Parenting and Salience Network Connectivity Among African Americans: A Protective Pathway for Health-Risk Behaviors

Supplementary Information

Methods: Participants' substance use dependence, psychiatric status, and obesity

Based on AUDIT scores, 93.4% of the sample was classified as normal low risk drinking, 4.4% was classified as hazardous drinking, and 2.2% was classified as alcohol dependence likely. Nicotine dependence score was low (2% with moderate dependence, 9% with low-to-moderate dependence, all others low dependence [9%] or non-smokers [75%]). Rates of mental health were high on average, 75.8% classified as having none-minimal depression according to their patient health questionnaire score, 18.7% classified as mild depression; 2.2% classified as moderate depression; 2.2% classified as moderately severe depression; and 1.1% classified as severe depression. Mean body mass index was 29.06 (*SD* = 8.66), with 38.5% of the sample classified as obese (BM ≥ 30).

Methods: Motion correction

TRs were censored when motion between TRs exceeded 0.2 mm or when motion within a TR resulted in at least 25% outlier voxels. Outlier voxels were identified using standard AFNI procedures implemented via proc.py. We specified that censoring should occur when motion between TRs exceeded 0.2 mm and/or when 25% or more of the voxels within a TR were identified as outliers. While the specific value AFNI uses to determine outlier status varies based on the number of TRs included in the analysis, voxels are typically identified as outliers in a given TR if their activation value exceeds 5.5 mean absolute deviations from the overall trend.

Given the number of TRs collected in the current study, a value close to this was used for all subjects. Censoring a TR is accomplished by changing the activation value for that TR to the overall grand mean, in this case 0, which effectively removes it from the analysis. All participants were required to have had least 5 minutes of resting state data after motion censoring; for the final sample, the average amount of resting state data time was 7.4 minutes, with a minimum of 6.4 minutes.

Methods: Averaging ROI-ROI connectivity estimates

Despite the increasing popularity of ICA based rsFC analyses, ROI-ROI connectivity analyses are still more common and the influence of motion on ROI-ROI connectivity estimates has been better characterized, allowing us to control better for its effects [1-3]. Moreover, ROI-ROI connectivity analyses allow a priori hypothesis generation and ROI definition based on specific coordinates previously identified in the literature in a way that is not possible using data-driven approaches like ICA. ROI-ROI analyses also maintain a constant size for all ROIs, which ensure that all ROIs contribute equally to error estimates and no one ROI is overrepresented. The use of relatively small ROI spheres as opposed to larger ICA identified components also facilitates specificity in results reporting, and avoids attributing functions to larger anatomical areas that research has increasingly shown to consist of multiple functional areas. By pre-defining ROIs of a specific size using specific coordinates, we have greater confidence in assigning functions to specific areas within a functional network, and guard against the threat of reverse-inference.

Results: Decomposing SEM into two different models

As a final consideration, we sought to confirm that the pathways under consideration demonstrated significance even when considered separately. To do so, we fit two separate models with harmful alcohol use and emotional eating separately examined as the outcome of interest. For the harmful alcohol use model, the pattern of results from the combined model remained the same. Similarly, for the emotional eating model, the pattern of results from the combined model remained the same. As a result, we remain confident that a singular model provides the most parsimonious test of the hypotheses (tabulated results of supplemental analyses available from first author).

Supplemental References

1. Power JD et al. (2012): Spurious but systematic correlations in functional connectivity MRI networks arise from subject motion. NeuroImage. 59:2142-2154.
2. Power JD et al. (2014): Methods to detect, characterize, and remove motion artifact in resting state fMRI. NeuroImage. 84:320-341.
3. Satterthwaite TD et al. (2012): Impact of in-scanner head motion on multiple measures of functional connectivity: Relevance for studies of neurodevelopment in youth. NeuroImage. 60:623-632.