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Original Article

Brain connectivity and academic skills in English learners

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English learners (ELs) are a rapidly growing population in schools in the United States with limited experience and proficiency in English. To better understand the path for EL's academic success in school, it is important to understand how EL's brain systems are used for academic learning in English. We studied, in a cohort of Hispanic middle-schoolers ($n = 45$, 22F) with limited English proficiency and a wide range of reading and math abilities, brain network properties related to academic abilities. We applied a method for localizing brain regions of interest (ROIs) that are group-constrained, yet individually specific, to test how resting state functional connectivity between regions that are important for academic learning (reading, math, and cognitive control regions) are related to academic abilities. ROIs were selected from task localizers probing reading and math skills in the same participants. We found that connectivity across all ROIs, as well as connectivity of just the cognitive control ROIs, were positively related to measures of reading skills but not math skills. This work suggests that cognitive control brain systems have a central role for reading in ELs. Our results also indicate that an individualized approach for localizing brain function may clarify brain-behavior relationships.

Key words: English learners; functional connectivity; reading; math; cognitive control.

Introduction

English learners (ELs) are individuals who come from non-English speaking backgrounds or homes, and matriculate into English-speaking schools (McCardle et al. 2005). Unique from their grade-level peers, ELs are asked to perform academically in their non-dominant language, which often contributes to extensive achievement and skill gaps in reading and math (Fry 2007; Calderón et al. 2011; Richards-Tutor et al. 2016; Garcia and Kleifgen 2018). The "EL" label is a school-level designation of English proficiency and includes individuals with a wide range of language experiences and socioeconomic backgrounds (McCardle et al. 2005; Garcia and Kleifgen 2018). However, many ELs, especially Spanish-English ELs who make up a majority of ELs in the United States, tend to come from lower socioeconomic backgrounds (NCES 2018; Our Nation's English Learners 2018). Past experience (or lack thereof) with speaking and formal schooling in English in this student population has likely shaped the neural architecture for reading and math with pronounced individual differences across ELs. The goal of the current study was to use fMRI to map the brain systems that support cognitive control and academic skills in ELs, and then to examine how these systems relate to each other at rest, and to standardized tests of academic skills outside of the scanner. This work builds toward a neurocognitive framework for understanding and optimizing outcomes for this diverse group.

Domain general brain systems, such as those supporting cognitive control, are important neurocognitive factors for understanding learning in ELs. Cognitive control systems are critical for flexibly orchestrating complex behaviors and carrying out behavioral goals over different time scales (Diamond 2013; Power and Petersen 2013; Botvinick and Braver 2015). In non-EL students, task-specific language or number processing brain regions are recruited along with domain-general cognitive control regions during reading or math task performance (Emerson and Cantlon 2012; Nugiel et al. 2019; Roe et al. 2018; Sokolowski et al. 2017). Task brain engagement and functional connectivity of cognitive control systems are also related to out-of-scanner reading skills (Aboud et al. 2018; Roe et al. 2018; Jolles et al. 2020), math skills (De Smedt et al. 2013; Wilkey and Price 2019), and response to academic intervention (Horowitz-Kraus et al. 2015b; Nugiel et al. 2019). The burden of acquiring an academic skill is higher for ELs: they need to manage communication across two languages and they generally need to maintain their non-dominant language over the school day (Calderón et al. 2011; Garcia and Kleifgen 2018). Both of these demanding language tasks likely require heavy support from domain general cognitive control systems (Kapa and Colombo 2013).

The current study uses graph metric measures of the brain in a resting state to understand the functional interactions between brain regions supporting reading, math, and cognitive control. The

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resting state is thought to reflect an individual's historical co-activation of brain regions that are active together for different tasks demands (Biswal et al. 1995; Fox et al. 2007; Demeter et al. 2020). Resting state functional connectivity (RSFC) data, which is collected while individuals are awake in the scanner without an overt task or stimulus, has been widely used to characterize brain function, and then to relate that brain function to cognitive skills (Vaidya and Gordon 2013).

There are a number of studies done in monolingual samples spanning childhood through adulthood that show that the RSFC of reading-related brain regions is related to out-of-scanner reading (Koyama et al. 2011; Jolles et al. 2020; Cross et al. 2021), while the RSFC of math-related brain regions is related to out-of-scanner math skills (Evans et al. 2015; Price et al. 2018; Zhang et al. 2019; Lynn et al. 2021).

The RSFC of the brain's domain-general cognitive control systems are also linked in monolingual samples to tests of reading skills (Bailey et al. 2018; Horowitz-Kraus et al. 2015b; Twait et al. 2018) and math skills (Nemmi et al. 2018; Lynn et al. 2021). This work has been done in groups of students whose reading and math skills are being tested in their native language. ELs likely need to exert effortful control above and beyond monolingual/native English-speaking students when reading and doing math lessons in English-speaking schools. Based on neuroimaging evidence from bilingual (though not necessarily EL) samples, managing two languages over time can shape the function of brain regions recruited for reading and math (Jones et al. 2012; Van Rinsveld et al. 2017), as well as cognitive control brain systems (Bialystok et al. 2012; Abutalebi and Green 2016; Sun et al. 2019). Examining RSFC in ELs both within the systems important for reading, math, or cognitive control, as well as across these three functional systems, could help us better understand individual differences in academic outcomes and the role cognitive control plays in academic success.

Mapping out academic-specific and domain-general brain regions important for learning in ELs can provide a brain basis for variability in academic outcomes in this group. This endeavor highlights a current challenge in cognitive neuroscience: how to accurately map heterogeneity in brain organization across individuals. Cognitive neuroscience research has long focused on localizing brain areas with putative functional roles. Using a group-average approach, the field has successfully mapped many neurocognitive processes, such as the brain systems supporting reading (e.g. Price 2012) and math (Menon 2015). However, these processes are also known to vary across individuals and groups (Welcome and Joanisse 2012; De Smedt et al. 2013). Pronounced individual differences in the cognitive processes we want to map, such as reading in English in heterogenous ELs, may muddle any results in a group-average approach. The influence of individual differences may also make a literature-applied regions of interest (ROI) approach non-optimal.

The issues with functional region definition across individuals have been met with a call for "personalized neuroscience," including using methods for mapping the brain at the individual level (Gordon et al. 2017; Gratton and Braga 2021). When done with large quantities of data per person, personalized brain mapping has revealed robust individual variability in the functional connectivity of canonical brain systems and structures (Gordon et al. 2020; Greene et al. 2020). One significant caveat to this approach, as reported thus far, is that it requires a substantial amount of motion-free functional data from an individual (30–100 min; Gordon et al. 2017). Obtaining highly sampled individual fMRI data is especially challenging for the analyses of developmental and clinical groups, and necessarily limits sample size. A compromise between the fully personalized and the group/literature-based approaches are methods that use cognitive tasks to localize brain function at the individual level, while leveraging robust group-level constraints. Such approaches have been previously used to successfully capture individual specificity in visual (Julian et al. 2012) and language systems (Fedorenko et al. 2010).

The current study used both task-based fMRI localizers and resting state data in a set of EL middle-school students to assess the functional interactions of academic and cognitive control-related brain regions. We used graph theory to calculate graph metrics that concisely summarize information about functional connectivity between sets of many brain regions (Bullmore and Sporns 2009; Bullmore and Bassett 2011). Based on the evidence discussed above from work done in monolingual cohorts (e.g. Freedman et al. 2020; Horowitz-Kraus et al. 2015a; Price et al. 2018), and given the unique experiences and control-demanding learning contexts for ELs, we had several predictions about relationships between graph metrics indexing RSFC and academic skills. We predicted that (i) graph metrics indexing stronger RSFC *across* all regions (cognitive control, reading, and math) would relate to better reading and math skills. As discussed above, there is evidence from monolingual samples that the strength of RSFC of control regions to reading *or* math regions is related to reading or math skills. We expected to see a similar pattern of results in ELs when examining all three sets of regions together as well as examining graph metrics that index how connected cognitive control regions are to regions outside of their group. (ii) Due to the important contributions of cognitive control brain systems for academic performance, we predicted graph metrics indexing stronger functional connectivity of cognitive control ROIs to each other would positively relate to standardized measures of reading and math skills. There is some evidence from monolingual samples that RSFC within cognitive control regions is related to better reading (Horowitz-Kraus et al. 2015b), and we predicted that this would also be true in ELs, due to the effortful control needed in their learning context. (iii) Due to the co-recruitment of reading-related regions to read, and math-related regions to do math tasks, we predicted graph metrics indexing stronger functional connectivity of reading regions to each other, or math regions to each other, would relate to higher reading or math skill, respectively. (iv) Importantly for this sample, since ELs have varied English proficiency which can shape both brain function and academic skills, we predicted that English proficiency would account for variance in the brain-behavior relationships. We predicted that Spanish proficiency would not account for variance in these brain-behavior relationships, both because students were less variable overall in their Spanish proficiency, and because of primary instruction occurring in English for both reading and math. This work provides key neurobiological evidence for the patterns of interaction between cognitive control-, reading-, and math-related brain regions that are important for academic skills in ELs, an understudied but growing student population in the United States (NCES 2018) with unique learning needs.

Methods and materials

Participants

Participants were recruited as part of a larger Texas Center for Learning Disabilities study (TCLD, NICHD P50 HD052117) focused on reading interventions in Spanish-English ELs. Individuals in 6th and 7th grade ($n = 74$, mean age = 12.32 yr, sd = 0.9, 31

Table 1. Participant group demographics.

N	45
Female	22 (49%)
Age in years (SD)	12.7 (0.78)
# identified as struggling readers	26
Reading fluency	85.02 (15.58)
Word reading	87.78 (17.27)
Reading comprehension	87.73 (12.51)
Math fluency	88.64 (10.45)
Math computation	92.55 (11.62)
English proficiency	7.26 (1.9) $n = 41$
Spanish proficiency	7.68 (1.83) $n = 41$
Hispanic/Latino	45

Notes. Standardized scores of Word Recognition Fluency, Letter Word Recognition, Math Computation, and Math Fluency were measured with the Kaufman Test of Education Achievement III (Kaufman 2014); reading comprehension was measured with the Gates-MacGinitie Reading Test, (MacGinitie et al. 2000); standard deviations are in the parentheses; Spanish and English proficiency were measured with an adapted version of The Language and Social Background Questionnaire (Anderson et al. 2018) on a scale of 1–10, with higher scores meaning better proficiency. ELs who failed the reading portion of the State of Texas Assessment of Academic Readiness (STAAR testing) from the previous year were identified as struggling readers. $n = 45$ for all measures except for language proficiency measures where $n = 41$.

females,) were recruited from middle schools in Houston, Hutto, and San Antonio, Texas. The current study analyzed a subset of individuals who met study and inclusion criteria ($n = 45$; Table 1, see exclusion reasons in *MRI processing*). All students recruited for the study were currently labeled as ELs or 'English low proficiency' based on their school's specific criteria. Our sample also included students who had been reclassified out of EL status within the last 2 years but were still being monitored for English low proficiency. All study participants were able to comprehend all research instructions in English. ELs who failed the reading portion of the State of Texas Assessment of Academic Readiness (STAAR testing) from the previous year were also identified as struggling readers, though for the purpose of this study reading ability is treated as continuous. Parents were consented and interacted with in either Spanish or English, depending on their preference. Given the focus of the larger TCLD study, 100% of participants were Hispanic (including Hispanic multiracial). Participants were excluded from the MRI aspect of the study if they were reported to have head trauma, epilepsy, MRI scanner contraindications such as a non-removable metal implant, or vision that could not be corrected with MR-compatible glasses. Participants were compensated for their time, while families were compensated for travel. All collection aspects were approved by the University of Texas at Houston Institutional Review Board.

Measures of academic skill and language proficiencies

An in-school standardized testing battery included reading measures, such as reading fluency and word reading (Word Recognition Fluency and Letter Word Recognition, subtests of the Kaufman Test of Education Achievement III; KTEA-3 [Kaufman 2014]), reading comprehension (Gates-MacGinitie Reading Test, [MacGinitie et al. 2000]), as well as measures of computation and math fluency (Math Fluency and Computation subtests of the KTEA-3). These measures were collected at the beginning of the school year. Additionally, a self-report measure of Spanish and English proficiency was collected 1 yr after cohort data collection began, using an adapted version of The Language and Social Background Questionnaire (Anderson et al. 2018).

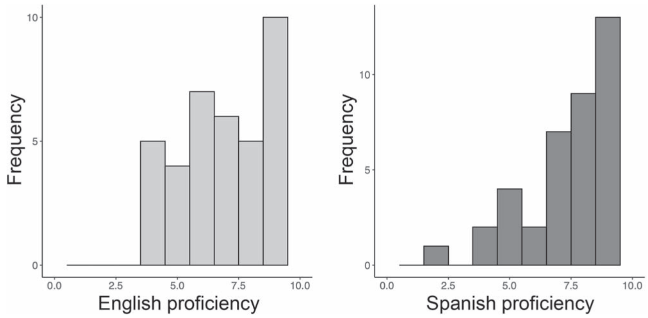

Fig. 1. Variability in English and Spanish proficiency. Histograms of English and Spanish proficiency for the EL students who completed The Language and Social Background Questionnaire ($n = 41$). Measures of reading, speaking, understanding, and writing in English and Spanish were averaged to create one self-reported measure of English proficiency and one self-reported measure of Spanish proficiency.

Measures of reading, speaking, understanding, and writing in English and Spanish were averaged to create one self-reported measure of English proficiency and one self-reported measure of Spanish proficiency (for variability in language proficiency measures see Fig. 1). Of note, four participants did not complete the language proficiency questionnaire and were excluded from relevant analyses (Table 1).

MRI acquisition

All MRI data were acquired using Siemens 3 T scanners in Houston (Prisma) and Austin (Vida). We have aligned multiple aspects of our protocol with the NIH-funded Adolescent Brain Cognitive Development (ABCD) study (Casey et al. 2018) for future data sharing purposes. High resolution anatomical images covering the entire brain were obtained using an accelerated 3d T1-weighted sequence. Isotropic images ($0.8 \times 0.8 \times 0.8$ mm^3) were acquired in the sagittal plane (FoV = 256×256, TR/TE = 2,400/2.18 ms, $\alpha = 8$ [time = 6′38″]). A T2-weighted sequence was also collected ($0.8 \times 0.8 \times 0.8$ mm^3) acquired in the sagittal plane (FoV = 256×256, TR/TE = 3,200/564 ms, α = variable [time = 5′57″]). Task and rest scans were collected in a fixed interleaved order of resting state, reading and math task, cognitive control task, and this order was repeated a second time. A 2d EPI-based, whole brain functional sequence consisting of axial 2.4 mm isotropic slices ($n = 60$) was used for each of the resting state and functional runs (FOV = 216×216, TR/TE = 800/32 ms, MB = 6, 403–450 frames per run). Each scan session lasted ~90 min.

Reading and math task. A block-design fMRI task was used to delineate brain regions that respond to facets of reading and math (Fig. 2A. There were eight task blocks per run, consisting of two each of a phonological rhyming task (do two words rhyme?), an orthographic matching task (do two words visually match?), an addition confirming task (does the equation match the solution?), and a subtraction confirming task (does the equation match the solution?). Each skill pair (reading, math) had a simpler task (matching, addition) and a less automatic task (rhyming, subtraction). The tasks used high frequency words (Balota et al. 2007) and single digit stimuli to enable strong performance. Each task block consisted of 8 3-s trials of a single task type with a two-choice response (yes/no). Task blocks were preceded by a 3 s instruction screen informing participants which task was happening next. Task blocks were separated by 15 s of baseline. Up to two runs of the eight task blocks (2 runs × 8 trials per block × 2 blocks per run = 32 trials per task) were collected (5′54″ mins each,

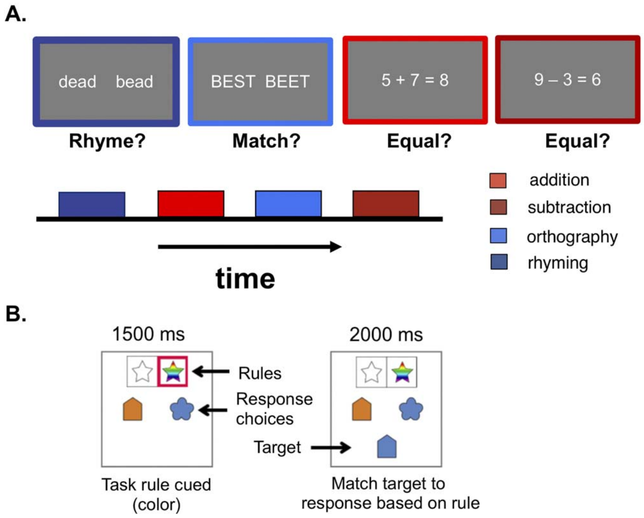

Fig. 2. Sample trials from fMRI tasks. (**A**) The block-design reading and math task. The four tasks (rhyming, matching, addition, and subtraction) were presented in eight 27 s task blocks interspersed with 15 s fixation blocks per run. (**B**) The cognitive control task was event-related and consisted of 4 s cue-target paired trials and 4 s cue only trials.

~12 mins total). The order of task blocks was counterbalanced across participants.

Cognitive flexibility task. To localize cognitive control regions, we used an fMRI cued switching task of cognitive flexibility (Bauer et al. 2017; Engelhardt et al. 2019), Fig. 2B). This task reliably elicits putative cognitive control brain networks in youth (Engelhardt et al. 2019; Nugiel et al. 2020). Participants were cued to focus on one of two features (shape or color) of a target stimulus for each trial. When the target stimulus appeared, participants then matched the target to one of two response choices based on the cued feature. Each response choice matched the target on one feature (shape or color) so attention to the cued feature was critical for success. A red box outline appeared for the first 1.5 s of the trial around the relevant feature to apply to the target ("color" in Fig. 2B). The target stimulus appeared 0.5 s after the red box disappeared, and remained on screen for 2 s, during which the participant had to respond via button press. In nine trials interspersed throughout the run, a target did not appear, and a red fixation cross was displayed for 0.5 s, followed by a white fixation cross for 0.5 s. Here combined cue + target stimulus trials were analyzed as a control systems localizer. All trials were followed by a jitter of 0–8 s. Up to 2 runs of the task were collected at 5′22″ per scan, (~11 mins total).

Resting state fMRI. To examine the inherent organization and connectivity of reading, math, and cognitive control brain regions, we collected up to two resting state fMRI scans from every individual. Individuals were instructed to keep their eyes open, stay awake, and look at a white fixation cross on a black screen for 6 min per scan (12 min total).

MRI processing

Anatomical image processing. T1 and T2 images were skull-stripped, AC/PC aligned, and parcellated with non-brain matter removed using Freesurfer version 5.3.0 (Reuter et al. 2010). The T1 and T2 parcellated, AC/PC aligned images were used to create individual surface meshes in 32 k fs_LR surface space, including pial, white matter, and midthickness (gray matter ribbon) surfaces per steps from the Human Connectome Project (HCP) processing pipeline (Marcus et al. 2011).

Task data preprocessing. Task imaging data were preprocessed using the FMRIB Software library (FSL) version 5.9 (www.fmrib.ox.ac.uk/fsl). Registration of the high resolution structural to standard MNI space was done with FMRIB's Linear Image Registration Tool (FLIRT; (Jenkinson et al. 2002; Jenkinson and Smith 2001). Images were spatially smoothed using a Gaussian kernel of FWHM 5 mm and the 4D dataset was grand-mean intensity normalized by a single multiplicative factor high pass temporal filtering (Gaussian-weighted least-squares, straight line fitting, with sigma = 100 s).

Task data first level individual run modeling. Level 1 modeling was carried out in fMRI Expert Analysis Tool (FEAT). A double-gamma HRF time-series model was carried out using FILM with local autocorrelation correction (Woolrich et al. 2001). The high-pass filter was set at 100 s. First-level models included six motion regressors, temporal derivatives for each regressor for the flexibility task only, and nuisance regressors that censor individual volumes identified to have excessive motion, defined as framewise displacement greater than 0.9 mm (Siegel et al. 2013). Task runs with <50% of frames remaining after motion censoring were not included in further analyses (2 runs of the reading and math and 4 runs of the cognitive flexibility task were dropped for motion across participants), and some participants only performed one run of a task ($n = 6$ for read-math, $n = 5$ for cognitive flexibility), thus several individuals had 1 low motion run for a given task, while most individuals had 2 runs below motion threshold ($n = 62/70$ for read-math, $n = 56/63$ for cognitive flexibility).

Functional connectivity processing. Our in-house standard processing pipeline (Demeter et al. 2020) combining tools from FSL (Smith et al. 2004), Freesurfer (Greve and Fischl 2009), and Connectome Workbench (Marcus et al. 2011) was used to process all resting state scans. Following current best practices, resting state scans were motion corrected using MCFLIRT (Jenkinson et al. 2002), mode 1 k normalized, temporal band pass filtered (0.009 HZ < f < 0.08 HZ) and demeaned and detrended. Nuisance parameters including white matter, cerebral spinal fluid, global signal (Murphy et al. 2009; Power et al. 2014), and six directions of motions plus their derivatives were regressed from the data. Functional connectivity estimation was all done in cortical surface space. Each person's surface is unique to the shape of their gray matter ribbon, allowing for more individual specificity in localizing brain function and estimating functional connectivity between brain regions. Surface processing steps were carried out on the fully processed but unsmoothed resting state data according to the steps described below. The outputs from the volume functional connectivity processing were mapped to 32 k fs_LR surface space using the following steps specified by the HCP Pipeline: (i) an individualized gray matter ribbon was created using an individual's white and pial boundaries, (ii) the gray matter ribbon was then downsampled to functional scan dimensions, (iii) voxels with high coefficient of variation were excluded to improve SNR, and (iv) volume processed resting state scans were mapped to the 32 k fs_LR surface mesh and spatially smoothed (2 mm FWHM). A CIFTI dense scalar time-series file was created for functional connectivity analyses in surface space. For all functional connectivity analyses we used strict movement-censoring, removing all frames >0.3 mm FD with at least five contiguous frames necessary to keep any frame (Power et al. 2014, 2015). At least 5 min of resting state data after motion censoring were required for any individual to be included in further analyses. Out of 70 individuals who contributed data from the reading and math tasks, 54 had enough resting state data remaining after motion censoring. For further quality control, the resting state was parcellated into 333 parcels (Gordon et al. 2016) and whole brain connectivity matrices were visually examined. An additional three individuals did not pass visual inspection of their whole-brain surface parcellated functional connectivity matrices and were excluded from further analyses. Six more individuals did not contribute enough ROIs from at least one task (see *ROI selection* sections below) and were excluded from further analyses, leaving a final group of 45 individuals.

Task-based ROI selection

Brain regions responding to each of the reading, math, and cognitive flexibility tasks were delineated for each individual. The three tasks were analyzed using second-level modeling across runs, averaged (when more than one run existed) for each participant, carried out by specifying a fixed effects structure within FMRIB Local Analysis of Mixed Effects (FLAME, Beckmann et al. 2003).

Reading and math task. The reading and math blocks were modeled as *reading* > *math* and *math* > *reading* statistical maps to extract voxels unique to each learning process. We combined across orthography and phonology tasks for reading, and across addition and subtraction tasks for math. These two group-level maps of unique math activation and reading activation were then used to extract clusters for the individualized approach.

The group activation maps of *reading* > *math* and *math* > *reading* contrasts for the reading and math tasks were taken from a larger group of ELs, which included all the individuals in the current analysis, as well as those who didn't pass criteria for the current analysis (see *Functional connectivity processing* section above, $n = 70$, mean age = 12.64, sd = 0.84). We opted to use this larger group of ELs ($n = 70$) to create more robust group maps of reading and math brain activity that weren't biased by just the individuals used in this paper's principal analyses ($n = 45$). Second level *reading* > *math and math* > *reading* maps from this larger group were combined across individuals in a 3rd level GLM using FSL's FLAME stage 1 (Woolrich et al. 2004) and thresholded using cluster-based thresholding with a $Z > 3.1$ and a $P < 0.05$ to define activations common for the group. Individualized ROIs for the $n = 45$ in this analysis were then delineated from these group-level maps.

Cognitive flexibility task. The cognitive flexibility task was modeled as *all trials* versus *fixation* to extract voxels responsive to cognitive control demands. We then applied a mask of core control regions that were activated across a set of three control-demanding tasks in a large group of children (Engelhardt et al. 2019). Activation from regions within the control mask were used to extract clusters at the individual level.

Individualized ROI approach. Our method of extracting an individual's task-based functional clusters is based on a group-constrained, subject-specific method (Fedorenko et al. 2010; Julian et al. 2012) used previously for delineating individualized face or language responsive regions.

Masking in volume space: The group defined reading, math, and cognitive control regions in volume space (Supplementary Table 1) were used as masks and applied to each individual's unthresolded Z-stat map of the corresponding contrasts (e.g. reading ROIs applied to the *read* > *math* individual level 2 Z-stat map). All activity outside the group ROIs was removed and activity within the ROIs was threshold at $Z > 0$. This allowed us to capture individual variability in responsive voxels within each group-constrained set of regions (for an example, see Fig. 3C).

Mapping individual maps to surface space and ROI identification. Once all activity outside of the group-level masks were removed,

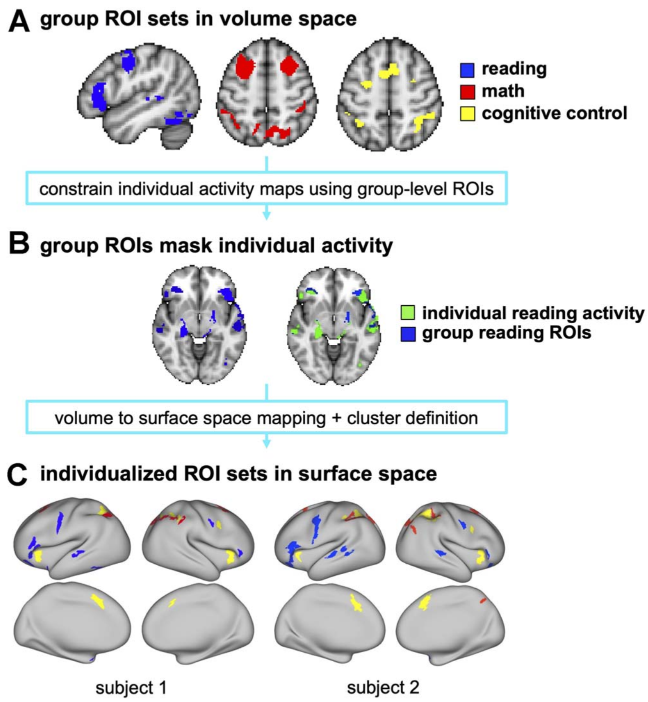

Fig. 3. Group ROIs (**A**) as constraints for individual activity. A total of 30 (10 reading, 10 math, 10 cognitive control) were used for surface individualized analyses. As an example, individual reading activity is derived from the *reading* > *math contrast* (**B**).Individualized ROIs were then projected onto an individual's gray matter ribbon using the 32 k fs_LR very inflated space (**C**), and the largest 10 ROIs were used. ROI = region of interest.

we used Connectome Workbench tools (*—volume-to-surface-mapping*) to register and project the three individualized maps of activity onto an individual's gray matter ribbon in 32 k fs_LR surface space. By using individualized cortical surfaces, we can delineate task-responsive ROIs that don't include signal from other tissue such as white matter and cerebrospinal fluid (Ghosh et al. 2010). Surface-based analyses also allow us to map activity onto individual specific gray matter, which is an advantage for an individualized ROI approach. Any activity in the medial wall below the cortex was removed from the three individualized maps, restricting analyses to the surface of the cortex. Since control systems are known to be engaged and co-opted for learning purposes (Aboud et al. 2018; Roe et al. 2018; Wilkey and Price 2018; Nugiel et al. 2019), any overlap within an individual between the cognitive control task surface maps, and the reading and math surface maps was labeled as part of the cognitive control map, and those vertices were removed from the math or reading map. Using workbench's cluster finder tool (*—metric-find-clusters*) with a threshold of $Z > 1$ we identified clusters within the individualized task-maps for each individual for each of the three maps of interest. The 10 biggest clusters for each task-map were binarized and extracted resulting in a set of 30 task-based group-constrained individualized ROIs for each individual: 10 reading, 10 math, and 10 cognitive control ROIs (Fig. 3C). ROIs for each individual varied in their size and exact location (Fig. 4). Only individuals who could contribute 10 ROIs from each task-map were included in further analyses, excluding six individuals who did not contribute enough ROIs. These individuals did not have the highest or lowest academic skills (see Supplemental Fig. 1). In the case that the 10th and 11th largest ROIs were the exact same size, but from opposite hemispheres, the 10th ROI was

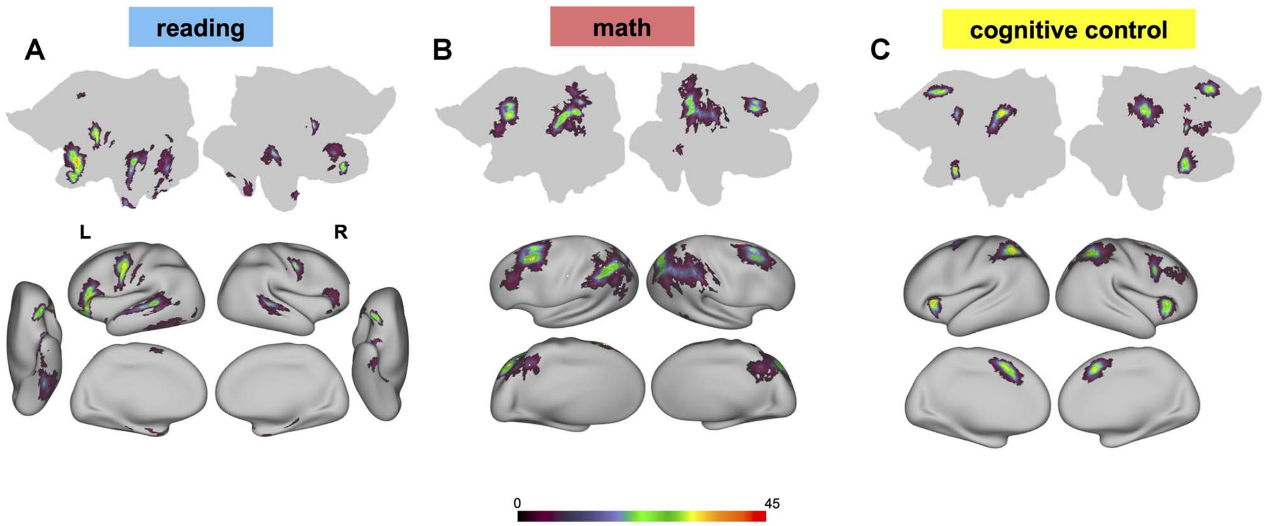

Fig. 4. Overlap of individualized ROI sets across participants. Individualized regions from (**A**) reading, (**B**) math, and (**C**) cognitive control tasks are binarized, overlaid, and projected on a 32 k fs_LR flat map (top row) and CONTE-69 32 k fs_LR very inflated surface mesh (bottom row). $N = 45$. The heat bar represents the number of individuals who have that vertex included in their ROI set. Note the sparse 100% overlap vertices.

taken from the right hemisphere since the right hemisphere is underrepresented compared to the left hemisphere in the reading maps (Fig. 4). This occurred for three individuals' reading ROIs, two individuals' math ROIs and two individuals' cognitive control ROIs. None of these individuals were the same across multiple tasks.

Resting state functional connectivity

The individualized ROIs were used to extract timecourses of BOLD activity across the processed, concatenated runs of resting state, which were averaged across all surface vertices within each ROI. Pairwise Pearson correlation matrices were computed between all ROIs, resulting in a 30 × 30 matrix, indexing functional connectivity between each pair of ROIs. Each correlation matrix was made up of the three ROI sets (reading, math, and cognitive control).

Graph metrics

To extract properties of connectivity strength, we calculated graph metrics on each correlation matrix using a combination of *igraph* and *brainGraph* (Csardi and Nepusz 2006; Watson 2019) and in-house scripts executed in R Studio (R Development Core Team 2017). By using graph metrics we can parsimoniously integrate information about functional connectivity across many brain regions that form systems and even between those brain systems (Bullmore and Bassett 2011; Bassett and Sporns 2017). This is a powerful approach given modern theories of neurocognition that suggest dynamic communication between distributed brain regions gives rise to cognition and behavior (Fries 2005; Cohen and D'Esposito 2016). To calculate graph metrics, correlation matrices were Fisher Z-transformed and then transformed into undirected, weighted adjacency matrices, wherein each ROI constituted a *node* and each correlation between a pair of ROIs or nodes constituted an *edge* in the brain graph (Bullmore and Sporns 2009; Bullmore and Bassett 2011). Graphs were thresholded at $z = 0$ to remove all negative edges.

We selected three graph metrics across all ROIs, *global efficiency*, *density*, and *mean functional connectivity* (calculated before thresholding), to index global properties of connectivity across all three ROI sets. To interrogate local properties of connectivity within and between ROI sets, we also selected three node-level graph metrics: *participation coefficient*, *node dissociation index,* and *within-module degree.*

Global efficiency. Global efficiency measures the efficiency of information transfer across all nodes in a graph across all sets. Nodal efficiency is calculated for each node using minimum path length; a measure of the smallest number of edges necessary to get from node x to all other nodes in the graph. Global efficiency is the average nodal efficiency across all nodes in a graph (Latora and Marchiori 2001; Achard and Bullmore 2007).

Density. The percentage of connections left after thresholding. Graphs for our analyses were thresholded at 0 and included all positive connections.

Mean functional connectivity. The average strength of all connections before applying thresholding (positive and negative connections).

Participation coefficient. Participation coefficient is a nodal measure indexing how connected a node is across all ROI sets. We calculated binarized participation coefficient using a node's degree, or number of connections a node has to each ROI set. Participation coefficient for a given node approaches 0 if its connections are all within its own ROI set and approaches 1 if the node's connections are distributed evenly throughout all ROI sets (Guimerà and Nunes Amaral 2005).

Node dissociation index. We calculated weighted node dissociation index, which is a modified form of participation coefficient that accounts for the set membership of a given node and indexes the ratio of connections to nodes within its own set to connections with nodes in all other sets (Cary et al. 2016).

Within-module degree. Within-module degree indexes the "cliquishness" of nodes within a set, i.e. how interconnected are nodes within a given set. We calculated an unstandardized weighted within-module degree for each node as the sum of weighted connections with all other nodes in its set (Guimerà and Nunes Amaral 2005).

All nodal metrics were averaged across all the ROIs within its set (e.g. mean participation coefficient for all cognitive control ROIs).

Statistical analyses

Linear regressions were used test for relationships between graph metrics and academic skills. Models wherein a reading skill (word

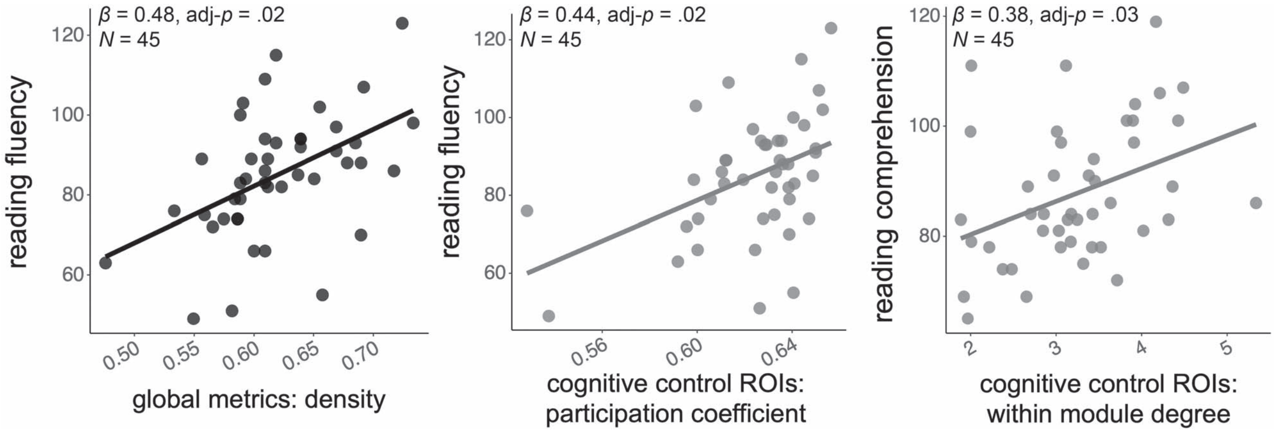

Fig. 5. Graph metrics related to reading skills. (Left to right) Relationship between density across all three ROI sets and reading fluency; relationship between participation coefficient of control ROIs indexing between sets connectivity and reading fluency; relationship between within-module degree of control ROIs and reading comprehension. The correlation between participation coefficient and reading fluency remains significant but weaker when both outliers are removed ($r = 0.34$, uncorrected $p = 0.02$).

reading, reading fluency, or reading comprehension) was the outcome variable separately tested the global metrics, nodal metrics of the reading ROIs, and nodal metrics of the control ROIs as predictors. Models wherein a math skill (math computation or math fluency) was the outcome variable separately tested the global metrics, nodal metrics of the math ROIs, and nodal metrics of the control ROIs as predictors. Models were corrected for multiple comparisons with FDR correction (Benjamini and Hochberg 1995), for global metric models (9 corrections for reading models, 3 reading skills × 3 global metrics; 6 corrections for math, 2 math skills × 3 global metrics), cognitive control models (9 corrections for reading models, 3 reading skills × 3 cognitive control ROI metrics; 6 corrections for math, 2 math skills × 3 cognitive control ROI metrics), and within academic skill sets (3 corrections for reading; 2 corrections for math).

Since the ELs in our study exhibited a wide range of language proficiency, we were interested in how English and Spanish proficiency related to brain connectivity, as well as whether language proficiency accounted for variance in the relationships between brain connectivity measures and academic skills. For the subset of individuals who self-reported English and Spanish proficiency measures ($n = 41$), we used multiple linear regression models to test whether language proficiency changed significant relationships between brain connectivity and academic skills. Language proficiency measures were added to models that had a significant relationship between brain measures and academic skills to test for whether language proficiency accounted for a portion of the variance in that relationship (FDR correction for 10 significant models, see *Results*).

Results

Academic skills related to global metrics and measures

Global metrics and measures related to reading skills

Density indexing across all positive correlations between the reading, math, and cognitive control ROIs was related to reading fluency, word reading, and reading comprehension (corrected $ps < 0.05$, Table 2, Fig. 5). Mean functional connectivity was also related to word reading, reading fluency, and reading comprehension (corrected $ps < 0.05$, Table 2). The global efficiency graph metric was not significantly related to measures of reading skill.

Global metrics and measures related to math skills

None of the three global graph metrics were significantly related to measures of math skills before correction (Supplementary Table 2).

Academic skills related to functional connectivity of cognitive control regions

Cognitive control regions related to reading skills

We found that participation coefficient—indexing the connectivity of the cognitive control ROIs to all other ROIs—was related to measures of word reading, reading fluency, and reading comprehension (corrected $ps < 0.05$ corrected for nine tests, Table 2, Fig. 5). We also found that the metric within-module degree—indexing the connectivity of the cognitive control regions to each other—related to reading comprehension (corrected $p = 0.03$), but not word reading or reading fluency (Table 2, Fig. 5). Node dissociation index of the cognitive control regions was not related to reading measures.

Cognitive control regions related to math skills

The three nodal metrics (participation coefficient, node dissociation index, and within-module degree) of the cognitive control ROIs were not significantly related to measures of math skills (all uncorrected $ps > 0.05$; Supplementary Table 2).

Academic skills related to within-set connectivity of reading and math regions

Within-module degree of the reading ROIs—indexing connectivity of the reading ROIs to each other—was not significantly related to reading skills (all uncorrected $ps > 0.05$, Table 2). Within-module degree of the math ROIs —indexing connectivity of the math ROIs to each other—was not significantly related to math skills (all uncorrected $ps > 0.05$, Supplementary Table 2).

Language proficiency influences on significant relationships between brain connectivity and reading skills

To test whether self-reported measures of English and Spanish proficiency were explanatory variables in our brain connectivity and reading skill relationships (Fig. 1), we first tested whether there was a relationship between English or Spanish proficiency and the brain connectivity metrics we found to be significantly

Table 2. Regression table for linear regressions predicting reading skill from graph metrics.

	Word reading					Reading fluency					Reading comprehension				
	B	**SE B**	β	***p***		**B**	**SE B**	β	***p***		**B**	**SE B**	β	***p***	
GE	60.81	80.31	0.11	0.45		72.93	72.05	0.15	0.32		110.81	56.02	0.29	0.05	
R^2					0.01					0.02					0.08
F					0.57					1.02					3.91
density	147.98	44.47	0.45*	0.00		142.14	39.40	0.48*	0.00		87.56	33.53	0.37*	0.01	
R^2					0.20					0.23					0.14
F					11.07					13.01					6.82
mean FC	155.25	66.27	0.34*	0.02		146.95	59.37	0.35*	0.02		126.01	47.17	0.38*	0.01	
R^2					0.11					0.12					0.14
F					5.49					6.13					7.14
NDI CC	37.62	41.43	0.14	0.37		20.60	37.58	0.08	0.59		−10.37	30.23	−0.05	0.73	
R^2					0.02					0.01					0.00
F					0.82					0.30					0.12
PC CC	251.81	92.57	0.38*	0.01		261.45	81.10	0.44*	0.00		166.78	67.93	0.35*	0.02	
R^2					0.15					0.19					0.12
F					7.40					10.39					6.03
WMD CC	4.92	3.20	0.23	0.13		4.97	2.87	0.26	0.09		5.99	2.20	0.38*	0.01	
R^2					0.05					0.07					0.15
F					2.37					3.01					7.42
WMD RD	2.28	4.50	0.08	0.61		−0.46	4.07	−0.02	0.91		1.43	3.26	0.07	0.66	
R^2					0.01					0.00					0.00
F					0.26					0.01					0.19

Note. SE = standard errors on unstandardized betas; *On standardized betas denotes significant predictors $P < 0.05$ corrected for nine multiple comparisons. GE = global efficiency; FC = functional connectivity; NDI = node dissociation index; PC = participation coefficient; WMD = within-module degree; CC = cognitive control; RD = reading. $n = 45$ for all models. All *p*s in table are uncorrected for multiple comparisons.

related to reading skills (density across all ROIs, mean functional connectivity across all ROIs, participation coefficient of the cognitive control ROIs, and within-module degree of the cognitive control ROIs; Table 2). After correction, we found no measures of brain connectivity related to language proficiency (all corrected *p*s > 0.05, FDR corrected for four tests). Before correction, we found English proficiency was related to density across all ROIs (β = 0.34, uncorrected $p = 0.029$, Supplementary Table 3) and participation coefficient of the cognitive control ROIs (β = 0.35, uncorrected $p = 0.021$, Supplementary Table 3). Spanish proficiency was not related to any brain connectivity measures (Supplementary Table 3).

Our main interest, however, was to test how language proficiency might explain variance in any significant relations we observed between brain connectivity metrics and academic skills. To this end, we used multiple linear regression and included English or Spanish proficiency as predictors in the 10 post-correction significant relationships between brain connectivity metrics and academic skills (see Table 2). After correction for the 10 models, we found that English proficiency was a significant predictor of reading skills in five of the 10 models. Specifically, English proficiency accounted for unique variance in all of the brain models predicting reading comprehension and in the model of mean functional connectivity predicting reading fluency (Table 3, corrected *p*s < 0.05). Interestingly, for four of those five models (reading comprehension predicted by density, mean functional connectivity, and within-module degree; reading fluency predicted by mean functional connectivity), once English proficiency was added as a predictor the brain connectivity measure was no longer a significant predictor of reading skill (Table 3). After correction, Spanish proficiency was not a significant predictor of reading skills in any models (corrected *p*s > 0.05, Supplementary Table 4). Before correction, Spanish proficiency was a significant predictor in the model where participation coefficient of the cognitive control ROIs predicted reading comprehension ($p = 0.046$, Supplementary Table 4).

Discussion

The aim of the current work was to understand how resting state functional connectivity of brain systems underlying reading, math, and cognitive control in middle-school English learners (ELs) was related to their academic skills. To best capture individual differences in brain function and connectivity, we localized reading, math, and cognitive control processes using task-derived fMRI activations in the same sample, and then identified the strongest activations for each individual within group ROIs. Using this individualized ROI approach, we found that two of three global metrics (i.e. density and mean functional connectivity strength) indexing functional connectivity across reading, math, and cognitive control ROIs were related to measures of word reading, reading fluency, and reading comprehension. Connectivity between putative cognitive control ROIs and other ROI sets (i.e. participation coefficient) was related to word reading and reading fluency, while within-set connectivity of the control ROIs (i.e. within-module degree) was related to reading comprehension. We did not find any brain connectivity measures related to math skills. Though we predicted that within-set connectivity of the reading and math ROIs to themselves would relate to their respective academic skills, those relationships were not significant. We also found that English proficiency accounted for some of the variance in relationships between brain connectivity measures and academic skills, especially in models predicting reading

Table 3. Regression table for models predicting reading skill from graph metrics and English proficiency using significant results from individualized ROI approach.

	Word reading					Reading fluency					Reading comprehension				
	B	**SE B**	β	***p***		**B**	**SE B**	β	***p***		**B**	**SE B**	β	***p***	
English prof	0.92	1.35	0.10	0.50		2.50	1.15	0.31	0.04		2.50	0.96	0.38*	0.01	
density	125.27	47.11	0.41	0.01		102.78	40.16	0.37	0.01		57.20	33.34	0.25	0.09	
R^2					0.21					0.31					0.28
F					4.97					8.53					7.26
English prof	1.58	1.34	0.18	0.24		3.05	1.14	0.38*	0.01		2.70	0.91	0.41*	0.01	
mean FC	141.39	66.84	0.32	0.04		114.18	56.95	0.28	0.05		89.30	45.41	0.27	0.06	
R^2					0.16					0.27					0.29
F					3.59					6.96					7.85
English prof	0.92	1.37	0.10	0.51		2.50	1.17	0.31	0.04		2.51	0.97	0.38*	0.01	
PC CC	238.77	95.95	0.39	0.02		196.74	81.68	0.35	0.02		107.29	67.59	0.24	0.12	
R^2					0.19					0.30					0.27
F					4.50					8.07					6.99
English prof											2.90	0.88	0.45*	0.00	
WMD CC											4.53	2.09	0.29	0.04	
R^2															0.31
F															8.40

Note. Models which showed significant brain-behavior relationships after controlling for multiple comparisons had English proficiency added to the mode to test whether language proficiency accounted for variance in the relationship. SE = standard errors on unstandardized betas; all *p*s are uncorrected for multiple comparisons; GE = global efficiency; FC = functional connectivity; PC = participation coefficient; WMD = within-module degree; CC = cognitive control. $n = 41$ for all models. *Denotes English proficiency betas that were significant after correction for multiple comparisons.

comprehension. Taken together, these results contribute to mounting evidence that cognitive control systems play an important role in support of reading skills. Additionally, this work highlights the potential benefit of localizing brain engagement at the level of the individual when relating metrics to individual outcomes, particularly in heterogeneous samples.

Functional connectivity is related to reading skills in ELs

The brain at rest is thought to reflect an individual's baseline state, not driven by any particular stimulus or demands (Gusnard and Raichle 2001; Demeter et al. 2020), but reflecting a history of the brain's co-activation patterns over time. Given that the proficiency of reading in English in ELs varies widely due to differences in language experience and exposure, we expected this variability to be reflected in RSFC. We did find that individual differences in RSFC were related to reading skills—even without current reading demands in the scanner. This relationship is further evidence, here in an understudied sample, that historical co-activation of brain regions creates intrinsic functional connections that are meaningful for academic success. Interestingly, we found that cognitive control ROIs were the ones primarily driving the graph metric relationships between RSFC and reading skills.

The importance of cognitive control in academic learning is well-established with evidence from behavioral (Arrington et al. 2014; Cirino et al. 2019) and neuroimaging (Aboud et al. 2018; Bailey et al. 2018; Horowitz-Kraus et al. 2015b; Jolles et al. 2020; Margolis et al. 2019; Nugiel et al. 2019; Roe et al. 2018) literature. Previous RSFC work in monolingual samples has found that both functional connectivity within cognitive control regions (Horowitz-Kraus et al. 2014; Bailey et al. 2018; Twait et al. 2018; Freedman et al. 2020), as well as the functional connectivity of cognitive control regions to other brain systems (Aboud et al. 2018; Bailey et al. 2018; Horowitz-Kraus et al. 2015a; Horowitz-Kraus and Holland 2015; Wise et al. 2017) is related to reading abilities. In line with our predictions, we found that brain metrics indexing both how strongly cognitive control regions communicated to reading or math regions (i.e. participation coefficient) and how strongly cognitive control regions communicated with each other (i.e. within-module degree) were positively related to reading skills.

These results are also consistent with previous work showing within-network connectivity of cognitive control systems, such as the cingulo-opercular and salience systems, and between-network connectivity of cognitive control systems to visual systems during the resting state are positively related to reading ability (Twait et al. 2018) and reading skill gains after intervention (Horowitz-Kraus et al. 2015a, 2015b).

To our surprise, we did not find that the connectivity within just the reading regions to each other related to any reading measures. This result particularly highlights the contribution of cognitive control regions for reading skills in this EL group; even when at rest, the connectivity of the control system and its functional connections to reading-related regions is predictive of reading ability more than reading-regions alone. Our previous work from the same collection also found that brain activity *during* the cognitive flexibility task also predicted out-of-scanner reading performance (Nugiel et al. 2023). Combined, these data from ELs point to multiple aspects of control engagement, both during task and in intrinsic functional organization, as important for reading skills.

Given that ELs have varied English language proficiency, we predicted to see English proficiency account for some of the variance in the relationships we found between functional connectivity and academic skills. In line with these predictions, we did find that English proficiency was significant predictor in models predicting reading fluency and comprehension. Previous work from our own group with this dataset also found that language proficiency had an interactive effect in models relating brain activity during a cognitive control-demanding task to reading skills, while language proficiency skills alone did not relate to brain activity (Nugiel et al. 2023). Similarly, in our current study we did not find strong relationships between functional connectivity and language proficiency itself. Together, these works suggests that although English proficiency may not be a strong predictor of non-lexical or resting brain function, English proficiency is clearly a factor tying brain function and academic skills together in ELs.

Theories of how complex cognitive processes emerge suggest that bilingualism and cognitive control interact on a neural level throughout development in order to support more complex processing (Hernandez et al. 2018). The nature of this interaction could underlie the variability in the relationship between cognitive control brain connectivity and reading in a second acquired language in ELs. Observing these relationships at rest suggests that ELs vary in their co-activation of domain-specific (reading) regions with domain-general cognitive control regions, and that this co-activation has important implications for skill development. There is evidence that ELs have unique challenges and needs when it comes to reading (Cho et al. 2019). In our sample >50% of students failed the state mandated reading test. This is reflective of the national EL population where ∼68% of 8th grade EL students don't meet basic proficiency in reading (*NAEP Reading: National Achievement-Level Results*, 2022). Despite this, reading instruction designed for ELs is understudied (Hall et al. 2020). Instruction that specifically targets recruitment of cognitive control skills while reading, such as comprehension monitoring (Hall et al. 2020), may increase co-activation of these brain systems, which over time could be helpful for supporting reading in this group.

The reading "network" is a task-defined group

Previous research has examined the "reading network," and found that regions of the brain that are consistently active during reading tasks do not form a single cluster or strong functional community at rest, but rather split into multiple brain networks (Vogel et al. 2012; Vogel et al. 2013; Bailey et al. 2018). In the current work, the regions making up our putative reading network were defined by a reading localizer task, but across the whole brain at rest join several canonical resting state brain networks, such as attention, motor, and visual (Fig. 4, Supplementary Table 1). During the reading tasks, these regions together formed a map of task positive activity across individuals (Fig. 3). However, at rest, the connectivity of just these regions to each other was not predictive of reading performance. Instead, the functional connectivity of the putative control regions, and the functional connectivity across the reading, math, and control sets was predictive of reading performance. Considering that these students are English learners, and that reading in English is something they developed later in life than monolingual English speakers, or are actively still developing, these students may be especially likely to lack meaningful connectivity within reading-related regions at rest. In other words, where RSFC is thought to reflect a history of co-activation, the history of coactivation between these reading-related regions could be less than observed in monolinguals, and could provide one reason for the lack of within-reading set results. As we discuss below for math, the context in which we study these brain-behavior relationships, such as a task versus a resting state, could be especially important to consider in future studies of putative reading networks in young children, bilinguals or ELs, when interpreting patterns of historical coactivation.

Brain connectivity measures at rest were not related to math skills.

Though we predicted we would see functional connectivity results related to math skills, as we did for reading skills, we did not observe any strong relations. This was surprising, given some previous work has found relationships between RSFC and math skills. RSFC of frontal and parietal regions has been found to relate to counting skills in 4–6 yr olds (Zhang et al. 2019), as well as future gains in numerical skills in 1st graders (Price et al. 2018) and 2nd–3rd graders (Evans et al. 2015). One study using connectome predictive modeling found that, at rest, a diverse set of functional connections beyond canonical math regions predicted math skills (Lynn et al. 2021). A key difference between these studies and the current study is that they include samples of primarily monolingual speakers and, possibly more importantly, samples whose math skills were taught and tested in their native language. Our sample of ELs had overall lower standardized math scores (mean scores ∼88–92) compared to mean scores of ∼103 (Price et al. 2018; Lynn et al. 2021) and ∼102–112 (Evans et al. 2015). Given that we don't have a comparable higher performing monolingual sample to these previous studies, it is hard to state definitively why we don't find comparable RSFC–math skill relationships as we do with reading skills, but we have a few suggestions.

One reason we might have found graph metrics related to reading skills but not math skills could be that the ELs in our sample show more variability in the reading skills than they do in the math skills (F test of variances for reading fluency vs. math fluency $F = 2.22$, $p = 0.009$), and less variability in math skills might have made brain-behavior relationships harder to observe. Prior studies testing relationships between brain connectivity and behavior have also suggested that relationships can be strengthened based on the context when the brain is being measured. Task states, as opposed to the resting state, have been shown to maximize individual differences (Finn et al. 2017) and to result in stronger relationships between brain measures and behavioral constructs (Greene et al. 2018; Jiang et al. 2020). The resting brain may not be assessed in a way that maximizes predictive features about the neurobiology underlying these math processes, as the brain would during a "math" context. For the current study, we examined RSFC to capture the intrinsic functional organization that is thought to reflect historical co-activation (Fox et al. 2012). We would encourage future studies to consider looking at functional connectivity both at rest and during tasks to capture both intrinsic and task-driven aspects of brain functional connectivity.

Another possibility for our lack of math results is that our restricted set of ROIs used in these analyses did not capture the regions or connections important for predicting math performance at rest in ELs. Previous work predicting math skills from RSFC (e.g. Lynn et al. 2021) found a diverse set of functional connections among control, limbic, visual, and other networks to be most predictive, including many negative functional connections that our study did not include. More studies broadening the brain search space and context will be helpful in honing-in on brain features related to math skills. Overall, there are fewer studies of brain function in struggling math students than struggling readers, calling for more specific explorations of variability in brain function related to math abilities.

Individually localized brain function for clarifying brain-behavior relationships

While "EL" is a single label applied at the school level, ELs exhibit remarkable individual variability in their experience, proficiency, and exposure to English (Luk and Bialystok 2013). A primary goal of this work was to examine individual differences in brain connectivity underlying reading, math, and cognitive control in ELs that could stem from these varied experiences. To this end, we adapted a method for using fMRI tasks to localize individual brain activity to relate to our constructs of interest (Fedorenko et al. 2010; Julian et al. 2012). Notably, ROI selection is a complicated task in and of itself, with each method of selection carrying its own assumptions and strengths (Poldrack 2007; Falco et al. 2019; Fedorenko 2021). We did not have 30+ minutes of resting state in our sample with which to derive an individual's whole brain resting state parcellations, as has been done by some groups in small samples of adults (e.g. Gordon et al. 2017). However, our study benefited by having multiple task localizers within the same sample, improving the specificity of our ROI selection relative to literature-applied or group-based ROIs.

When trying to understand brain-behavior relationships, particularly in a group known to have variability in the construct of interest (i.e. academic skills), optimized individual measurements improve the signal of the relationships we are testing. Our work contributes to the larger discussion of ROI/parcel selection in neuroimaging studies (Poldrack 2007; Fedorenko 2021). Further, we emphasize the need to consider the sample, question, and prior literature when making a choice about how to select ROIs and how to map neurocognitive constructs. Our findings suggest that individualized approaches may be particularly useful in localizing neurocognitive processes in a group where those behavioral constructs vary considerably. Looking toward future work, we and others are working toward delineating the guidelines for mapping brain and behavior to each other, as well as optimizing ROI selection methods for the specific question of interest.

Limitations and future directions

This work extends the EL literature in several exciting ways. First, ELs are understudied, and yet are a growing population in U.S. schools (Garcia and Kleifgen 2018) that may need more tailored intervention strategies if they are struggling to achieve at expected levels. Second, our sample has a wide range of reading and math abilities in an age group (middle school) where remedial skill change is harder to accomplish (Vaughn and Fletcher 2012). Third, we used a method for ROI selection (Julian et al. 2012) that was attentive to individual variation in brain activity within systems of interest.

However, this work has some notable limitations and room for future expansion. Our approach required 10 sizeable ROIs from each of three tasks, and at least 5 min of stringently motion-corrected RSFC data from a pediatric sample. These requirements impacted our sample size. While our sample is still sizeable, and one of the few neuroimaging studies focused on ELs, future larger studies of this population are needed to support and build upon our findings here. Further work using individualized ROI approaches will also help clarify when using an individualized ROI approach is an appropriate and fruitful option. We believe individualized ROI approaches may be especially useful in identifying brain-behavior relationships—particularly when the ROIs are identified within-sample from tasks related to the construct of interest. Future studies using large consortium samples, such as the ABCD Study with ample fMRI task and behavioral measures (Casey et al. 2018), may help identify which methods of ROI selection are most useful for particular questions or for studying certain groups.

Another notable limitation of the current work is the use of both volume and surface brain imaging spaces. Our task-based general linear model analyses used standardized MNI volume space to localize reading, math, and cognitive control activity. This approach analyzes every individual's functional brain data in a uniform space made up of cubic voxels that do not conform to any aspect of brain anatomy. The first step of individualized ROI masking was done in standard volume space as well. We then took the ROIs from volume space and mapped them onto individualized gray matter ribbons, which gave us a better estimation of the surface of that individual's cortex and excluded all non-gray matter tissue. All subsequent functional connectivity analyses were done in this surface space. While we believe using individualized cortical surfaces for RSFC analyses is a strength of this work, we acknowledge that starting in a non-individualized volume space and then mapping the ROI data into surface space added some considerations. Mapping ROIs into surface space from volume space is not a seamless process; some ROIs became fragmented by the underlying anatomy and changed shape or became too small to include in our ROI sets. Despite this, we believe using individualized cortical surface spaces to localize brain activity to be the most accurate approach to mapping individualized ROIs. Volume-based approaches are not restricted to cortical tissue and thus can include white matter, dura, or cerebrospinal fluid. Traditional group-level approaches may be somewhat statistically protected from these noisier signals, but at the individual level we opted to use surface-based methods to exclude them. Future studies utilizing task-based analyses and ROI identification entirely in surface (and the advancement of software analysis packages to accomplish these analyses) are needed to help further clarify the strengths of individualized ROI selection.

Lastly, this study focused on English learners, and does not include the same analyses done in monolingual English-speaking (or monolingual Spanish-speaking) students. While we believe this work is valuable for examining functional connectivity related to learning in an understudied underserved population, without a monolingual group we cannot yet claim the findings from this study are specific to ELs. As more datasets including bilingual and EL students along with monolingual students are collected, we can start to hone-in on EL- and bilingual-specific signatures of academic abilities in the brain.

Conclusion

The singular label of "English learner" belies large variability in language and academic skills across EL students. Here we used an individualized approach for delineating brain regions supporting reading, math, and cognitive control to better understand that variability. We found functional organization of reading, math, and cognitive control brain regions during rest was related to standardized reading skills, with the cognitive control brain regions playing a particularly strong role. Overall, this work highlights the organizational role of cognitive control systems in reading ability in an understudied and growing population in U.S. schools. Our results encourage further use of methods that acknowledge individual variability in the brain.

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Supplementary data

Supplementary material is available at *Cerebral Cortex* online.

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Data availability

Upon publication acceptance, a publicly available repository on Open Science framework https://osf.io/7hmdf/ will be populated with the following: Connectivity matrices, individualized surface ROI masks for the three tasks, group level unthresholded z-statistic maps in volume space for the contrasts used to create ROIs, and behavioral variables (academic skills, language proficiency).

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