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Research Report

Socioeconomic resources in youth are linked to divergent patterns of network integration/segregation across the brain's transmodal axis

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Abstract

Socioeconomic resources (SER) calibrate the developing brain to the current context, which can confer or attenuate risk for psychopathology across the lifespan. Recent multivariate work indicates that SER levels powerfully relate to intrinsic functional connectivity patterns across the entire brain. Nevertheless, the neuroscientific meaning of these widespread neural differences remains poorly understood, despite its translational promise for early risk identification, targeted intervention, and policy reform. In the present study, we leverage graph theory to precisely characterize multivariate and univariate associations between SER across household and neighborhood contexts and the intrinsic functional architecture of brain regions in 5,821 youth (9–10 years) from the Adolescent Brain Cognitive Development Study. First, we establish that decomposing the brain into profiles of integration and segregation captures more than half of the multivariate association between SER and functional connectivity with greater parsimony (100-fold reduction in number of features) and interpretability. Second, we show that the topological effects of SER are not uniform across the brain; rather, higher SER levels are associated with greater integration of somatomotor and subcortical systems, but greater segregation of default mode, orbitofrontal, and cerebellar systems. Finally, we demonstrate that topological associations with SER are spatially patterned along the unimodal–transmodal gradient of brain organization. These findings provide critical interpretive context for the established and widespread associations between SER and brain organization. This study highlights both higher-order and somatomotor networks that are differentially implicated in environmental stress, disadvantage, and opportunity in youth.

Keywords: socioeconomic resources, brain development, transmodal gradient, graph theory, multivariate predictive modeling

Significance Statement

Brain development is not identical across individuals but is rather powerfully influenced by experience. Socioeconomic resource (SER) levels vary widely across households and exert widespread effects on the developing brain. Here, we implement graph theory and multivariate predictive modeling in youth (9–10 years) to characterize how SER levels are related to the organization of the entire brain with parsimony and interpretability. We demonstrate that associations with SER are not uniform across the brain but are spatially patterned along an evolutionary hierarchy of brain organization. Specifically, higher SER levels were associated with more integrated sensorimotor, but more segregated association, networks. These nuanced effects reveal spatially constrained neural signatures associated with exposure to environmental disadvantage (or opportunity) during development.

Introduction

Socioeconomic resources (SER) powerfully influence concurrent and lifelong outcomes, especially during childhood and adolescence when environmental experiences have particularly strong and cascading effects on health and functioning (1–3). For example, SER in youth, typically measured through household income, parental education, and neighborhood resources, have been associated with disparities in educational and occupational attainment, cognitive and socioemotional functioning, and physical (e.g. cardiovascular disease and cancer) and mental health (e.g. anxiety, depression, suicide, criminality, and substance use) (4–6). Technological and computational advancements in non-invasive neuroimaging methods have allowed researchers to demonstrate that SER may influence behavior through their

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effects on brain development (7, 8). Elucidating how SER levels impact the developing brain, especially during early adolescence when many psychosocial challenges emerge (9), can inform early risk identification, facilitate targeted intervention, and inform public policies related to socioeconomic and health inequities.

With growing recognition that brain regions exhibit coordinated activity (10), empirical studies probing associations between SER and neurodevelopment have increasingly leveraged task-free "resting-state" functional magnetic resonance imaging (fMRI). This technique uses coherence in spontaneous neural activity to map the strength of communication between brain regions (i.e. functional connectivity) (10, 11). To date, these studies have predominantly relied on individual, region-specific connections to delineate how SER may calibrate communication within selected brain circuits of interest (e.g. prefrontal–amygdala connectivity) (12).

There is, however, convergent evidence demonstrating that the brain is organized into large-scale intrinsic connectivity networks (ICNs), such that coordinated activity within and between ICNs gives rise to diverse cognitive and socioemotional processes (11, 13–16). Against this backdrop, studies are now indicating that neurodevelopmental associations with SER are not localized to specific circuits but are instead distributed across ICNs throughout the entire brain (12, 17–19).

To expand on these univariate network-level studies, our group has recently conducted a multivariate predictive modeling study interrogating brain-wide connectivity differences associated with SER (20) in the Adolescent Brain Cognitive Development (ABCD) Study, the largest neuroimaging study of youth to date (21, 22). We identified robust and generalizable associations between SER and resting-state functional connectivity, with connectivity changes explaining 9% of the variance in SER out-of-sample—a relatively large effect size in the social sciences. These connectivity changes were widespread across most ICNs (72 out of 110 network pairs). A key limitation of this work, however, is in terms of interpretation. While this study comprehensively *described* the magnitude of the multivariate association between SER and over 80,000 connections, it did not identify ways to meaningfully reduce these data to afford clear interpretations of *what* these neural alterations mean and *how* they are organized in the brain.

In the present study, we address this knowledge gap by leveraging graph theory, a mathematical technique that can quantify parsimonious and interpretable properties of the overall organization of the brain (23). Prior work has focused on network segregation (i.e. neural communication within distinct ICNs) and network integration (i.e. neural communication across different ICNs), given their relevance for neurodevelopment, cognition, and mental health (24, 25). Segregation gives rise to differentiated networks that execute specialized cognitive functions, whereas integration efficiently coordinates these processing streams across the brain (26, 27). A combination of high segregation and high integration represents an "optimized" small-world architecture that rapidly integrates specialized, multimodal information at low wiring and energy costs (26, 27). Segregation and integration are reflected in two graph theoretic metrics that capture within-network connectivity (within-module degree) and between-network connectivity (participation coefficient) (28). Profiles of higher within-module degree and lower participation coefficient result in more clearly defined and separable ICNs that reflect segregation. In contrast, profiles of lower within-module degree and higher participation coefficient result in greater functional communication between ICNs that reflect integration.

ICNs exhibit developmental refinements in segregation and integration during sensitive developmental windows (24, 29–31), though recent work indicates that the segregation and integration of ICNs may be influenced by SER levels. Socioeconomic disadvantage has been associated with weaker age-related variation in the segregation and integration of ICNs across adolescence, suggesting accelerated network development in low-SER contexts (18, 32, 33), although the reverse pattern of potentially delayed network development has also been found (19). Environmental experiences shaped by SER levels, such as household instability and parenting, have similarly been linked to alterations in graph theoretic indicators of network integration, such as the efficiency of information flow, in youth (34, 35).

ICNs are organized along a unimodal–transmodal gradient, which represents the degree to which networks are specialized for encoding specific sensory features versus integrating representations across modalities (36–38). Motor and sensory processing networks (e.g. visual and somatomotor) anchor the unimodal end, and association networks (e.g. default mode) anchor the transmodal end. Across development, unimodal networks become more integrated and transmodal networks become more segregated (30, 31). As different ICNs exhibit unique developmental refinements based on their rank on the unimodal–transmodal gradient, the topological effects of SER may differ along the transmodal axis. This possibility currently remains unexplored but would provide a parsimonious and developmentally informed contextualization of how SER levels influence the architecture of maturing ICNs.

Accordingly, in the present study, we quantify multivariate and univariate associations between SER and the segregation (within-module degree) and integration (participation coefficient) of major ICNs across the brain. Further, we assess whether SER levels are differentially related to the segregation and integration of different ICNs (e.g. greater segregation and lower integration in certain networks; the reverse in others). Finally, to understand whether the network-specific effects of SER are random or systematic, we interrogate whether associations between SER and brain architecture are spatially patterned along the sensorimotor-association axis.

We performed our analyses in the ABCD Study, a population-based consortium study of 11,875 9- and 10-year-olds with substantial sociodemographic diversity (39). As in our prior report (20), we constructed a latent factor of SER across household and neighborhood contexts. We establish that SER has robust multivariate links with network integration/segregation. Moreover, we delineate network-specific effects, with higher SER related to greater integration of sensorimotor networks but greater segregation of association networks. Lastly, we demonstrate that associations with SER strongly relate to the transmodal axis. These findings add valuable interpretive information by establishing that associations between SER and functional connectivity spatially conform to the sensorimotor-association axis during development.

Materials and methods

Sample and data

The ABCD Study is a multisite longitudinal study with 11,875 children between 9 and 10 years of age from 22 sites across the United States. The study conforms to the rules and procedures of each site's Institutional Review Board, and all participants provide informed consent (parents) or assent (children). Data for this study are from ABCD Release 3.0.

Data acquisition, fMRI preprocessing, and connectome generation

High spatial (2.4 mm isotropic) and temporal resolution (800 ms) resting-state fMRI was acquired in four separate runs (5 min per run, 20 min total). Preprocessing was performed using fMRIPrep v1.5.0 (40). Briefly, T1-weighted (T1w) and T2-weighted images were run through recon-all using FreeSurfer v6.0.1, spatially normalized, rigidly coregistered to the T1, motion corrected, normalized to standard space, and transformed to CIFTI space.

Connectomes were generated for each functional run using the Gordon-333 atlas (13), augmented with parcels from high-resolution subcortical (41) and cerebellar (42) atlases. Volumes exceeding a framewise displacement (FD) threshold of 0.5 mm were marked to be censored. Covariates were regressed out of the time series in a single step, including linear trend, 24 motion parameters (original translations/rotations, derivatives, and quadratics), aCompCorr 5 cerebrospinal fluid (CSF) and 5 white matter (WM) components and ICA-AROMA aggressive components, high-pass filtering at 0.008 Hz, and censored volumes. Next, correlation matrices were calculated. See Supplementary material and fMRIPrep Supplementary material for full processing details.

Inclusion/exclusion

There are 11,875 subjects in the ABCD Release 3.0 dataset. Subjects were excluded for: failing ABCD quality control (QC), insufficient number of runs each 4 min or greater, failing visual QC of registrations and normalizations, and missing data required for regression modeling (see Supplementary material for details). This left $N = 5{,}821$ participants across 19 sites for the main analysis.

Graph theoretic analysis

Since most graph theory measures require unsigned edge weights, each participant's connectome resulted in two separate sets of graphs—one for positive edges and another for negative edges (43, 44). We focused on positive graphs consistent with previous graph theoretical investigations (43, 44), though supplementary analyses revealed that negative graphs did not add meaningful predictive information (see Supplementary material).

To estimate network segregation, we calculated *within-module degree*, a node-wise measure that captures each node's strength (i.e. magnitude of summed connectivity weights) within its own network. This measure is a modification of the "module degree z-score" metric (28), but without within-network z-scoring of node strength to better capture differences across participants, rather than differences across nodes within each network. Formally, the within-module degree of a node i is given by:

$$\sum_{j=1}^{N_i} e_{ij},$$

where e_{ij} is the edge weight between nodes i and j, and N_i is the set of nodes incident to node i that are in the same network as i. Greater network segregation involves stronger within-network connectivity and is thus reflected in higher within-module degree.

To estimate network integration, we calculated participation coefficient, a node-wise measure that captures the diversity of a node's connections with nodes outside its own network (28). Intuitively, if a node distributes its connectivity evenly across all networks, its participation coefficient will be 1, while departures from equality yield commensurately lower scores. Formally, the participation coefficient of a node i is given by:

$$1 - \sum_{m}^{M} \left(\frac{e_i(m)}{e_i} \right)^2,$$

where M is the set of networks, $e_i(m)$ is the sum of edge weights between node i and all nodes in network m, and e_i is the sum of edge weights between node i and all other nodes. Greater network integration involves stronger between-network connectivity and is thus reflected in higher participation coefficient.

For both metrics, we used the community structure defined by the applied parcellation schemes to determine network boundaries. Within-module degree (MDP) and participation coefficient (PCP) for positive edges were calculated for 418 nodes, yielding 836 node-wise graph theoretic features per participant.

Latent variable modeling

We constructed a latent variable for SER by applying exploratory factor analysis to household income-to-needs, parental education, and neighborhood disadvantage (20) (see Supplementary material for details). Household income-to-needs represents the ratio of a household's income relative to its need based on family size. Parental education was the average educational achievement of parents or caregivers. Neighborhood disadvantage scores reflect an ABCD consortium-supplied variable (reshist_addr1_adi_wsum). In brief, participants' primary home address was used to generate area deprivation index values (45), which were weighted based on results from Kind et al. (46) to create an aggregate measure.

Statistical analyses

To quantify the multivariate relationship between these 836 graph theoretic metrics and SER, we used principal component regression predictive modeling (47, 48) (Fig. S2). Briefly, this method performs dimensionality reduction on the set of predictive features (i.e. MDP/PCP), fits a regression model on the resulting components (where the number of components is determined in nested cross-validation), and applies this model out-of-sample using leave-one-site-out cross-validation (LOSO-CV). We control for multiple covariates including sex assigned at birth, parent-reported race/ethnicity, age, age-squared, mean FD, and mean FD-squared. We controlled for race/ethnicity, a social construct, to account for differences in exposure to personal/systemic racism, disadvantage, and opportunity among people of color (49). Statistical significance was determined with nonparametric permutation tests, using the procedure of Freedman and Lane (50) to account for covariates. Exchangeability blocks were used to account for twin, family, and site structure and were entered into permutation analysis of linear models (51) to produce permutation orderings (see Supplementary material for details).

To quantify the univariate relationship between each of the 836 graph theoretic metrics and SER, we conducted 836 separate univariate linear regression models predicting SER from the MDP and PCP of each node. These models controlled for the same covariates as our multivariate analyses, as well as study site. We extracted standardized regression coefficients and evaluated statistical significance after correcting for multiple comparisons separately for MDP (418 models) and PCP (418 models) using the Benjamini–Hochberg false discovery rate (FDR) (52).

To characterize the spatial patterning of associations between brain architecture and SER, we downloaded the CIFTI data for the principal gradient of functional connectivity in a previous report (38) and calculated an average transmodality score for each region of interest (ROI). As both the prior and current studies are in the

same CIFTI space, this gradient data spanned cortical, subcortical, and cerebellar ROIs. We correlated node-wise transmodality scores with the MDP/PCP standardized regression coefficients from the univariate analyses described above. As distance-dependent spatial autocorrelation can inflate this relation, statistical significance was determined using Moran spectral randomization, which can be used for brain data beyond the cortical surface (53, 54). This procedure uses an inverse distance matrix based on spatial data, which is decomposed into spatial eigenvectors that estimate spatial autocorrelation (55). These eigenvectors are then applied to random normal data to generate null data with a similar spatial structure, which can be compared to the observed results.

Results

Within-module degree and participation coefficient are strongly related to socioeconomic resources

As reported in our previous study (20), the LOSO-CV out-of-sample multivariate relationship between SER and the entire connectome (87,153 connections) was $r_{cv} = 0.274$, $P_{PERM} < 0.0001$. Against this benchmark result, we found that the LOSO-CV out-of-sample multivariate relationship between SER and these 836 node-wise graph theoretic measures (MDP/PCP) was $r_{cv} = 0.162$, $P_{PERM} < 0.0001$. Thus, the linear MDP/PCP–SER relationship is 59.1% as strong as the whole connectome–SER relationship.

We next examined whether the 836 MDP/PCP features reflect distinct or overlapping variance in predicting SER relative to the 87,153 connections of the entire connectome. We built a stacked model that predicted SER from both the full connectome predictive model, and the MDP/PCP predictive model. This stacked model's LOSO-CV out-of-sample performance was $r_{cv} = 0.268$; that is, the stacked model performed no better than the full connectome model alone.

These results suggest two conclusions. First, the graph theoretic features represent a subset of the variance explained by the whole connectome. Second, there is strong concentration of SER predictivity in the MDP/PCP features, wherein these 836 graph theoretic features account for the majority of the multivariate relationship between the functional connectome and SER.

Associations between socioeconomic resources and patterns of integration/segregation differ across intrinsic connectivity networks

We next conducted univariate analyses to characterize how topological associations with SER are spatially distributed across ICNs. SER was significantly related to the MDP of 67 nodes (16.0% brain regions) and the PCP of 45 nodes (10.8% brain regions), broken down by ICN in Table S2. As depicted in Fig. 1, different ICNs exhibit strongly divergent relationships with SER, with four notable zones. Zone 0 contains the majority of nodes that lack significant relations with SER. In zone 1, we observe significant positive betas for MDP in default mode network, an unlabeled network (dubbed "None") primarily anchored in orbitofrontal cortex, and cerebellum, indicating stronger within-network connectivity (greater segregation) within these networks with higher SER. In zone 2, we observe significant positive betas for PCP primarily in subcortical networks, indicating stronger between-network connectivity (greater integration) within this network with higher SER. In zone 3, we observe significant betas for both MDP (negative betas) and PCP (positive betas) primarily in the somatomotor network, indicating weaker within-network connectivity (lower segregation) and stronger between-network connectivity (higher integration) within this network with higher SER.

Socioeconomic resources exhibit divergent relationships with network integration/segregation across the unimodal–transmodal gradient

As SER levels were differentially linked to the segregation/integration profiles of different ICNs, we examined whether these differences spatially conform to the transmodality axis. As shown in Fig. 2, we found that transmodality scores were positively associated with regression coefficients that characterize the relationship between SER and MDP ($r = 0.42$, $P_{PERM} < 0.001$), and negatively associated with regression coefficients that characterize the relationship between SER and PCP ($r = -0.21$, $P_{PERM} = 0.011$); note that permutation P-values for this analysis were calculated using the Moran spectral randomization method (see Materials and methods section) to account for spatial autocorrelation. These results provide quantitative support that SER levels exhibit divergent topological associations across the transmodality gradient, with higher SER levels yielding greater integration (lower MDP and higher PCP) at the sensorimotor processing pole and greater segregation (higher MDP and lower PCP) at the association processing pole.

Associations between socioeconomic resources and network integration/segregation are robust to methodological variation

To verify the robustness of our results, we performed two sensitivity analyses (see Supplementary material for details). First, while our LOSO-CV approach facilitates out-of-sample generalizability, we also followed a similar procedure to previous ABCD studies (56, 57) and replicated our finding that SER exhibits a strong multivariate relation with node-wise MDP/PCP after splitting our sample into sociodemographically matched discovery/replication datasets. Second, as regional boundaries, network affiliations, and topological properties are conditional on the selected parcellations, we replicated our results using an alternate (Schaefer-300) cortical atlas (14). These sensitivity analyses confirm the robustness of our findings characterizing the topological associations, and their spatial patterning, of SER.

Discussion

SER across childhood and adolescence calibrate structural and functional neurodevelopment, with potent implications for physical health, occupational attainment, and emotional wellbeing across the lifespan (7, 8). In the present report, we leverage graph theory and the largest neuroimaging cohort of youth to date to inform our understanding of how variation in SER may become biologically expressed along the developing functional architecture of cognitive, affective, and sensorimotor brain systems. We found that SER was robustly associated with two graph theoretic metrics that decompose brain organization in terms of segregation (separability of different ICNs) and integration (communication between different ICNs). Importantly, topological associations with SER were not uniform across the brain; rather, higher SER levels were related to greater integration of somatomotor and subcortical systems, but greater segregation of default mode, orbitofrontal, and cerebellar systems. Finally, we demonstrate that SER-related network associations were spatially patterned along the brain's transmodal axis. These findings provide critical interpretive context for the established and widespread associations of SER with the intrinsic functional architecture of the developing brain.

Previous studies characterizing the neural embedding of SER have predominantly examined connections between individual pairs of regions (e.g. prefrontal–amygdala connectivity) (12).

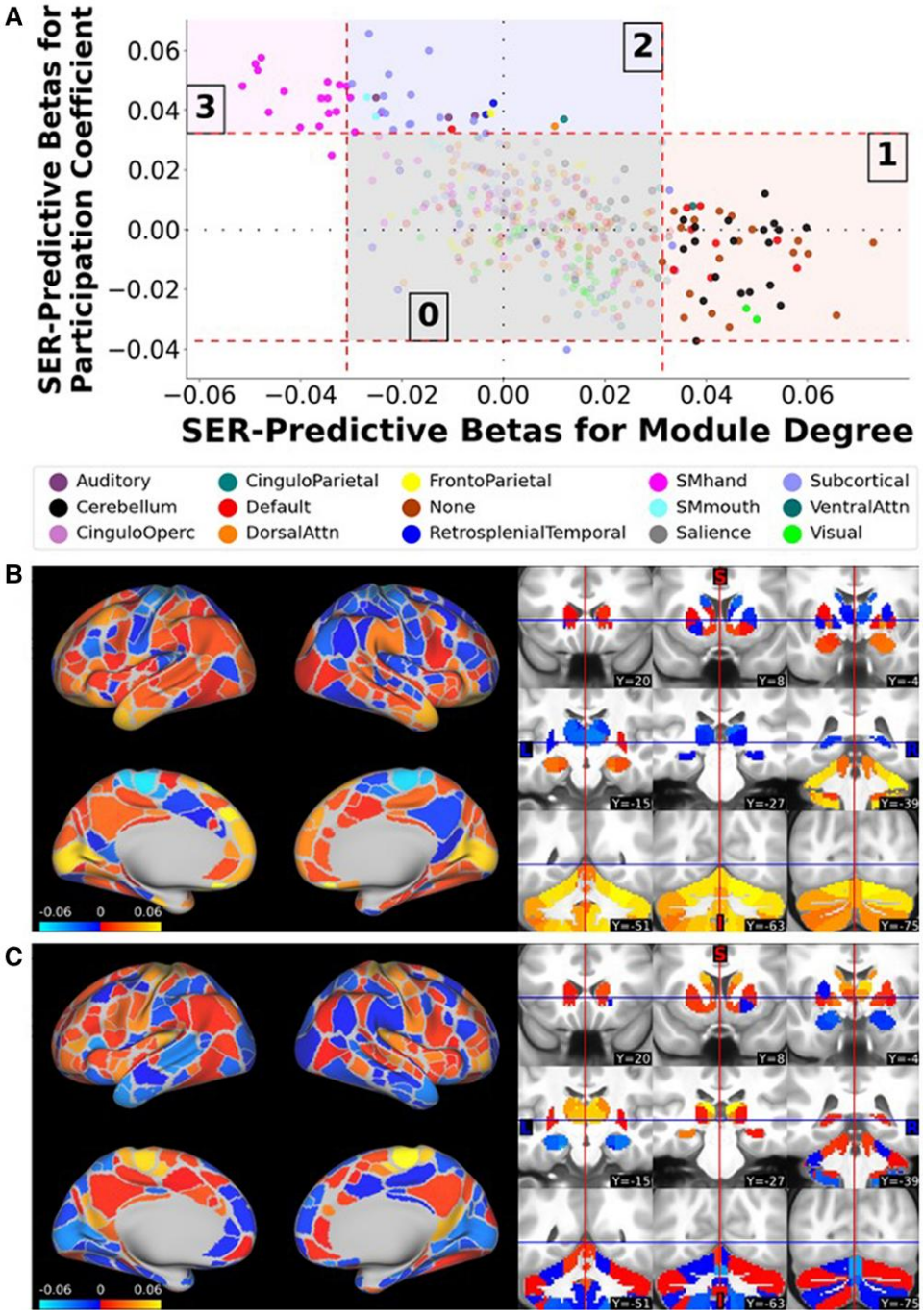

Fig. 1. Associations between socioeconomic resource (SER) levels and functional brain architecture. A) Profile plot. For each of the 418 brain regions, we conducted a univariate regression analysis predicting SER from within-module degree (MDP) and participation coefficient (PCP) for positive edges. This plot depicts the pair of standardized regression beta weights (MDP and PCP) for each node (referred to as "SER-predictive beta"), with nodes shaded by network affiliation. Positive values reflect that higher SER levels are associated with greater segregation on the x axis (MDP) and greater integration on the y axis (PCP), and vice versa for negative values. As such, from Left to Right and Top to Bottom, higher SER levels become associated with increasingly higher segregation and lower integration. Dashed lines represent the thresholds for statistically significant univariate relationships following multiple comparison correction using the false discovery rate (418 models for MDP and 418 models for PCP). Zone 0 (transparent nodes) contains the majority of nodes that lack statistically significant relations with SER. Zone 1 nodes exhibit positive SER-predictive betas for MDP, consistent with greater segregation of these nodes with higher SER. Zones 2 and 3 exhibit higher SER-predictive betas for PCP (zones 2 and 3) and lower SER-predictive betas for MDP (zone 3), consistent with greater integration of these nodes with higher SER. The hand somatomotor network in the upper left stands out as exhibiting particularly extensive integration with higher SER. CinguloOperc, Cingulo-Opercular network; DorsalAttn, dorsal attention network; SMhand, somatomotor hand network; SMmouth, somatomotor mouth network; VentralAttn, ventral attention network. B, C) Brain figures visualizing the spatial pattern of the univariate relationship (standardized regression coefficients) between SER levels and B) MDP and C) PCP of cortical, subcortical, and cerebellar nodes.

Given brain-wide associations with SER (12, 18–20), and the thousands of connections that undergird behavior (11), our group recently conducted a multivariate predictive modeling study of SER in the ABCD Study (20). We revealed that the correlation between actual SER and SER predicted from 87,153 connections at rest was 0.27, yet the neuroscientific meaning of these findings remained unclear. In the present study, we implemented graph theory to distill and reduce these 87,153 connections into only

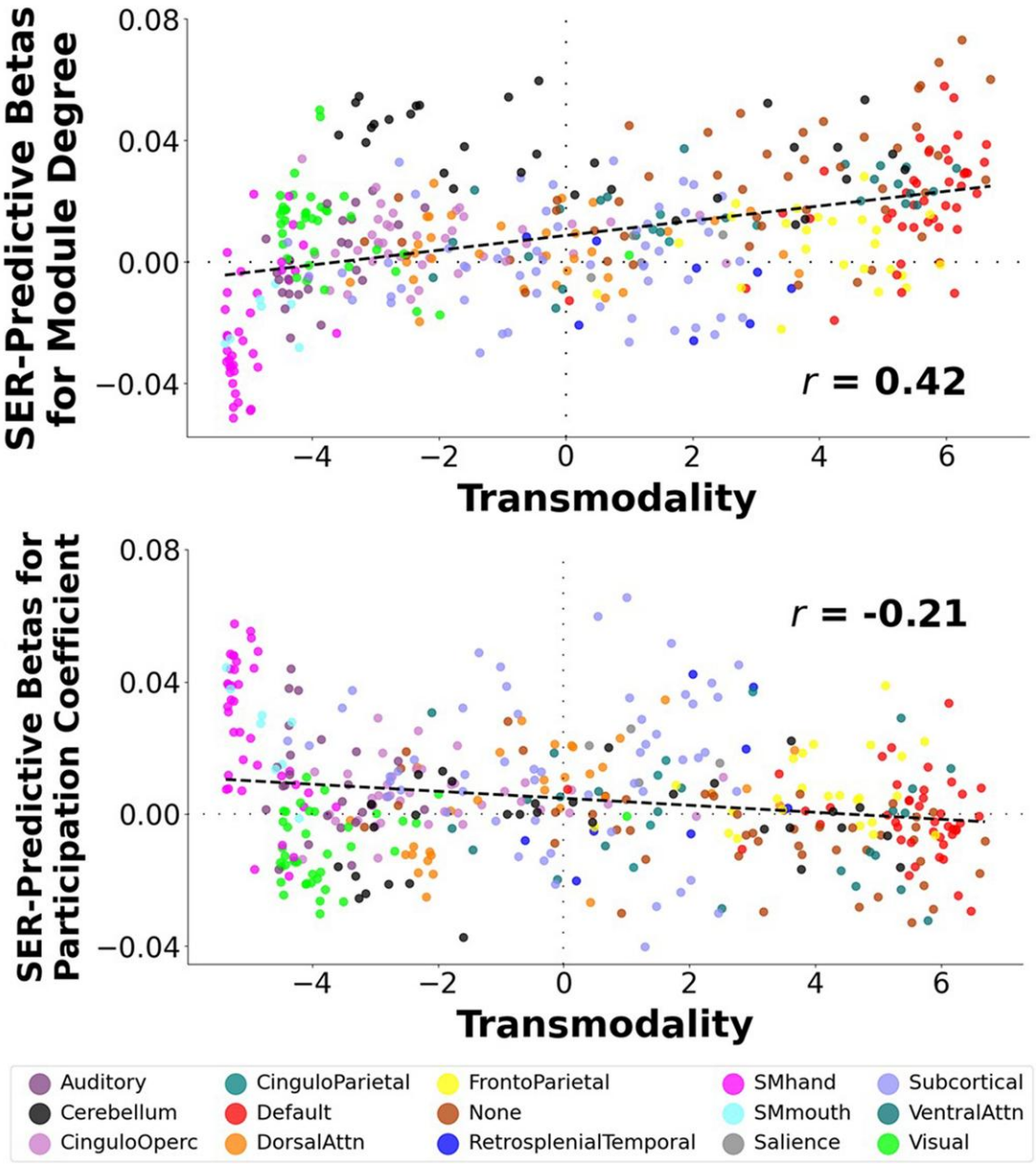

Fig. 2. Spatial pattern of associations between socioeconomic resource (SER) levels and functional brain architecture along the unimodal–transmodal axis of brain organization. Transmodality scores from 418 nodes were extracted from a previous report (38), which locates nodes along a continuous gradient with lower-order somatosensory processing networks at one end (lowest transmodality scores) and higher-order association networks at the other end (highest transmodality scores). As such, from Left to Right, brain regions become increasingly more transmodal. In addition, we conducted univariate regression analyses predicting SER from node-wise within-module degree (MDP; "SER-Predictive Betas for Module Degree" in Top panel) and participation coefficient for positive edges (PCP; "SER-Predictive Betas for PCP" in Bottom panel). As such, from Bottom to Top, higher SER levels become associated with increasingly higher segregation in the Top panel, and increasingly higher integration in the Bottom panel. We found a significant positive association between transmodality scores and SER-predictive betas for MDP (Top), such that higher SER levels are associated with greater segregation as brain regions become more transmodal. We found a significant negative association between transmodality scores and SER-predictive betas for PCP (Bottom), such that higher SER levels are associated with lower integration as brain regions become more transmodal. Nodes shaded by network affiliation. CinguloOperc, Cingulo-Opercular network; DorsalAttn, dorsal attention network; SMhand, somatomotor hand network; SMmouth, somatomotor mouth network; VentralAttn, ventral attention network.

836 features that describe the neural associations of SER with greater neuroscientific interpretability in terms of intra- and inter-network relationships. Specifically, we probed node-level integration and segregation using participation coefficient (between-network connectivity) and within-module degree (within-network connectivity), and found that these two metrics capture more than half of the original association with SER ($r = 0.16$). These findings indicate that these two nodal graph properties largely capture the backbone of functional brain architecture, particularly in relation to SER. Overall, our multivariate findings suggest that the developmental construction of an "optimal" small-world-like configuration may be impacted by SER.

To spatially localize the topological effects of SER, we next conducted univariate analyses probing the segregation and integration of brain regions within 15 major ICNs. First, we found that higher SER levels were associated with greater segregation (higher

within-module degree) of the default mode network, an unlabeled network (dubbed "None") primarily anchored in orbitofrontal cortex, and the cerebellum. These systems have been previously linked to SER, despite some inconsistencies in directionality (18, 19, 58, 59), and are respectively purported to support self-referential and introspective cognition, reward processing and decision-making, and cognitive and motor control (60–63). Thus, these findings may reflect neural mechanisms of goal-directed behavior as a function of the socioeconomic environment.

Second, we found that higher SER levels were associated with greater integration (higher participation coefficient) of the subcortical network implicated in emotion processing and motor planning (64, 65). These findings converge with extensive evidence linking SER to structural, functional, and connectivity profiles of subcortical regions, such as the amygdala and hippocampus (12). Given their dense expression of glucocorticoid receptors (66), these structures may be particularly sensitive to both nurturing and stressful experiences often associated with SER levels (8). Integration of subcortical regions with cortical systems subserves adaptive, contextually bound emotional learning and regulation (67), indicating a plausible network-level neural basis for adaptations in emotional behavior depending on developmental context.

Lastly, higher SER levels were strongly associated with greater integration (lower within-module degree, higher participation coefficient) of the somatomotor network. This network is not commonly considered in theoretical accounts linking SER to brain development (7, 8), despite being consistently implicated in SER and transdiagnostic psychopathology in individual studies (18, 68, 69). The somatomotor network supports motor planning and execution (60), and recent data point to its involvement in a "somatocognitive action" network that integrates motoric function with goal-directed planning (70). One possibility is that SER levels not only calibrate association systems that generate and evaluate abstract cognitive representations but also somatomotor systems that translate these abstract representations into goal-relevant behavior. These findings highlight the need for theoretical accounts and empirical studies to delineate how adversity modulates somatomotor development to confer vulnerability and resilience.

Since SER displayed divergent associations with the integration/segregation of different ICNs, we investigated whether this heterogeneity could be explained by considering how ICNs are organized along the brain's unimodal–transmodal axis. This evolutionarily rooted, hierarchical axis of brain organization is anchored by sensory and motor networks on one end and association networks on the other (36–38). This sensorimotor-association gradient captures developmental sequences of multiple neurobiological properties, from structure and myelination to plasticity and gene expression (29). In the present investigation, we hypothesized that this axis may also provide a unifying framework for characterizing the network-specific effects of SER. Consistent with this hypothesis, we found that topological associations with SER were spatially patterned along the transmodal axis, with higher SER levels associated with greater integration at the unimodal/somatosensory pole and greater segregation at the transmodal/association pole.

Over the course of neurodevelopment from childhood to young adulthood, lower-order unimodal networks (e.g. somatomotor network) become more integrated, whereas higher-order association networks (e.g. default mode network) become more segregated (30, 31). Thus, the construction of integrated somatomotor systems and segregated association systems may represent a universal milestone of functional neurodevelopment. Against this backdrop, our findings suggest that higher SER may facilitate the emergence of this sensorimotor-association hierarchy. Conversely, lower SER may delay the emergence of this configuration, consistent with cross-sectional and longitudinal findings suggesting disadvantage-related delays in the pace of neurodevelopment (19, 71–74). Candidate mechanisms for protracted neurodevelopment following disadvantage include material hardship (e.g. resource access and lower-quality nutrition), less complex social and cognitive stimulation (e.g. under-resourced schools and complex reading materials), and toxicant exposure (e.g. lead) (8, 73). These exposures may alter synaptic proliferation and pruning, and ultimately maturational refinements in network communication (integration) and specialization (segregation) (75).

Nevertheless, an alternative interpretation of our findings is that developmental trajectories, milestones, and outcomes of brain development may be qualitatively different depending on SER. While higher SER youth may establish an integrated unimodal and segregated transmodal pole across development, lower SER youth may develop distinct topological profiles that allow them to successfully navigate the unique demands of disadvantaged environments. At the same time, these profiles could also incur cognitive and socioemotional challenges across the lifespan (76). This latter hypothesis dovetails with data indicating that functional connectivity patterns that optimize cognition differ in high- versus low-SER contexts (77), as well as a recent review of longitudinal studies concluding that disadvantage may engender unique, rather than temporally shifted, trajectories of structural brain development (75).

In a separate report (in preparation), we conducted similar analyses investigating associations between sleep duration, rather than SER, with the integration/segregation of the same 15 ICNs in the ABCD Study. Strikingly, we found that sleep duration displayed similar but even stronger associations with brain architecture. Consistent with the reported associations of SER, these effects were strongest for the organization of the somatomotor network, such that shorter sleep duration was associated with a more segregated somatomotor network. Overall, these findings suggest that somatomotor architecture may represent a robust neural signature associated with multiple forms of environmental stress and opportunity during development.

Our study has several limitations that will be important to address in future research. First, our analyses are cross-sectional and thus do not support inferences about the direction of causality or patterns of neurodevelopment. As neuroimaging data from future ABCD waves are released, future studies should disentangle the direction of effects and assess how the spatially divergent effects of SER unfold longitudinally across development. Second, SER levels in the ABCD Study are overall higher compared to the national population, an issue further exacerbated by our exclusion criteria (e.g. head motion cutoffs) (78, 79); thus, caution should be exercised when attempting to generalize our findings to the broader population nationally and worldwide. Third, given our focus on defining how topological associations of SER unfold along the transmodality axis, we did not seek to examine how these complex context–brain associations mediate or are moderated by behavior and mental health. Lastly, in our previous multivariate study of SER (20), granular analyses demarcated that parental education was the primary factor related to functional connectivity (compared to family income-to-needs and neighborhood disadvantage). Here, our focus is on interpreting and spatially localizing these multivariate effects. This objective introduces challenges in dissecting the unique role of each SER component, which constitutes an important future direction to inform priorities for policy, prevention, and intervention.

The present study provides essential neuroscientific meaning to the established and widespread effects of SER on brain

connectivity. By integrating methodological advancements in network neuroscience with theoretical frameworks of brain organization, we demonstrate that associations between SER and network integration/segregation in youth unfold differentially along the brain's transmodal axis, with stronger effects on default mode, cerebellar, subcortical, and somatomotor networks. Our findings suggest that SER may calibrate the intrinsic graphical architecture of the developing brain, highlighting the importance of preventive interventions and policy changes that mitigate exposure to disadvantage and scaffold healthy neurobehavioral development regardless of context.

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The ABCD Study is a multisite, longitudinal study designed to recruit more than 10,000 children aged 9–10 years and follow them over 10 years into early adulthood. A full list of supporters is available at: https://abcdstudy.org/about/federal-partners/. A listing of participating sites and a complete listing of the study investigators can be found at: https://abcdstudy.org/principal-investigators.html. ABCD consortium investigators designed and implemented the study and/or provided data but did not necessarily participate in analysis or writing of this report. This manuscript reflects the views of the authors and may not reflect the opinions or views of the NIH or ABCD consortium investigators. The ABCD data repository grows and changes over time.

Supplementary Material

Supplementary material is available at *PNAS Nexus* online.

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Author Contributions

C.M. conceptualization, formal analysis, investigation, methodology, and writing—original draft; A.T. and M.A. data curation, formal analysis, methodology, resources, and visualization; O.K., A.W., M.F.M., and K.L.M. writing—review & editing; L.W.H. resources and writing—review & editing; M.M.H. funding acquisition, resources, and review & editing; C.S. conceptualization, funding acquisition, investigation, methodology, resources, visualization, and writing—original draft.

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Data Availability

The present project used data from the ABCD Study (https://abcdstudy.org), held in the NIMH Data Archive (NDA), an open-source dataset of >10,000 youth followed longitudinally to understand brain and behavioral development across adolescence. The data used in this report came from the National Institute of Mental Health Data Archive (NDA) Study 901, 10.15154/1520591 (https://nda.nih.gov/study.html?id=901), and the data used in our analyses can be found at: NDA DOI: 10.15154/ebhq-f780. The code for the analyses presented is publicly available through a Github repository (https://github.com/SripadaLab/ABCD_Resting_SER_GraphTheory).

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