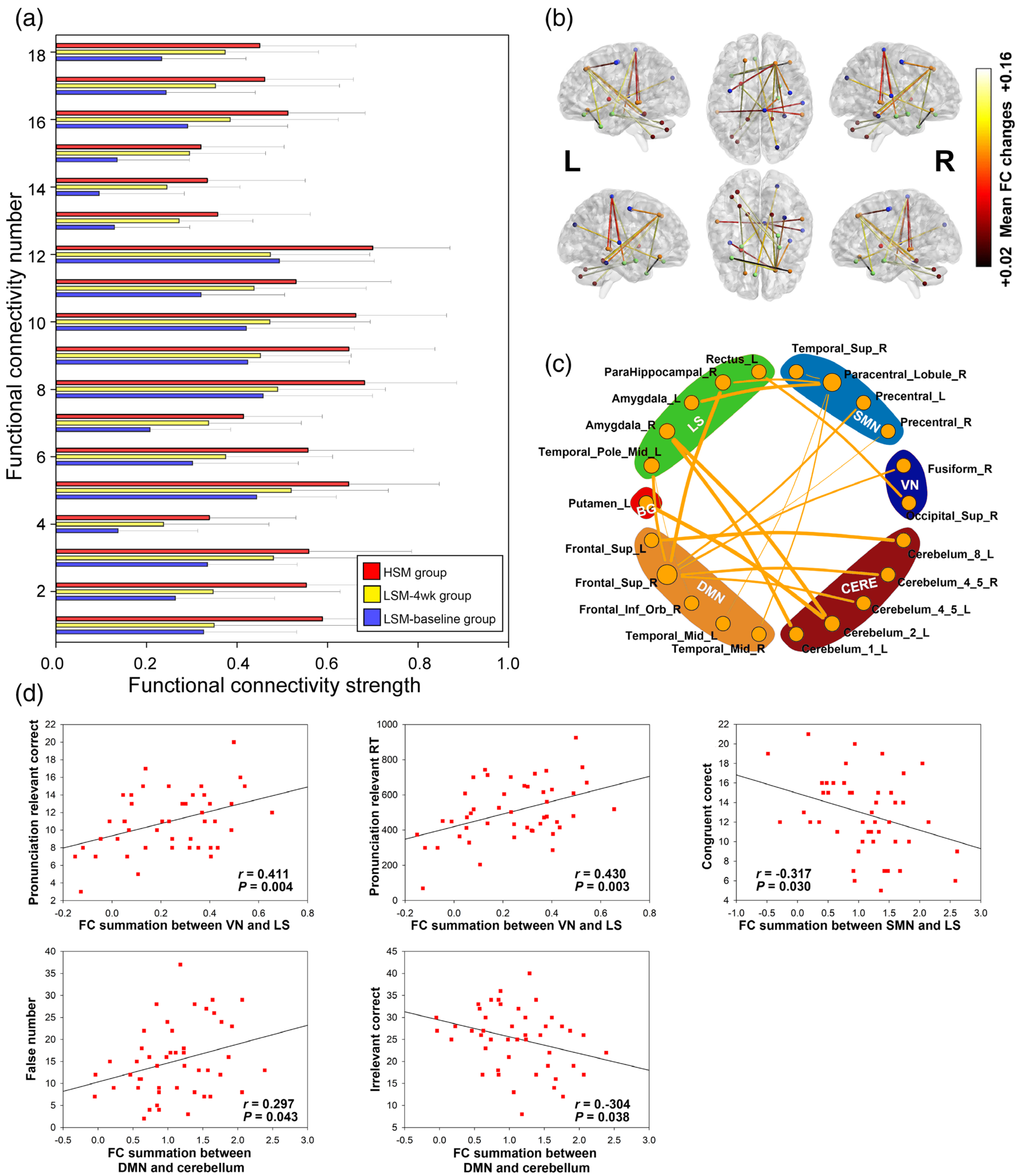

FIGURE 6 Impact of long-term social media use on brain FCs and its relationship with cognitive assessments. (a) FCs were selected from the comparison between HSM and LSM-baseline groups; we observed that the difference was attenuated after the LSM group conducted a 4-week social media task. (b) Mean value of FC changes displayed in brain maps. (c) Mean value of FC changes displayed in network maps, mostly involving the LS, DMN, and CERE. (d) Significant relationship between network-wise FCs and cognitive performances (SWCT scores) at baseline state. CERE, cerebellum; DMN, default mode network; HSM, heavy social media user; LS, limbic system; LSM, light social media user; SCWT, Stroop color and word test

SMN and LS was negatively correlated with the congruent correct number of SWCT ($r = -.317$, $p = .030$). FC between DMN and the cerebellum was positively correlated with the false number of SWCT ($r = .297$, $p = .043$), and negatively correlated with the irrelevant correct number of SWCT ($r = -.304$, $p = .038$).

In summary, we used a traditional 2-sample *t*-test to validate our hypothesis again. In the following correlation analysis, we found correlations between selective attention and FC that were most affected by social media.

4 | DISCUSSION

We showed through a longitudinal study design with ISC methods that cerebral FC can be affected by social media. First, we found through ISC at group and individual levels that the FC-matrices of HSMs were more similar to those of LSMs after a four-week social media task than at the baseline state. Second, using ISC at the brain-region level, we found the 56 brain regions most affected by long-term social media, which involved almost all brain networks. Third, we found that the difference of FC between HSM and LSM was attenuated after LSMs conducted a four-week social media task. Finally, we found correlations between selective attention and FC that were most affected by social media. We validated all of our findings by conducting several sensitive analyses, including head motion, brain atlas, data size, global signal regression, and statistical methods.

To some extent, our research added in the illumination of the causality between social media and biological traits, which may have significance in clinical practice. For example, multiple scans of social media users at regular intervals can help to monitor the change of FC, and thus screen for people who are susceptible to social media. Previous research has used similar methods to monitor the process of mild cognitive impairment (Castelnovo et al., 2020) and progressive supranuclear palsy (Brown et al., 2017). FC changes can also be monitored to assess the effect of therapy on social media-related disorders, using FC characteristics based on a huge social media-free cohort as the standard reference. This method was recently combined with transcranial magnetic stimulation to predict and monitor the therapeutic effect of depressive (Chen et al., 2020; Corlier et al., 2019; Ge, Downar, Blumberger, Daskalakis, & Vila-Rodriguez, 2020) and bipolar disorders (Olejarczyk et al., 2020), which shows promise for people with social media-related disorders.

The association between daily social media use and watching film and TV was stronger in the HSM group than in the LSM group, indicating that people use video social media platforms (such as TikTok) to watch film and TV. Although the difference in CPT performance among the three groups was not significant, the sustained attention, attentional instability, and attentional fatigability of the HSM group tended to be more similar to those of the LSM-4wk group than to those of the LSM-baseline group. The lack of statistical significance may be due to the difference in the daily time spent on social media between the HSM and LSM-baseline groups in this research not being large enough, or because the cognitive task was too simple (considering that our subjects were young adults with normal intelligence) to detect differences between the two groups. Ralph, Thomson, Seli, Carriere, and Smilek (2015) used a longer task (over 20 minutes) to estimate the sustained attention of social media users, and they found subjects with heavier social media use had a decrease in sustained attention. However, the correlation was also attenuated to trend level when controlling for age.

The ISC method has been used in several domains (Finn et al., 2020; Nastase et al., 2019). Connolly et al. 2012 found similar activation patterns in visual cortex during the viewing of animals belonging to the same biological classes. ISC was found to be sensitive in finding shared neural processing by directly correlating raw BOLD signals between subjects (also called functional hyperconnectivity) (Nummenmaa et al., 2014; Schmälzle, Häcker, Honey, & Hasson, 2015). Our research investigated the effect of social media on cerebral FC by combining a series of ISC methods on FC features (from group-, to individual-, to brain region-level ISC), which may provide methodological guidance to other researchers. However, it should be noted that ISC is not a specific concept, but rather a reference to the correlation analysis of imaging or behavioral representations, or both (Finn et al., 2020).

We found that the FC characteristics of over half the brain regions could be shaped by four-week social media use. These brain regions involve almost all brain networks, which may be due to the diversity of stimuli in social media, such as visual, acoustic, and emotional stimulus, as well as semantic comprehension and social interaction. Previous studies found that looking at photos with lots of likes showed increased activity in brain regions associated with reward processing, social cognition, imitation, and attention (Sherman, Payton, Hernandez, Greenfield, & Dapretto, 2016). In addition, daily media multitasking was associated with increased recruitment of brain areas involved in attentional and inhibitory control (Moisala et al., 2016). When viewing personalized videos, there was higher brain activations in DMN, ventral tegmental area, and discrete regions including lateral prefrontal, anterior thalamus, and cerebellum (Su et al., 2021). These findings are consistent with our findings, which indicates that the impact of social media on brain is extensive due to the diverse stimuli. However, the FC of 15 brain regions (mainly included somatosensory, somatomotor, and motor regulation systems) of the HSM group were more similar to the LSM group at baseline state than after the four-week social media task. This may be due to the fact that the data of these two groups at baseline status were collected over the same time period. Considering the subjects are all students at the same grade, the similar states of their sensory and motor systems may be due to the similar temperature, weather, academic courses, or physical training plan during the period of experiment.

The current research has limitations. The sample was relatively small; we will recruit more subjects in future studies. We only conducted SCWT at the baseline for all subjects and found several correlations between it and FC characteristics, however, the correlation between SCWT changes and FC changes before and after the long-term task may provide more direct evidence of training-induced plasticity. As a result, future research should conduct all cognitive tests at baseline state and after the longitudinal task. Besides, a four-week task may not be sufficient to fully understand the impact of social media on human brain, and this may also be why the behavior performance and paired t-test results of FC (intragroup comparison before and after the task) were not significant. Even this difference could be detected by our ISC methods, the effect size of group-level result was small to medium. Consequently, a longer study period should be used in future research. We showed that social media can cause cognitive brain and FC changes, but this does not preclude the possibility that individuals with certain biological traits are more likely to use social media. Consequently, future neuroimaging research may combine with genomic research may have to comprehensively illuminate this issue. Because of the heavily imbalanced sex ratio in neuroimaging cohort (only eight females in all 175 subjects), and only 3 of them were willing to take part in the longitudinal research, only male subjects were included to prevent the bias. It's a tough decision, given that females usually use social media more frequently than males (Spiller, Ackerman, Spiller, & Casavant, 2019); therefore, it would be our research target to include female subjects in the future.

5 | CONCLUSION

The impact of social media use on cerebral functional connectivity changes is revealed by ISC method and longitudinal design, which provides guidance for clinical practice. ISC methods can be used in similar domains.

ACKNOWLEDGMENT

Bo Hu would like to thank his girlfriend Miss Xin Wen for the long-term accompany during the whole experiment. Even if she did not know exactly what he was doing, but she could sense his excitement and joy at new discoveries, and now, he is going to marry her. Our gratitude also goes for Dr. Wu-Xun Cui, Si-Jie Xiu from Department of Radiology of Tangdu Hospital, as well as Dr. Xiao-Cheng Wei from MR Research China of GE Healthcare for their outstanding technique support. We thank LetPub (www.letpub.com) for its linguistic assistance during the preparation of this manuscript.

CONFLICT OF INTERESTS

The authors declare that they have no conflict of interests.

ETHICAL APPROVAL

The experiment conformed to the principles of the Declaration of Helsinki and was approved by the ethics committee of Tangdu Hospital of Fourth Military Medical University.

PATIENT CONSENT STATEMENT

All participants provided informed written consent.

AUTHOR CONTRIBUTIONS

Conceptualization: Wen Wang and Guang-Bin Cui; *Data curation*: Bo Hu and Ying Yu; *Formal analysis:* Bo Hu; *Funding acquisition*: Ying Yu, Wen Wang, and Guang-Bin Cui; *Investigation*: Bo Hu; *Methodology*: Lin-Feng Yan and Ying Yu; *Project administration*: Bo Hu and Wen Wang; *Resources*: Yu-Ting Li; *Software*: Yu-Ting Li and An-Ping Shi; *Supervision*: Wen Wang and Guang-Bin Cui; *Validation*: Chen-Xi Liu and Ze-Yang Li; *Visualization*: Bo Hu, Yu-Xuan Shang, Guo-Qing Qi, and Dong Wu; *Roles/writing—original draft*: Bo Hu and Ying Yu; *Writing—review and editing*: Wen Wang and Guang-Bin Cui.

DATA AVAILABILITY STATEMENT

All codes and data were uploaded to https://github.com/hubolll/Social_media_ISRSA.

ORCID

Bo Hu https://orcid.org/0000-0002-1135-0669

REFERENCES

Beaty, R. E., Kenett, Y. N., Christensen, A. P., Rosenberg, M. D., Benedek, M., Chen, Q., … Silvia, P. J. (2018). Robust prediction of individual creative ability from brain functional connectivity. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(5), 1087–1092. https://doi.org/10.1073/pnas.1713532115

Becker, L. A. (2000). *Effect size (ES)*. http://web.uccs.edu/lbeker/Psy590/es.htm

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society*. *Series B: Methodological*, *57*(1), 289–300.

Brown, J. A., Hua, A. Y., Trujllo, A., Attygalle, S., Binney, R. J., Spina, S., … Seeley, W. W. (2017). Advancing functional dysconnectivity and atrophy in progressive supranuclear palsy. *Neuroimage Clinical*, *16*, 564–574. https://doi.org/10.1016/j.nicl.2017.09.008

Castelnovo, V., Canu, E., Calderaro, D., Riva, N., Poletti, B., Basaia, S., … Agosta, F. (2020). Progression of brain functional connectivity and frontal cognitive dysfunction in ALS. *Neuroimage Clinical*, *28*, 102509. https://doi.org/10.1016/j.nicl.2020.102509

Chao-Gan, Y., & Yu-Feng, Z. (2010). DPARSF: A MATLAB toolbox for “pipeline” data analysis of resting-state fMRI. *Frontiers in Systems Neuroscience*, *4*, 13. https://doi.org/10.3389/fnsys.2010.00013

Chen, F. J., Gu, C. Z., Zhai, N., Duan, H. F., Zhai, A. L., & Zhang, X. (2020). Repetitive transcranial magnetic stimulation improves amygdale functional connectivity in major depressive disorder. *Frontiers in Psychiatry*, *11*, 732. https://doi.org/10.3389/fpsyt.2020.00732

Choi, J., Cho, H., Choi, J. S., Choi, I. Y., Chun, J. W., & Kim, D. J. (2021). The neural basis underlying impaired attentional control in problematic smartphone users. *Translational Psychiatry*, *11*(1), 129. https://doi.org/10.1038/s41398-021-01246-5

Connolly, A. C., Guntupalli, J. S., Gors, J., Hanke, M., Halchenko, Y. O., Wu, Y. C., … Haxby, J. V. (2012). The representation of biological classes in the human brain. *The Journal of Neuroscience*, *32*(8), 2608–2618. https://doi.org/10.1523/jneurosci.5547-11.2012

Corkum, P. V., & Siegel, L. S. (1993). Is the continuous performance task a valuable research tool for use with children with attention-deficit-hyperactivity disorder? *Journal of Child Psychology and Psychiatry*, *34*(7), 1217–1239. https://doi.org/10.1111/j.1469-7610.1993.tb01784.x

Corlier, J., Wilson, A., Hunter, A. M., Vince-Cruz, N., Krantz, D., Levitt, J., … Leuchter, A. F. (2019). Changes in functional connectivity predict outcome of repetitive transcranial magnetic stimulation treatment of major depressive disorder. *Cerebral Cortex*, *29*(12), 4958–4967. https://doi.org/10.1093/cercor/bhz035

Crone, E. A., & Konijn, E. A. (2018). Media use and brain development during adolescence. *Nature Communications*, *9*(1), 588. https://doi.org/10.1038/s41467-018-03126-x

Finn, E. S., Glerean, E., Khojandi, A. Y., Nielson, D., Molfese, P. J., Handwerker, D. A., & Bandettini, P. A. (2020). Idiosynchrony: From shared responses to individual differences during naturalistic neuroimaging. *NeuroImage*, *215*, 116828. https://doi.org/10.1016/j.neuroimage.2020.116828

Finn, E. S., Shen, X., Scheinost, D., Rosenberg, M. D., Huang, J., Chun, M. M., … Constable, R. T. (2015). Functional connectome fingerprinting: Identifying individuals using patterns of brain connectivity. *Nature Neuroscience*, *18*(11), 1664–1671. https://doi.org/10.1038/nn.4135

Firth, J., Torous, J., Stubbs, B., Firth, J. A., Steiner, G. Z., Smith, L., … Sarris, J. (2019). The "online brain": How the internet may be changing our cognition. *World Psychiatry*, *18*(2), 119–129. https://doi.org/10.1002/wps.20617

Gao, J., Chen, G., Wu, J., Wang, Y., Hu, Y., Xu, T., … Yang, Z. (2020). Reliability map of individual differences reflected in inter-subject correlation in naturalistic imaging. *NeuroImage*, *223*, 117277. https://doi.org/10.1016/j.neuroimage.2020.117277

Ge, R., Downar, J., Blumberger, D. M., Daskalakis, Z. J., & Vila-Rodriguez, F. (2020). Functional connectivity of the anterior cingulate cortex predicts treatment outcome for rTMS in treatment-resistant depression at 3-month follow-up. *Brain Stimulation*, *13*(1), 206–214. https://doi.org/10.1016/j.brs.2019.10.012

Guo, C. C., Hyett, M. P., Nguyen, V. T., Parker, G. B., & Breakspear, M. J. (2016). Distinct neurobiological signatures of brain connectivity in depression subtypes during natural viewing of emotionally salient films. *Psychological Medicine*, *46*(7), 1535–1545. https://doi.org/10.1017/s0033291716000179

Hu, B., Yan, L. F., Sun, Q., Yu, Y., Zhang, J., Dai, Y. J., … Wang, W. (2019a). Disturbed neurovascular coupling in type 2 diabetes mellitus patients: Evidence from a comprehensive fMRI analysis. *Neuroimage Clinical*, *22*, 101802. https://doi.org/10.1016/j.nicl.2019.101802

Hu, B., Yu, Y., Dai, Y. J., Feng, J. H., Yan, L. F., Sun, Q., … Wang, W. (2019b). Multi-modal MRI reveals the neurovascular coupling dysfunction in chronic migraine. *Neuroscience*, *419*, 72–82. https://doi.org/10.1016/j.neuroscience.2019.09.022

Hu, B., Yu, Y., Wang, W., & Cui, G. B. (2021). MICA: A toolkit for multimodal image coupling analysis. *Journal of Neuroscience Methods*, *347*, 108962. https://doi.org/10.1016/j.jneumeth.2020.108962

Hutton, J. S., Dudley, J., Horowitz-Kraus, T., DeWitt, T., & Holland, S. K. (2020). Associations between screen-based media use and brain white matter integrity in preschool-aged children. *JAMA Pediatrics*, *174*(1), e193869. https://doi.org/10.1001/jamapediatrics.2019.3869

Lamblin, M., Murawski, C., Whittle, S., & Fornito, A. (2017). Social connectedness, mental health and the adolescent brain. *Neuroscience and Biobehavioral Reviews*, *80*, 57–68. https://doi.org/10.1016/j.neubiorev.2017.05.010

Li, Q., Wang, X., Wang, S., Xie, Y., Li, X., Xie, Y., & Li, S. (2018). Musical training induces functional and structural auditory-motor network plasticity in young adults. *Human Brain Mapping*, *39*(5), 2098–2110. https://doi.org/10.1002/hbm.23989

Loh, K. K., & Kanai, R. (2016). How has the internet reshaped human cognition? *The Neuroscientist*, *22*(5), 506–520. https://doi.org/10.1177/1073858415595005

Madore, K. P., Khazenzon, A. M., Backes, C. W., Jiang, J., Uncapher, M. R., Norcia, A. M., & Wagner, A. D. (2020). Memory failure predicted by attention lapsing and media multitasking. *Nature*, *587*(7832), 87–91. https://doi.org/10.1038/s41586-020-2870-z

Marins, T., Rodrigues, E. C., Bortolini, T., Melo, B., Moll, J., & Tovar-Moll, F. (2019). Structural and functional connectivity changes in response to short-term neurofeedback training with motor imagery. *NeuroImage*, *194*, 283–290. https://doi.org/10.1016/j.neuroimage.2019.03.027

Moisala, M., Salmela, V., Hietajärvi, L., Salo, E., Carlson, S., Salonen, O., … Alho, K. (2016). Media multitasking is associated with distractibility and increased prefrontal activity in adolescents and young adults. *NeuroImage*, *134*, 113–121. https://doi.org/10.1016/j.neuroimage.2016.04.011

Nakagawa, S., & Cuthill, I. C. (2007). Effect size, confidence interval and statistical significance: A practical guide for biologists. *Biological Reviews of the Cambridge Philosophical Society*, *82*(4), 591–605. https://doi.org/10.1111/j.1469-185X.2007.00027.x

Nastase, S. A., Gazzola, V., Hasson, U., & Keysers, C. (2019). Measuring shared responses across subjects using intersubject correlation. *Social Cognitive and Affective Neuroscience*, *14*(6), 667–685. https://doi.org/10.1093/scan/nsz037

Nummenmaa, L., Saarimäki, H., Glerean, E., Gotsopoulos, A., Jääskeläinen, I. P., Hari, R., & Sams, M. (2014). Emotional speech synchronizes brains across listeners and engages large-scale dynamic brain networks. *NeuroImage*, *102*(Pt 2), 498–509. https://doi.org/10.1016/j.neuroimage.2014.07.063

Olejarczyk, E., Zuchowicz, U., Wozniak-Kwasniewska, A., Kaminski, M., Szekely, D., & David, O. (2020). The impact of repetitive transcranial magnetic stimulation on functional connectivity in major depressive disorder and bipolar disorder evaluated by directed transfer function and indices based on graph theory. *International Journal of Neural Systems*, *30*(4), 2050015. https://doi.org/10.1142/s012906572050015x

Ophir, E., Nass, C., & Wagner, A. D. (2009). Cognitive control in media multitaskers. *Proceedings of the National Academy of Sciences of the United States of America*, *106*(37), 15583–15587. https://doi.org/10.1073/pnas.0903620106

Ralph, B. C., Thomson, D. R., Seli, P., Carriere, J. S., & Smilek, D. (2015). Media multitasking and behavioral measures of sustained attention. *Attention, Perception, & Psychophysics*, *77*(2), 390–401. https://doi.org/10.3758/s13414-014-0771-7

Rosenberg, M. D., & Finn, E. S. (2016). A neuromarker of sustained attention from whole-brain functional connectivity. *Nature Neuroscience*, *19*(1), 165–171. https://doi.org/10.1038/nn.4179

Scarpina, F., & Tagini, S. (2017). The Stroop color and word test. *Frontiers in Psychology*, *8*, 557. https://doi.org/10.3389/fpsyg.2017.00557

Schaefer, A., Kong, R., Gordon, E. M., Laumann, T. O., Zuo, X. N., Holmes, A. J., … Yeo, B. T. T. (2018). Local-global parcellation of the human cerebral cortex from intrinsic functional connectivity MRI. *Cerebral Cortex*, *28*(9), 3095–3114. https://doi.org/10.1093/cercor/bhx179

Schmälzle, R., Häcker, F. E., Honey, C. J., & Hasson, U. (2015). Engaged listeners: Shared neural processing of powerful political speeches. *Social Cognitive and Affective Neuroscience*, *10*(8), 1137–1143. https://doi.org/10.1093/scan/nsu168

Sherman, L. E., Payton, A. A., Hernandez, L. M., Greenfield, P. M., & Dapretto, M. (2016). The power of the like in adolescence: Effects of peer influence on neural and behavioral responses to social media. *Psychological Science*, *27*(7), 1027–1035. https://doi.org/10.1177/0956797616645673

Spiller, H. A., Ackerman, J. P., Spiller, N. E., & Casavant, M. J. (2019). Sex- and age-specific increases in suicide attempts by self-poisoning in the United States among youth and young adults from 2000 to 2018. *The Journal of Pediatrics*, *210*, 201–208. https://doi.org/10.1016/j.jpeds.2019.02.045

Su, C., Zhou, H., Gong, L., Teng, B., Geng, F., & Hu, Y. (2021). Viewing personalized video clips recommended by TikTok activates default mode network and ventral tegmental area. *NeuroImage*, *237*, 118136. https://doi.org/10.1016/j.neuroimage.2021.118136

Uncapher, M. R., Lin, L., Rosen, L. D., Kirkorian, H. L., Baron, N. S., Bailey, K., … Wagner, A. D. (2017). Media multitasking and cognitive, psychological, neural, and learning differences. *Pediatrics*, *140*(Suppl 2), S62–s66. https://doi.org/10.1542/peds.2016-1758D

Uncapher, M. R., & Wagner, A. D. (2018). Minds and brains of media multitaskers: Current findings and future directions. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(40), 9889–9896. https://doi.org/10.1073/pnas.1611612115

Yan, C. G., Cheung, B., Kelly, C., Colcombe, S., Craddock, R. C., Di Martino, A., … Milham, M. P. (2013). A comprehensive assessment of regional variation in the impact of head micromovements on functional connectomics. *NeuroImage*, *76*, 183–201. https://doi.org/10.1016/j.neuroimage.2013.03.004

Yan, C. G., Wang, X. D., Zuo, X. N., & Zang, Y. F. (2016). DPABI: Data processing & analysis for (resting-state) brain imaging. *Neuroinformatics*, *14*(3), 339–351. https://doi.org/10.1007/s12021-016-9299-4

Yu, Y., Yan, L. F., Sun, Q., Hu, B., Zhang, J., Yang, Y., … Wang, W. (2019). Neurovascular decoupling in type 2 diabetes mellitus without mild cognitive impairment: Potential biomarker for early cognitive impairment. *NeuroImage*, *200*, 644–658. https://doi.org/10.1016/j.neuroimage.2019.06.058

Zhu, Y., Li, X., Qiao, Y., Shang, R., Shi, G., Shang, Y., & Guo, H. (2021). Widespread plasticity of cognition-related brain networks in single-sided deafness revealed by randomized window-based dynamic functional connectivity. *Medical Image Analysis*, *73*, 102163. https://doi.org/10.1016/j.media.2021.102163

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

How to cite this article: Hu, B., Yu, Y., Yan, L.-F., Qi, G.-Q., Wu, D., Li, Y.-T., Shi, A.-P., Liu, C.-X., Shang, Y.-X., Li, Z.-Y., Cui, G.-B., & Wang, W. (2022). Intersubject correlation analysis reveals the plasticity of cerebral functional connectivity in the long-term use of social media. *Human Brain Mapping*, *43*(7), 2262–2275. https://doi.org/10.1002/hbm.25786