The Pennsylvania State University

The Graduate School

College of the Liberal Arts

INDIVIDUAL DIFFERENCES IN READING COMPREHENSION: A RESTING-STATE FUNCTIONAL CONNECTIVITY APPROACH

A Thesis in

Psychology

by

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Submitted in Partial Fulfillment

of the Requirements

for the Degree of

Master of Science

August 2018

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Abstract

Reading is one of the fundamental methods through which we acquire new knowledge and skills(Hanh et al., 2007; Macabasco-O'Connell et al., 2011), and reading comprehension has been shown to be a strong predictor of individual's quality of life as well as future success (Baker, Parker, Williams, Clark & Nurss, 1997; Ritchie & Bates, 2013). Individual executive function (EF) skills have been reported to be a significant factor that influences reading comprehension success in both children and adults (Cartwright, 2015). Text reading comprehension is a complex cognitive process, and relies on a distributed network of brain regions (Li & Clariana, 2018). It is therefore very likely that text reading comprehension is better captured by an interconnected and interactive neural network.

There has been ample literature investigating reading, however most neurocognitive investigations of language comprehension are limited to word-level rather than text-level reading (see reviews by Ferstl, 2010 and Mason & Just, 2013). Furthermore, most neuroimaging studies of text comprehension have been focused on investigating reading-related patterns via functional magnetic resonance imaging (fMRI), and evidence showing that resting-state functional connectivity (RSFC) can capture text reading comprehension is lacking. Our study aims to clarify the relationship between RSFC in the language network and reading comprehension performance as well as individual EF skills.

A step-wise algorithm was used to explore whether one or more two-way interactions could better explain variation in the reading comprehension scores. To address concerns about not adequately controlling for multiple comparisons and overfitting the data, we also used a model based on the decision regression tree algorithm (Breiman, 2001) that has been applied in functional connectivity studies (Richiardi, Eryilmaz, Schwartz, Vuilleumier & Van De Ville, 2010; Venkataraman, Whitford, Westin, Golland & Kubicki, 2012). All of the interactions that explained a significant amount of variance in the data are entered in a leave-one-subject-out cross-validation analysis.

The behavioral results confirmed a significant positive correlation between EF task performances and our reading task performance. While no single predictor had significant main effects with reading and EF indices, the decision tree model revealed significant effects in the temporoparietal connectivity interaction that had above chance predicting power on reading performance (Spearman's $\rho=.37$, $p=.01$). These patterns suggest that the temporoparietal connectivity can act as a reliable classifier distinguishing lower-ability and better-ability readers. This is convergent with DTI findings correlating temporoparietal white-matter tract integrity with reading performance (Kingberg et al., 2000), suggesting that the temporoparietal connectivity is particularly engaged in text comprehension.

Keywords: reading, text comprehension, executive function, functional connectivity, resting-state fMRI

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Acknowledgements

Many thanks first and foremost to my advisor, Dr. Ping Li, as well as to the members of our lab who have helped me immensely with the production of this thesis, especially Dr. Chun-Ting Hsu, Benjamin Schloss, as well as all the RAs who have helped with data collection. I’d also like to thank the committee members, Dr. Janet van Hell, Dr. Chaleece Sandberg, and Dr. Xiao Liu, for their comments that helped me revise the thesis as well as meetings during the semester that help me solidify the analyses logic as well as future directions. Finally, I’d like to thank all of my friends including Chih-Ting Chang, Monica Li, Hsiang-Yu Chen, Wan-Yu Shih, Victoria Gertel, Sara Winter, as well as my Mom for encouraging me and helping me through the writing process.

CHAPTER 1

Introduction

Significance

Reading is one of the primary forms of knowledge acquisition, and reading skill has often been shown as an important index that predicts quality of life and future success in measurements such as self-reported health, average income, as well as socioeconomic status (Baker, Parker, Williams, Clark & Nurss, 1997; Comber, 1997; Ritchie & Bates, 2013; Miles & Stipek, 2006; Whitehurst & Lonigan, 1998). How intrinsic neural networks in the brain can reflect reading comprehension skills is thus a crucial foundation for understanding learning, which has important scientific and social consequences. The current study attempts to investigate whether reading comprehension can be captured by resting-state functional connectivity (RSFC) in reading networks and how this functional connectivity is associated with individual executive function skills.

Reading comprehension is an abstract construct that has often been measured in various ways through the manipulations of text type (narrative versus expository), text cohesion (grammatical and lexical links within a text that gives it meaning), and difficulty in terms of text content and vocabulary. The same text stimuli will provide different levels of difficulty for different populations (e.g., adults versus children, monolinguals versus bilinguals), which impedes the fair comparison across groups (Koyama et al, 2011; Schlaggar & Church, 2009). Studies so far have worked around this by controlling critical factors, such as restricting the age range (Booth et al., 2008) or through the usage of implicit reading tasks that is performed equally well across age groups (Turkeltaub et al., 2003). If a task-free measurement in the form of RSFC in the brain can be used to capture reading comprehension, studies will be able to circumvent confounds of comparing across groups due to task constraints. To be a valid indicator representing reading comprehension skills, the RSFC between regions of interests (ROIs) in the reading networks should not only correlate with valid behavior measures of reading comprehension, but also correlate critical factors that influence reading comprehension, such as executive function skills.

By utilizing RSFC, the results will be free from the constraints of task, which then enables more equivalent comparisons between different reader demographics where the same task might elicit different levels of difficulty due to biological differences (traumatic brain injury patients versus healthy controls) or reader characteristics (monolingual versus bilingual readers). The goal of the project is thus to demonstrate that RSFC patterns in the reading network can accurately reflect both reading comprehension performance and executive function performance. If a norm for RSFC patterns in reading can be established through this project, the field will benefit from having a baseline for comparing atypical reading RSFC patterns to. This is especially valuable as some atypical populations are unable to perform reading tasks and can only provide resting-state functional data.

Executive function and reading comprehension

Executive functions have been described as a set of skills reflecting cognitive processes assisting goal-directed behavior (Anderson, 2002; Denckla, 1996; Eslinger, 1996; Garner, 2009). Specifically, executive functions have been subdivided into inhibition, shifting, and updating (Blair, 2016; Miyake & Friedman, 2012; Miyake et al., 2000). In a latent variable analysis, Miyake and colleagues showed moderate correlations between inhibition, shifting and updating. In addition, they demonstrated evidence that the executive functions contributed significantly yet differentially performances on tasks measuring planning, cognitive flexibility, and working (Miyake et al., 2000). Studies have found correlations between executive functions with different forms of text reading performances, specifically, narrative text as well as expository text reading comprehension (Chan, 2013; Georgiou & Das, 2016; Swanson, 2003; Sesma, Mahone, Levine, Eason & Cutting, 2009). Recent studies have further noted a stronger relationship between executive functions and success in reading expository text (Eason et al., 2012; Swett et al., 2013), which is the standard form of prose style found in most science, technology, engineering and math (STEM) reading material (Israel, Maynard & Williamson, 2013). Furthermore, reviews have shown that the role of executive function skills in modulating reading comprehension performance extends beyond the effects commonly ascribed to comprehension, such as decoding, reading fluency, and vocabulary (e.g., Cutting et al., 2009; Carretti, Borella, Cornoldi & Beni, 2009; Sesma et al., 2009). A meta-analysis of twenty-nine studies has shown a moderate overall correlation between executive function and reading comprehension, r=0.36 (Follmer, 2017). Table 1 presents definitions for the executive functions of inhibition, shifting, and updating, along with empirical works demonstrating the contributions of these executive functions to reading outcomes.

Table 1.
Definitions of Executive Functions and Representative Research Supporting Their Contributions to Cognitive and Academic Outcomes

Executive function	Other labels	Definition	Representative work
Inhibition	Response inhibition, Inhibitory control	Ability to suppress or override a pre-potent or dominant response	Arrington et al., 2014; Locascio et la., 2010; Borella et al., 2010
Shifting	Flexibility, Switching	Ability to switch flexibly between mental sets, tasks, and goals	Guajardo & Cartwright, 2016; Kieffer et al., 2013; Latzman et al., 2010
Updating	Working memory	Ability to monitor and update information stored in working memory	Garcia-Madruga et al,. 2014; Miller et al., 2013 ; Pelegrina et al., 2015

Note. Definitions are based on Miyake & Friedman (2012).

Within the three subdivisions of executive functions, inhibition, in particular, has been shown to be predictive of reading skill in children and adults. A number of studies have examined the link between inhibition and reading comprehension in children (e.g., Arrington et al., 2014; Altemeier et al., 2006; Borella et al., 2010; Locascio et al., 2010). Kieffer and colleagues (2013), found that inhibition predicted reading comprehension of narrative and expository text among a sample of low-income family elementary aged learners after controlling for word reading, working memory, and processed speed. Borella and colleagues (2010), examined inhibition among high- and low-ability readers, and found that low-ability readers demonstrated marked difficulty with interference control (i.e., maintaining and controlling the relevance of information during reading). Similarly, Locascio et al. (2010) as well as Arrington et al. (2014) found significant contributions of inhibition to reading comprehension of narrative and expository text above and beyond reading-related processes captured by standardized measures conventionally used in psycholinguistic studies (Chen & Vellutino, 1997; Gough & Tunmer, 1986).

Additionally, Chan et al. (2013) examined the contribution of inhibition and shifting as well as prosody to word reading and reading comprehension among a sample of undergraduate students. Prosody contributed significantly to word reading, while executive function contributed uniquely to reading comprehension after controlling for vocabulary, naming speed, and short-term memory. Finally, in Follmer (2017), a study focusing on the relationship between specific executive function skills and reading comprehension of expository text in adult native readers was conducted. Through hierarchical regression analysis and structural equation modeling, the study found that individual executive functions of inhibition, shifting, and updating as well as a latent executive function factor accounted for unique variance in reading comprehension above and beyond age, prior knowledge, reading time, vocabulary ability, and perceived interest (Follmer, 2017).

Overall, there appears to be a positive relationship between executive function skills and reading comprehension in adult readers across different texts types. This is an important relationship to establish for understanding mechanisms that contribute to reading comprehension success. The next step would be to utilize neural imaging data to further clarify the relationship between the two.

RSFC and individual differences

Functional magnetic resonance imaging (fMRI) has been critical in revealing specific functional brain regions related to various cognitive skills, including reading.

Task-based fMRI studies in field of reading have had a focus on word-level processing, which often contrasted the reading of words versus pseudo- or non-words (see reviews by Cattinelli, Borgheses, Gallucci & Paulesu, 2013; Turkeltaub, Eden, Jones & Zeffiro, 2002). In a recent meta-analysis of 35 studies by Cattinelli et al., (2013), the left hemisphere regions of the left angular gyrus, the left temporal middle lobule, as well as the left fusiform gyrus are key regions involved in word-processing. In terms of sentence reading, child studies have shown that higher word- and text-level reading fluency is correlated with higher BOLD response in the left occipitotemporal lobe (Rimrodt et al., 2009). In an adult study by Cutting et al. (2006), significant activations were found in the left inferior frontal gyrus and the inferior temporal gyrus for sentence comprehension after accounting for single-word processing and short-term memory. Results from these past studies are essential for informing ROI selection in functional connectivity analysis.

RSFC has been consistently applied to the investigation of cognition, and studies have shown that functional connectivity patterns in the brain correspond to relevant resting-state networks and behavior (De Luca, Beckmann, De Stefano, Matthew & Smith, 2005). This task-independent approach detects inter-regional correlations among spontaneous low-frequency fluctuations in the fMRI signal (Biswal et al., 1995), and has successfully characterized many brain networks that resemble patterns of activation observed during task performance (Toro et al., 2008; Smith et al., 2009). Connectivity profile has also been shown to be able to predict levels of fluid intelligence; the same networks that were most discriminating of individuals were also most predictive of cognitive behavior (Finn et al., 2015).

RSFC can be seen as a form of individual neural connectivity profile, and has been shown to be an index to distinguish individuals regardless of how the brain is engaged during imaging (Gorgolewski et al., 2014). Studies investigating relationships between RSFC and behavior have shown that individual differences in performance (Wang et al., 2012; Mennes, 2010) are associated with individual differences in the strength of the RSFC. Through studies published in recent years, RSFC has proven to be an effective tool to reflect native language proficiency in both English (Koyama et al., 2010; Koyama et al., 2011) and Chinese (Wang, Han, He, Liu & Bi, 2012; Zhou, Wang, Xia, Bi, Li & Shu, 2016) as well as the cumulative effect of foreign language experience on the functional organization of the human brain, as the methodology is not limited by a given experimental paradigm (Berken, Chai, Chen, Gracco, & Klein, 2016; Chai et al., 2016; Liu et al., 2017).

In a study conducted by Koyama et al. (2010), the RSFC patterns among six ROIs selected from fMRI studies on word reading in 25 adults were correlated with the task-based functional connectivity and activation patterns in word-reading. In addition, through conjunction analysis, which seeks to reveal the common activated voxels in multiple contrasts, the left inferior frontal gyrus and the posterior left middle temporal gyrus were identified as important loci of functional interaction in reading networks. This study provides critical results showing that reading at a word-level can be accurately captured via resting-state imaging, supporting the usage of RSFC.

In a follow-up study, RSFC of reading regions were compared with standardized word reading scores and verbal IQ in both children (8-14 years) and adults (21-46 years), and the results showed that RSFC indices between motor regions and between Broca's and Wernicke's areas were correlated with standardized reading scores in both children and adults. In addition, adult results showed better reading performance is associated with stronger RSFC between the visual word form area in left fusiform gyrus and phonology-related regions, such as the left inferior frontal gyrus and the left inferior parietal lobule (Koyama et al, 2011).

In a study by Zhou et al. (2016), measuring RSFC and reading fluency in 28 Chinese native speakers (average 22 years of age), they discovered that the RSFC between middle frontal gyrus and the intraparietal sulcus to show a significant correlation with reading fluency scores, as well as an overall significant top-down effects among the left middle frontal gyrus, the left intraparietal sulcus, and the visual word form area (Zhou, Wang, Xia, Bi, Li & Shu, 2016).

Although many fMRI experiments related to reading exist in the field, there are many demographics whose reading and language skills cannot be measured by tasks due to their inability to complete a given language task. Such groups include those who have experienced traumatic brain injuries, extreme language impairment from language disorders, etc. The ability to circumvent tasks is an advantage for resting-state fMRI, and in many clinical studies comparison between clinical group RSFC and healthy-control RSFC has been applied to investigate group differences for a variety of disorders including Alzheimer's, mild cognitive impairment (MCI), depression, schizophrenia, autism, chronic pain, etc. (for a complete list see review by Fox & Greicius, 2010). The application of RSFC in word-reading studies so far is extremely encouraging, and we hope to be able to extend and validate the usage of RSFC in text reading in the current study.

Regions of Interest (ROI)

Given the current reading literature, we present a summary of regions where BOLD response correlated with the reading (see review by Cattinelli, Borghese, Galluci, & Paulesu, 2013; Cutting et al., 2006; Koyama et al, 2011), including the left inferior parietal lobule (L.IPL), the left inferior frontal gyrus (L.IFG), the left visual word form area (L.VWFA), and the left dorsal lateral prefrontal cortex (L.dlPFC). The implicated functions of the selected ROIs are summarized below:

L.IPL: this region, including adjacent areas such as the supramarginal gyrus (SMG) and the angular gyrus (AG), has been implicated to be involved in phonological working memory, phonological storage, semantic integration, and vocabulary learning. The SMG has been linked with constructing representations, while the AG has specifically been implicated to be involved in event representation and episodic memory retrieval (Binder & Desai, 2011), as well as acting as a functional link with posterior language areas (e.g., Wernicke's area) for mapping visually presented onto linguistic representations (Demonet et al., 1992).

L.IFG: A critical brain region for language in the left hemisphere. It is involved in lexical retrieval, articulatory planning, and semantic processing, which are all critical for reading comprehension (Caplan et al., 2001; Cattinelli et al., 2013; Ferstl & von Cramon, 2001; Grossman et al, 2002). In a meta-analysis of 40 fMRI studies, it was found that the left IFG shows up as one of the strongest overlapping neural correlate for reading in both children and adult studies (Martin, Schurz, Kronbichler & Richlan, 2015).

L.VWFA: A region that has been implicated to be the locus for the early processing of orthography in visually presented letter strings, including both words and pseudo-words (Cohen et al., 2002; Price & Devlin, 2003; Price & Michelli, 2005), studies have suggested this region to be where early orthographic-phonological integration takes place (see Graves et al., 2010, Hillis et al., 2005; Price & Devlin, 2003). RSFC patterns between the VWFA and phonology-related regions have also been shown to correlate positively with standard word-reading scores in adults (Koyama et al., 2011).

L.dlPFC: A region typically shown to be involved in working memory and executive functions (Bookheimer, 2002; Carpenter & Reichle, 2000; Crottaz-Herbette et al, 2004; Gerton et al., 2004), which are critical to sentence reading. This region has shown activation involved in sentence-reading, interpreted as a part of executive function skills involved when reading sentences (Cutting et al., 2006; Hashimoto & Sakai, 2002).

The current study

The literature so far has been able to pinpoint key regions related to various levels of text processing via task-based fMRI results and correlations with behavior performances of reading comprehension. However, the existence of task is a critical confound for comparing across groups, as the same reading stimuli may elicit different difficulty levels in different groups. This confound can be circumvented via RSFC, which does not involve task, and has been consistently shown to be a reliable marker of proficiency and learning in L1 and L2 language learning (Hampson et al., 2006; Koyama et al., 2010; Wang et al., 2012; Zhou et al., 2016). However, very little investigation of reading comprehension has been done in terms of RSFC, much less text-reading comprehension.

The current study aims to fill the gaps in the literature by obtaining the RSFC of healthy adult native English readers, and investigate the correlation between key RSFC patterns related to behavioral measures of reading comprehension, as well as individual differences in executive function performance. Given that executive function performance has been shown as a stable index that predicts reading comprehension, if the RSFC patterns can accurately reflect reading comprehension and the influence of executive function on RSFC can be confirmed, we can establish RSFC as a valid tool for measuring reading comprehension. The findings in the current study may further encourage more equivalent comparisons of reading activation patterns across groups regardless of age, language background, or health.

Hypotheses

Behaviorally, it was predicted that a positive correlation between executive function performance and reading comprehension performance would be found, in concordance with previous studies (see review by Follmer, 2017).

In terms of neuroimaging results, given that many studies have successfully demonstrated RSFC to be an index of skills in non-language (Toro et al., 2008; Smith et al., 2009) and language tasks (Berken et al., 2016; Chai et al., 2016; Hampson et al., 2006; Koyama et al., 2010; Wang et al., 2012; Zhou et al., 2016), it was predicted that along with single-word reading, text-level text reading comprehension can also be captured by intrinsic functional connectivity between key reading regions in the brain. It is further predicted that such connectivity strength should also correlated with executive function skills measured across individuals.

CHAPTER 2

Methods

Participants

A total of 50 English monolingual adults were recruited from the Pennsylvania State University region. Recruitment criteria include right-handedness with typical and healthy neural and psychological medical histories. Left-handed individuals were excluded to avoid data with language regions lateralized to the right hemisphere as opposed to the left hemisphere, and non-monolinguals were also excluded to avoid noise in reading comprehension scores due to language background variations. Four participants were excluded for incomplete behavioral tasks. Participant demographic background information including gender, age, highest degree, field of degree and occupation were also collected.

Materials and Measures

Expository text reading comprehension (Follmer, Fang, Clariana, Meyer & Li, 2018). The reading materials used for the task-based fMRI consist of five short expository texts on different topics with in the STEM disciplines as well as one short practice text on fruit varieties. The texts were composed by a collaborating research team in English, and controlled for word length, accuracy, as wells as quality in terms of appropriateness for naïve readers of the content. Text topics include NASA Mars exploration, global positioning system, electrical circuits, combination and permutation, as well as oil supertankers and their transportation.

All five texts were controlled for length in terms of number of lines (around 30 lines per text) as well as total number of words (300 words per text). Bootstrapped One-way ANOVAs for each lexical variable were computed after converting each text to a bag of words (i.e., removing repeated words) and removing non-content words (i.e., function words, stop words, and numerical values). The ANOVA results revealed no significant difference between the average values across all five expository texts for the average number of syllables, $F = .05$, $p = .99$, average lexical decision time ($F = 1.07$, $p = .38$), average log frequency ($F = .25$, $p = .91$), average naming response time ($F = 1.41$, $p = .23$), average orthographic neighborhood density ($F = .04$, $p = .99$), average phonological neighborhood density ($F = .34$, $p=.85$), average concreteness ($F=.24$, $p=.91$), and average number of phonemes ($F=.02$, $p=.99$). For a complete listing of stimuli and stimuli characteristics, see Follmer et al., (2018).

The texts were presented line-by-line during task-based fMRI. The participants would press a button once they are done reading each line to go on to the next line of text. Once the participants finished reading a text, they answered 10 multiple-choice reading comprehension questions pertaining to the text. The accuracy and reaction time (RT) data were collected for each participant as a measure of reading comprehension skill.

Gray's Silent Reading Test (GSRT; Wiederholt & Blalock, 2000) was used to measure text-level reading comprehension. Up to 13 stories were provided and each story were followed by five questions. Adult participants (ages 18 and above) started with story eight, and were tested downward until the basal (all five questions were answered correctly) is reached, and upward until the ceiling (3 out of 5 answers were wrong) is reached. Scores can range from 0 to 65. Accuracy scores were collected, and total range of score is 0 to 65. The test has normed on 1,400 individuals in 31 states from ages 7 to 25 years of age, with reliability coefficients alpha at or above 0.97.

Raven's Progressive Matrices (Raven, 2003) was used to measure analogical reasoning. In each trial, a matrix was provided with a missing piece. The participants choose from several options to complete the matrix. The testing time was limited to 10 minutes, and the number of corrected trials were used as the score.

Attention Network Test (ANT; Fan et al., 2002) was used to measure the alerting and orienting effects on the attention network and the inhibitory control of the executive function. For the purposes of this thesis, only the conflict score reflecting inhibitory control was examined. The ANT constitutes a flanker test in which a central arrow was presented with congruent or incongruent flanking arrows, and the participants were asked to give the direction of the central arrow as fast and accurate as possible. The row of arrows might appear above or below the fixation cross. In some trials before the arrows appear, one or two asterisks would appear. They could either alert that the arrows will appear soon but without orienting the location of the arrows, or alert that the arrows will appear soon and orient the location. Three scores were derived from according to Fan et al. (2002), reflecting the RT differences caused by alerting, orienting, and flanker conflict manipulations. The higher the conflict effect on RT, the lower the participant's inhibitory control is.

Letter Number Sequencing Task (Adapted from Wechsler Adult Intelligence Scale III; Wechsler, 1956) was used to measure working memory. The task was adapted from the Wechsler Adult Intelligence Scale (WAIS; Wechsler, 1997; third edition). Participants heard a series of alternating letters and numbers and were asked to recall the numbers first in ascending order and then the letters in alphabetical order. The task began with a set size of two (one letter plus one number) and increased by one for every three trials until a set size of eight was reached. The participants' outputs were corrected for using capital letters and accidental usage of arrow keys. Size-weighted scores were calculated as the summation of correct items' set size, to properly reflect the difficulty of different items. Total range of score is 0 to 105.

All tasks were presented through E-Prime 2.0 (Schneider & Zuccoloto, 2007) and the RT and accuracy data were also recorded via E-prime. All tests have been validated by various studies and used in previous publications (*GSRT*: Katzir, Lesauz & Kim, 2009; Kavachy, Adams, Tamaresis & Feldman, 2016; Luu, Ment, Schneider, Katz, Allan & Vohr, 2009. *Expository text reading comprehension:* Follmer et al., 2018. *Raven's*: Kirby, Deacon, Bowers, Izenberg, Wade-Woolley & Parrila, 2012; Pan, McBride-Chang, Shu, Liu, Zhang & Li, 2011. *ANT*: Yang & Li, 2012; Yang et al., 2015. *LNS*: Gropper & Tannock, 2009; Jacobson, Ryan, Martin, Ewen, Mostofsky, Denckla & Mahone, 2011).

Participant self-reports. To evaluate the participants' reading habit as an individual characteristic, all participants filled out a Reading Background Questionnaire (RBQ; Follmer et al., 2017), which targets the reading habits and preferences of the participants across various forms of reading (i.e. reading books and reading on electronic devices) as well as electronic non-reading behavior (i.e. watching TV).

Procedure

All imaging data were acquired at the imaging center in the Pennsylvania State Hershey Medical Center in Hershey, Pennsylvania. After being informed of general procedures, all participants underwent six minutes of T1 structural scanning to acquire the anatomical imaging data, and six minutes of resting-state functional scanning to acquire the resting-state imaging data. Participants were shown a blank screen and informed that they can close their eyes for the T1 structural scan. After the structural scan, a fixation cross appeared on the screen for the resting-state scan and participants are told to stare at the cross without thinking about any topics in particular in a relaxed state. Finally, a reading task was administered, where participants will be shown expository text on STEM topics sentence by sentence. The specific reading task results will not be discussed in detail for the purposes of this thesis, but the peaks values correlated with reading during the task was used for guiding the ROI selection in the data analysis.

After imaging data acquisition, participants came back on a different day with an interval of approximately 7-14 days to undergo cognitive behavioral tests (Raven's Matrices, GSRT, ANT, and LNS) as well as to provide self-ratings measures (RBQ). See Figure 1 for an overview of the procedure.

Figure 1

SESSION 1: **Imaging acquisition** Structural data, resting-state data, and reading task data	Approximately 7-14 days	**SESSION 2:** **Behavioral tests and surveys** Raven's, PPVT, ANT, GSRT, LNS, and RBQ

Figure 1. Schematic overview of procedures

MRI Acquisition

All data was acquired via a 3T Siemens Magnetom Prisma Fit scanner. The structural scan is an MPRAGE scan with a T1 weighted contrast, 176 sagittal slices acquired in ascending order with an anterior to posterior phase encoding direction, 1 mm isotropic voxels, 256x256 mm field of view, a TR of 1540 ms, a TE of 2.34 ms, a 9° flip angle, and an in-plane acceleration factor of 2 using GRAPPA. The resting-state scan is an echo planar imaging (EPI) (3 mm x 3 mm x 4 mm) with a TR of 2000 ms, TE of 30 ms and a total of 34 4-mm-thick axial slices.

The reading task scan consisted of a total of 5 functional runs, which was collected using a T2* weighted echo planar sequence with 30 axial slices acquired in interleaved order with an anterior to posterior phase encoding direction, 3x3x4 mm voxels, 240x240 mm field of view, a TR of 400 ms, a TE of 30 ms, a multiband factor of 6, and a 35° flip angle. Multi-band acquisition was used for task-fMRI to allow for more volume acquisition given adult participants often show fast self-paced reading. Each functional run had varying numbers of volumes due to differences in reading speed across participants. A multiband factor of 6 means that slices were acquired in parallel six at a time. Thus, there were only be 5 readout periods (30 divided by 6). Multiband fMRI has the advantage of shorter TRs, or a smaller voxel size, as more data can be collected in a shorter amount of time (Tong, Hocke, & Frederick, 2013; Boyacioğlu, Schulz, Koopmans, Barth, & Norris, 2015). The cost of multiband fMRI is lower signal to noise ratio (Boyacioğlu et al, 2014).

Analyses

Correlations among behavioral measures. A Pearson two-tailed correlation was conducted on the behavioral measures (GSRT, expository text reading comprehension, Raven's, ANT, and LNS) to confirm the relationship between executive function and reading comprehension.

Fixation related fMRI (FiRe fMRI). The reading task functional data were analyzed with a technique of combining eye-tracking and fMRI to allow a more naturalistic reading experience for the participant, while having high levels of precision in onset determination for word-specific neural processing (Richlan et al, 2013). Past FiRE fMRI experiments have replicated word-level effects such as words versus pseudo-words (Cattinelli et al., 2013; Richlan et al, 2013; Choi, Desai, & Henderson, 2014; Schuster, Hawelka, Richlan, Ludersdorfer, & Hutzler, 2016) as well as low level psycholinguistic variables such as word length and word frequency (Schuster, Hawelka, Hutzler, Kronbichler, Richlan, 2016) in naturalistic reading designs using FiRe fMRI. The onset of the initial fixation on a word was used as the onset of the hemodynamic response function and models each fixation as an event in a fast-event related design. The peaks correlated with sentence reading in the reading task data help inform ROI selection in the resting-state results.

ROI selection. Functional ROIs selection for key reading regions has been streamlined by our review of relevant reading-related regions as discussed in the Introduction. We then selected peak coordinate values in these regions from the reading task data, collected after the resting-data during the scanning session. Peaks were selected from the parametric effect of the word position in a sentence from the reading task data, which reflects brain activity change correlated with the time course of sentence processing. In effect, the beginning of the sentence will be correlated with lower levels of activation and the end of the sentence will be correlated with higher levels of activation, as is natural in processing a sentence from beginning to end. All task-data have been corrected at a cluster level via family wise error correction ($p < 0.05$). Informed by both past literature as well as actual task data on sentence reading, our ROI selection include peaks in the L.IPL (divided into two strongest peaks—SMG and AG), the L.IFG, and the L.dlPFC. The VWFA did not show up as one of the peaks and was thus extracted via Marsbar toolbox as an ROI seed (2 mm^3 standard space, radius=6mm). ROI peak values are presented in Table 2 below.

Table 2. *ROI Coordinates*

Label	Coordinates			T	Cluster
	x	y	z		(equivk)
AG	-30	-76	30	5.5	17
dlPFC	-21	17	58	8.12	223
SMG	-39	-46	42	8.51	126
IFG	-48	26	30	6.39	50
VWFA	-55	-45	9	N/A	N/A

Note. FWE $p<.05$, k>5. AG=angular gyrus, dlPFC=dorsal lateral prefrontal cortex, SMG=supramarginal gyrus, IFG=inferior frontal gyrus, VWFA=visual word form area.

Functional MRI data preprocessing. Resting-state data was preprocessed with Functional MRI of the Brain Software Library (FSL; http://www.fmrib.ox.ac.uk/fsl/) and Analysis of Functional Neural Images (AFNI; Cox, 1996) using the Python nipype library to automate the pipeline. Preprocessing consist of: (1) Slice-timing correction, (2) segmentation of neural into white matter, gray matter, and cerebral spinal fluid via FSL FAST, (3) de-spiking via AFNI de-spike function, (4) motion-correction and co-registration to the structural data via FSL FNIRT, (5) normalization to MNI152 via FSL

FLIRT, (6) correction for physiological-related noise by taking the respiratory and pulse information to create voxel-wise confound regressors, (7) and spatial smoothing with an 8mm kernel FWHM Gaussian filter.

Participant-level connectivity analysis. The mean time series for each ROI was extracted for each participant and then transformed into standard space, after which a between ROI correlation for each participant as each ROI will be performed (AFNI 3dfim+ in individual native space). This will output a participant-level correlation maps of a total of 10 connectivity pairs (5*4/2). The connectivity strength values were then transformed with Fisher-*r*-to-*z* transformation (Z*r*) across all participants. A one-sample t-test was conducted to compare connectivity values against zero.

As IQ and reading scores have been shown to correlate, Raven's scores was modeled as a covariate of no interest to statistically remove contributions of general intelligence to RSFC-reading comprehension skills correlation. RSFC strength for each ROI pair was then correlated with both reading comprehension performance measured with GSRT and the expository text reading task as well as executive function performance measured via the ANT and LNS.

Exploratory analysis: regression. Text reading comprehension is a complex cognitive process relative to other processes (such as basic perception, spatial awareness, or even word reading comprehension), and relies on a distributed network of brain regions (Li & Clariana, 2018). It is therefore very likely that complex behavior such as text reading comprehension is better represented with networks, or interactions of the connectivity between multiple pairs of brain regions. As an exploratory analysis, a step-wise algorithm employing an ordinary least square (OLS) regression model was used to explore whether one or more of all possible two-way interactions could better explain variation in our depending variables, the mean-centered z scores of GSRT. All 45 the possible two-way interactions were entered as possible predictors. In a first pass, all predictors were removed which did not correlate significantly ($p < .05$) with the dependent variable, which left 1 predictor. Then, an OLS model was fit with an intercept and all remaining predictors repeatedly until all the predictors were significant. If all predictors were not significant, the predictor with the smallest t-value (except for the intercept) was removed, and the model was refit.

Exploratory analysis: cross-validation. Because of the large number of variables used in step-wise regression procedures, there are concerns about not adequately controlling for multiple comparisons and overfitting the data. Therefore, we also entered all of the interactions that explained a significant amount of variance in the data to a leave-one-subject-out (LOSO) cross-validation analysis using a decision regression tree. LOSO is a method in which a single subject is iteratively left out of model fitting and used as a test case (referred to as untrained data) to see whether the model can predict unseen data (Esterman et al., 2010), which should mitigate concerns about the possibility of overfitting the data.

In our analysis, a model is trained with the group connectivity pattern of the 45 data (referred to as trained data), which could then be applied to predict the untrained data (the left out subject point; all subjects are left out exactly once). In task-based fMRI studies, this method is often used to maintain the independence of the group mean data and the subsequent ROI results; the group data serve as an independent localizer for the subject data that is left out (Esterman et al., 2010). The LOSO method has been applied and validated in fMRI studies with ROI analyses (Esterman, Tamper-Rosenau, Chiu & Yantis, 2010), as well as in RSFC studies with connectivity analyses (Meszlenyi, Hermann, Buza, Gal & Vidnyanszky, 2017).

The decision tree algorithm would split the data before fitting a regression model. A regression decision tree is a set of recursive algorithms or features used to partition data into subsets or categories. The partitioning process starts with a binary split based on a feature and continues until no further split can be made. Features can be categorical (for categorical decision trees), such as “high” versus “low,” or they can be continuous (for regression decision trees; Breiman, Freidman, Olshen & Stone, 1984).

In our model, only an intercept was fit each time (average), and the patterns of connectivity found to be significant in the LOSO procedure were used as features for splitting the data. The algorithm attempts to capture the training data with the smallest possible tree, as the simplest possible explanation for a phenomenon (here, the relationship between RSFC and reading comprehension performance) is preferred over others. This provides a highly interpretable way of testing whether there are interactions between patterns of connectivity and reading comprehension performance, because the tree will tell the user explicitly which cutoff for connectivity strength between pairs of ROI best splits the data.

There are many advantages for applying a decision tree model for our exploratory analysis, first and foremost is that it is a white-box model, which is a system whose intervals can be viewed but not altered. In white box model, the level of mechanistic insights into a complex system are usually directly observable and easily explained, as opposed to a black box model, where individual-based mechanisms and dynamics remain opaque, such as an artificial neural network (Kalmykov & Kalmykov, 2015). The simplicity and clarity of the algorithm inherent in decision tree models makes it ideal for us to understand the relationship between the connectivity interactions. Second, it is possible to validate a decision tree model with statistical tests, which makes it easy to account for the reliability of the model, which is also critical for the data to be interpreted accurately. Third, the graphical representation of a decision tree is straight-forward, and easily interpretable, which is ideal for exploratory data analyses for complex systems and behavior such as neural networks of text reading comprehension. Finally, the decision tree model has been applied to various functional connectivity studies before as a classifier for features of interest, proving its potential for classification of fMRI data (Richiardi, Eryilmaz, Schwartz, Vuilleumier, Van De Ville, 2010; Tagliazucchi, von Wevner, Morzelewski, Borisov, Jahnke & Laufs, 2012; Vankataraman, Whitford, Westin, Golland & Kubicki, 2012).

In the current study, the feature values were connectivity strengths of the interacting ROI seed pairs. The decision tree algorithm was allowed to designate up to 5 rules (i.e., a maximum depth of 5, which means there can be a total of five splits from the root of the tree to the end of the tree), and the LOSO cross-validation accuracy for the highest performing decision tree containing between 1 and 5 rules was reported. Because decision trees models can over-fit data at higher depths, we controlled for the maximum depth at 5, and utilized the cross-validation data to determine which tree actually as the best predictive accuracy on untrained data (left-out participant data), rather than the best fit to the trained data (45 participant data). The decision tree constructed will attempt to answer the question: based on ordering, can we predict reading comprehension from worst to best?

CHAPTER 3
Results

The mean age of participants was 22.85 years (*SD* = 4.63; range = 18-40). Of the total participants (*N* = 46), 54% were female (*n* = 25) while 46% were male (*n* = 21). With regard to education level, 43% were students obtaining an undergraduate degree (*n* = 20), 26.1% had completed their undergraduate degrees (*n* = 12), and 30.4% had advanced degrees of Masters or higher (*n* = 14). Roughly half the participants were in or graduated from STEM (science, technology, engineering, and mathematics) majors (58%, *n* = 27), while the other half were in/graduated from humanities majors (42%, *n* = 19).

Behavioral Results

All participants completed the tasks. Participant performance descriptive statistics are shown below (see Table 3).

Table 3. *Behavioral results descriptive statistics*

	N	Minimum	Maximum	Mean	SD
GSRT	46	43	65	56.34	5.89
EXP	46	78	100	92.09	5.52
ANTc	46	36	300	109.98	45.49
LNS	46	21	82	51.91	14.69

Note. GSRT= Gray's Silent Reading Test, EXP = accuracy in expository reading task, ANTc = Attention Network Test conflict score, LNS= letter number sequencing task

Participants' average GSRT score was 56.34 (*SD* = 5.89), while participant average expository reading comprehension scores was 92.09 (*SD* = 5.52). Overall the participants all scored very high for their reading comprehension tests, as more than half of the participants (31 out of 46) fall in the 80-100 percentile rank for the GSRT scores (Figure 2). The same pattern is also observed in the participant performance of the expository reading task, where more than half (33 out of 46) obtained above 90% accuracy (Figure 3).

Figure 2

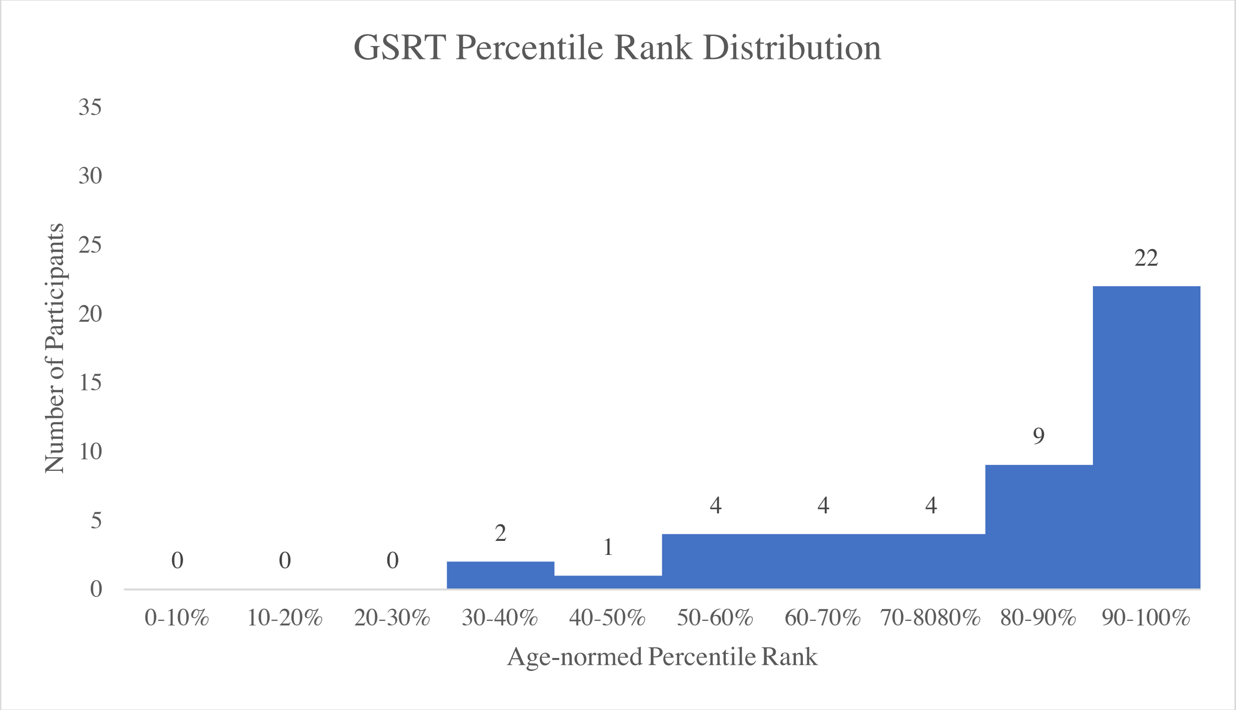

Figure 2. *GSRT Percentile Rank Distribution.*

Figure 3.

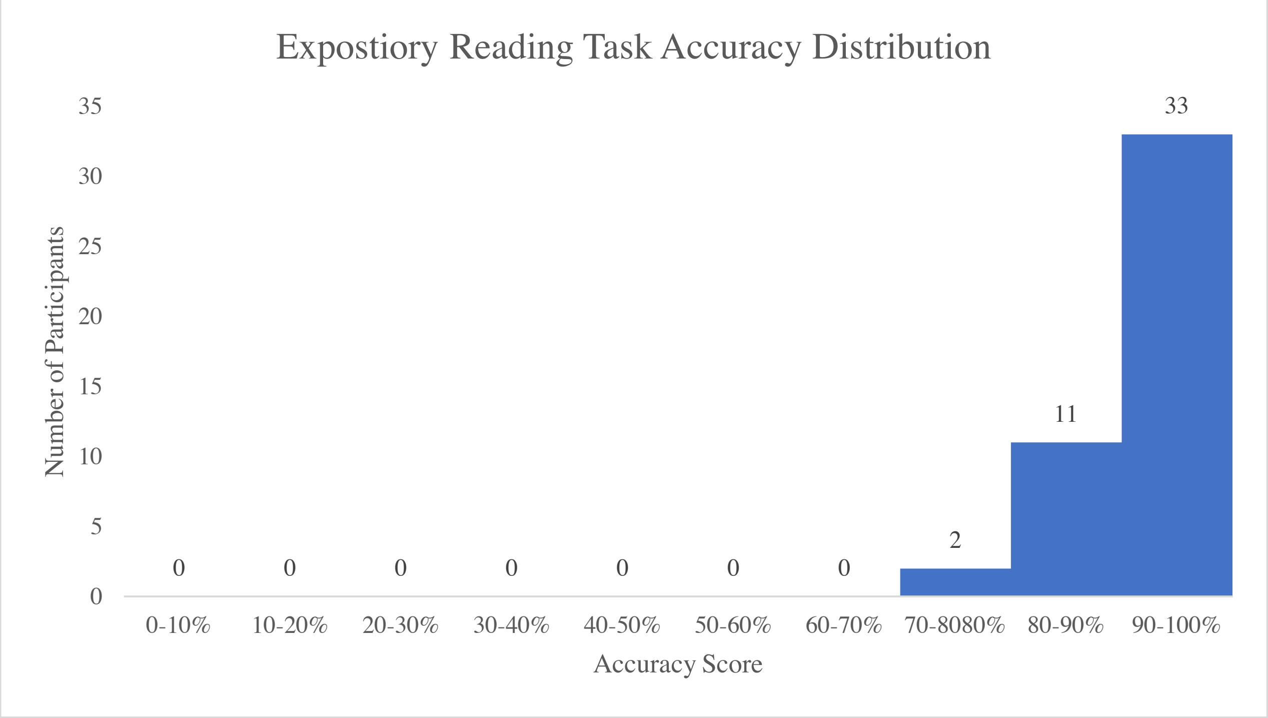

Figure 3. *Expository reading task accuracy performance distribution*

Participant average ANT conflict score was 109.98 (*SD* = 45.59), and the average score for LNS was 51.95 (*SD* = 14.49). The overall distribution of ANT and LNS performance had a higher variability in range compared to the reading tasks performances (Figure 4 and Figure 5).

Figure 4.

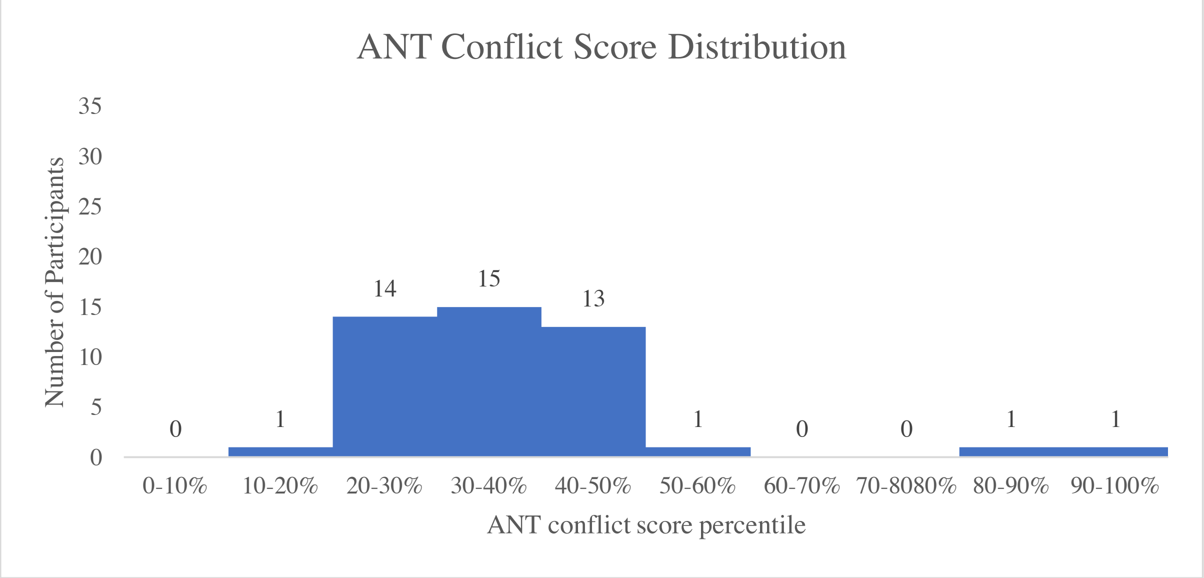

Figure 4. *ANT conflict score distribution. The raw conflict scores were transformed into percentile scores in this figure.*

Figure 5.

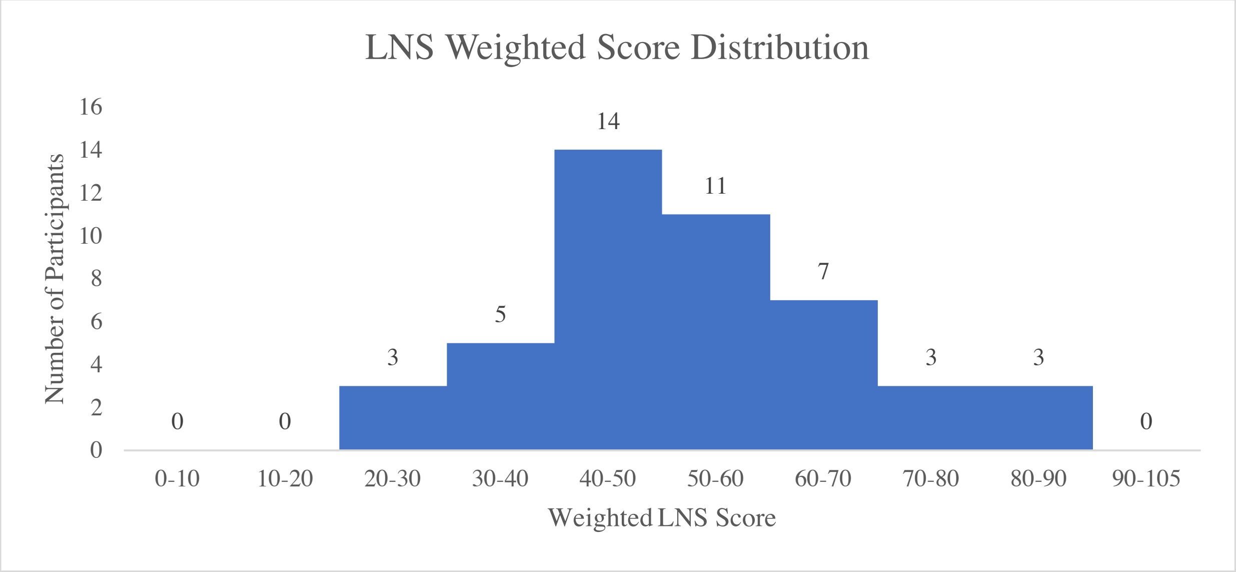

Figure 5. *LNS weighted score distribution.*

From the Pearson correlation results shown (see Table 4), performance in GSRT and the expository text reading comprehension (EXP_ACC in table) are strongly correlated with each other (*r* = .556, *p* < .01). This confirms the validity of the expository reading task (Follmer et al., 2018) against a well-normed measure that is GSRT. There is also a significant moderate correlation between the GSRT and LNS (*r* = .329, *p* < .05), and a significant moderate correlation between the expository reading task with the ANT conflict score (*r* = -.423, *p* < .01). The negative correlation observed between the ANT conflict score and the reading task score is expected, as higher conflict scores represent lower executive inhibition control.

Table 4. *Correlations among behavioral measures*

	GSRT	EXP	ANTc
EXP	.566**		
ANTc	-.219	-.423**	
LNS	.329*	.125	-.113

Note. GSRT = Gray's Silent Reading Test, EXP = accuracy in MRI expository reading task, ANTc = Attention Network Test conflict condition score, LNS= letter number sequencing task. *$p < 0.05$; **$p < 0.01$.

RSFC Results

Among all the Pearson correlation coefficients between ROI pair connectivities and behavioral measures, none was found to be statistically significant (see Table 5).

Table 5. *Correlation between ROI-pair RSFC and behavioral measures*

		AG-dlPFC	AG-SMG	AG-IFG	AG-VWFA	dlPFC-SMG	dlPFC-IFG	dlPFC-VWFA	SMG-IFG	SMG-VWFA	IFG-VWFA
GSRT	*r*	-.093	-.048	.108	.151	-.084	.073	-.178	.054	.188	.062
	p	.539	.751	.473	.315	.579	.632	.238	.721	.210	.683
EXP	*r*	-.069	.027	-.118	.140	-.053	.068	-.140	-.031	-.021	.055
	p	.648	.857	.434	.353	.729	.654	.355	.836	.890	.718
ANT	*r*	.023	-.042	.186	.148	-.051	.030	.009	.155	.137	.111
	p	.879	.782	.216	.328	.735	.845	.955	.303	.365	.461
LNS	*r*	.051	-.003	-.004	.024	.093	.047	-.172	-.182	.200	.055
	p	.734	.983	.981	.876	.539	.757	.252	.225	.184	.715

Note. AG=angular gyrus, dlPFC=dorsal lateral prefrontal cortex, SMG=supramarginal gyrus, IFG=inferior frontal gyrus, VWFA=visual word form area. GSRT= Gray's Silent Reading Test, EXP = accuracy in MRI expository reading task, ANTc = Attention Network Test conflict condition score, LNS= letter number

OLS Regression Model

A step-wise algorithm using OLS regression model was conducted to investigate whether two-way interactions between ROI connectivity values can better explain variation in the mean-centered z scores of GSRT (see Table 6). All 45 of the possible two-way interactions were entered as possible predictors. A backward elimination approach was used to select significant predictors. That is, non-significant predictors were removed from the model and the model was refitted with the remaining predictors iteratively until all remaining predictors were significant. In cases where all predictors were not significant, the predictor with the smallest t-value (except for the intercept) was removed, and the model was refitted. After this step-wise elimination process, only one predictor, SMG-VWFA x AG-SMG interaction, was kept in the model which explained 25% variation of GSRT.

Table 6. *Ordinary Least Square Regression Model*

No. Observations	46	**R-squared**	0.249
Df Residuals	44	**Adjusted R-squared**	0.232
Df Model	1	**Prob (F-statistic)**	14.58

	Coeff.	**Std err**	**t**	**p>|t|**	**[0.025**	**0.975]**
Constant	-1.816	.898	-2.022	.049	-3.626	-0.006
SMG-VWFA x AG-SMG	29.226	7.665	3.818	.000	13.798	44.654

Skew	-.589	**AIC**	283.6
Kurtosis	3.018	**BIC**	287.3

Note. Df Model=the model degree of freedom, defined as the rank of the regressor matrix minus 1 if a constant is included. Df Residuals=The residual degrees of freedom, defined as the number of observations minus the rank of the regressor matrix. SMG=supramarginal gyrus, VWFA=visual word form area, AG=angular gyrus.

Leave-One-Subject-Out Cross Validation and Decision Tree

We conducted a leave-one-subject-out procedure to cross validate the finding of our OLS regression that SMG-VWFA x AG-SMG interaction was a significant predictor for GSRT. The result demonstrates an above-chance performance (Spearman's $\rho = .365$, $p = .012$). A decision tree was generated (Figure 6) to show the interaction cascade between SMG-VWFA and AG-SMG.

From the decision tree we can see that, the first decision node is the level of SMG-VWFA connectivity; if SMG-VWFA is negative (<= -0.0048), the GSRT performance would be the worst with the z score of -5.63 (leftward leaf). For those with SMG-VWFA >- 0.048 (rightward leaf), their GSRT performance is then determined by the level AG-SMG. For those with AG-SMG connectivity >0.555, the GSRT performance was the best (z score = 5.78). The next best performers (z score = 1.652) were those with AG-SMG connectivity greater between 0.294 and 0.555. However, the GSRT performance in those with AG-SMG connectivity between 0.13 and 0.294 (z score = -4.35) was worse than those with AG-SMG connectivity less than 0.13 (z score = 1.08).

Figure 6

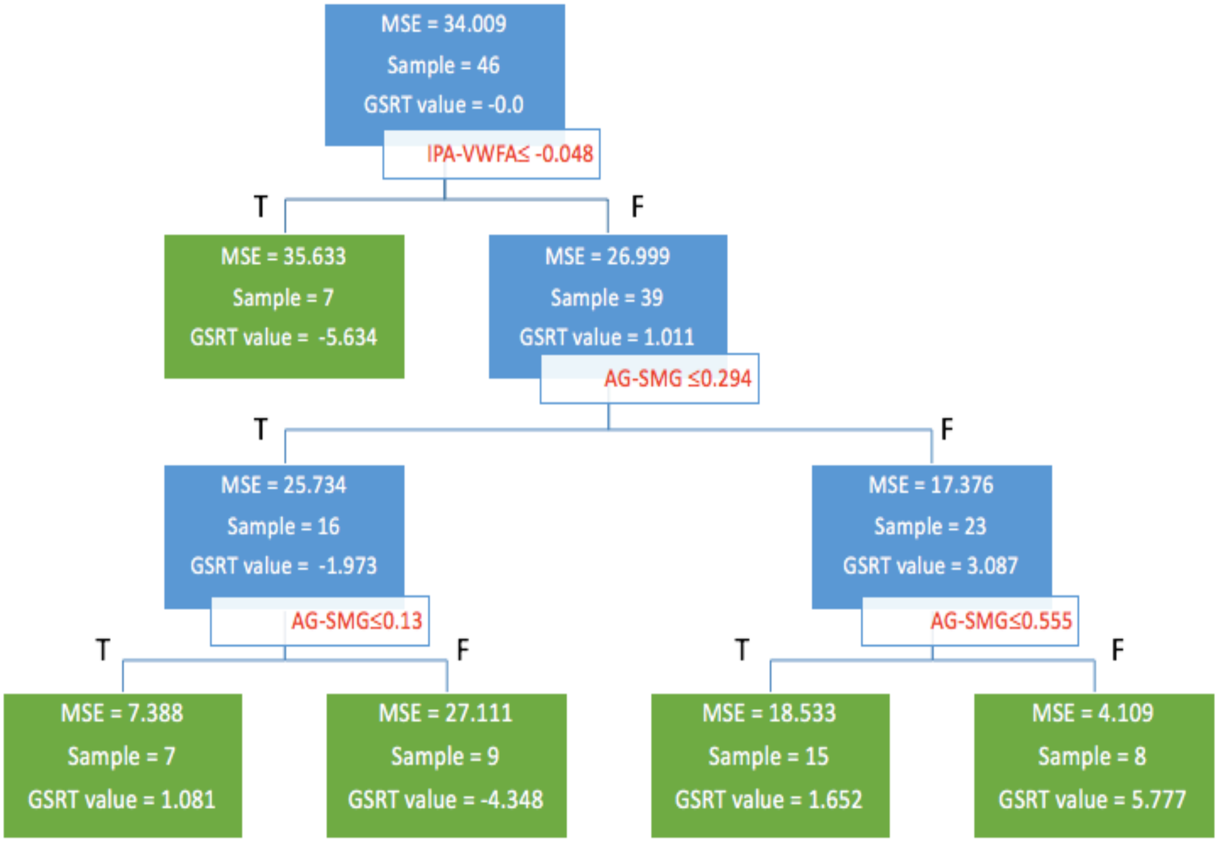

Figure 6. *Decision tree output.* Leftward branches are always true, and rightward branches are always false. MSE= mean square errors, samples = sample size, value=group mean GSRT z score. SMG=surpramarginal gyrus, VWFA=visual word form area, AG=angular gyrus

CHAPTER 4

Discussion

Overall, we see no main effects of resting state functional connectivity on reading comprehension or executive function as originally hypothesized. However, this is not too surprising given that we observe a limited range in participant reading task performance. In addition, it is not likely that a complex cognitive process such as text-reading should be reflected by just one ROI pair connection; rather, an interaction of more than one pair connection is a better represent the mechanism of text reading comprehension.

Interaction Between SMG-VWFA and SMG-AG Connectivity

In our exploratory analysis, we were able to narrow down to one interaction that had significant prediction power on participant GSRT performance, the SMG-VWFA and SMG-AG interaction. Overall, our exploratory analysis results demonstrate that SMG-AG connectivity, modulated by the SMG-VWFA connectivity, can accurately predict the best and the worst performers in reading comprehension. That is, the SMG-VWFA connectivity is the requirement predictor of okay reading performance, as seen in the first split in the decision tree model (see Figure 2) classifying the worst performers (GSRT mean-centered z-score < -5) and the slightly above average performers (GSRT mean-centered z-score > 1).

This makes sense as VWFA processes surface-level information (i.e. text form) and if information cannot get processed effectively at this stage via connectivity to a higher-level process, comprehension will be hard to achieve. This is consistent with findings showing that the left temporoparietal white matter connection integrity is correlated with reading (Klingberg et al., 2000; Vandermosten et al., 2012; Vigneau et al., 2006).

The second split in the decision tree for the above-average performers (group mean z-score > 1) has a cutoff connectivity value for the SMG-AG connection at .294. This predictor classifies the moderately-better performers (group mean z-score > 3) and the moderately-worse performers (group mean z-score <-1).

Based on the first two splits, it seems safe to say that the SMG-AG connectivity predicts reading comprehension above and beyond what the SMG-VWFA connectivity could, such that the SMG-VWFA connectivity serves as the bare minimum for reading comprehension, and SMG-AG reflects individual in higher-level integration. The SMG-AG connectivity has implication in higher-level lexical processing and multi-sensory integration (Gow, Segawa, Ahlfors, & Lin, 2008; Ohki et al., 2016).

In the rightward branching leaf of the final split in the decision tree, the predictor for best performance (group mean z-score > 5) is to have high connectivity in SMG-AG on top of having positive connectivity at SMG-VWFA. This is consistent with the interpretation of the data so far.

However, in the leftward branching leaf of the final split, the relationship is reversed, and we see that relatively stronger connectivity at the SMG-AG (cutoff at .13) actually predicted worse performance (group mean z score =-4.35), and relatively weaker connectivity predicted an unexpected above average performance (group mean z-score =1.08). Investigation into the group mean SMG-AG connectivity values reveals that the unexpected group actually had an average SMG-AG connectivity value of -.12, while the other group had an average SMG-AG connectivity value of .21.

Negative functional connectivity values in RSFC has been a subject of debate, as its origin and interpretation remains unclear (Chen, Chen, Xie & Li, 2011). Studies have suggested that negative functional connectivity is an artifact introduced by global signal regression (Giove et al., 2009; Murphy et al., 2009; Weissenbacher et al, 2009), while others have demonstrated that negative functional connectivity exists even in the absence of global signal regression (Chang & Glover, 2009). While some RSFC studies have opted to leave out the negative connectivity values from the analysis to avoid uncertainty (Buckner et al, 2009; Meunier et al., 2009), many studies keep the values in (Koyama et al., 2011, Zhou et al., 2016).

It can be interpreted that negative functional connectivity observed in the SMG-AG connection may be a source of uncertainty in the data. If we opt to ignore the negative connectivity, every other split in the decision tree fits the general interpretation of the SMG-VWFA and SMG-AG interaction. However, our current sample size of negative functional connectivity values is likely not large enough for conclusive remarks to be made of its validity, much less on what it potentially represents.

Limitations and suggestions

The limitations of the current study are two-fold, one on the behavior measure level and the other at the RSFC analysis level. First, we observe a limited range of behavioral variability in both our reading comprehension measures. Out of a total range of 0 to 65 for the GSRT, our observed range was 43-65, with the mean performance scores were 56.35 (*SD*=5.9). Out of a total range of 0-100% in accuracy for the expository reading task, our observed range was 78-100%, with the mean at 92.09 (*SD*=53). It is very likely that our participant group is a homogenous, high-performing group in terms of reading comprehension performance, as they are all people who have achieved enough reading comprehension to enroll in college, and in some cases, graduate school. This can be improved by the inclusion of participants who have more varied socioeconomic and education backgrounds, or the usage of more difficult reading and executive function tasks so that the scores among the current participants can be further differentiated. One suggestion for future investigations would be the inclusion of the Author Recognition Task (Moore & Gordon, 2015), which have been shown to be more sensitive in reflecting English reading comprehension skills in native readers. The Author's task, during which participants respond whether or not they have read works by various American authors, is a survey that can be sent to past participants to fill out, which can be a good for the current study as an additional measure that further differentiate between the good readers.

Second, the seed-based ROI analysis is elementary in terms of rigor, and our analysis so far has only consider two-way interactions; a truly network-based approach via independent component analysis (ICA) may be able to disentangle the relationship between the neural networks and reading comprehension performance in our current dataset. As mentioned before, a relatively high level cognitive process such as text reading comprehension is likely to involve a whole network of brain regions, rather than seed pairs or seed pair interactions. The current study only explores up to two-way interactions between the ROIs, which is a simplified representation of the reading neural network. A graph-theory based analysis such as ICA will allow the study to overcome the limits of the seed-based approach, and expand the scope of the key nodes investigated in the brain.

Future direction

Future directions for this line of investigation into RSFC and text reading comprehension include improvement in measurement, comparisons across groups, as well as a graph-theory approach in analysis of data.

As mentioned before, a limitation of the current study stems from the narrow distribution of reading performances from our participant group. Careful selection of a task that is sensitive enough to differentiate between higher performing subgroups, and a more elaborate pre-screening processing to ensure a wider range of sampling (instead of recruiting highly educated individuals) is highly recommended so that the fitted model has higher generalizability to the target population.

The current study can be expanded with comparisons against bilingual adults as well as children readers. The potential differences and similarities that may arise in the RSFC patterns between reader groups will be informative for how different readers achieve comprehension. RSFC networks as a predictor of reader characteristics between native experienced readers (native adults), native novice readers (native children), as well as non-native experienced readers (bilingual adults) will be critical to our understanding of text reading at a neural network level.

Finally, a graph-theory approach will allow the exploration of higher levels of interactions, which is a more accurate reflection of the actual brain network. The current study is limited to two-way interactions only, which is a limited representation of functional connectivity.

Conclusions

This study has shown that specific interactions between key RSFC can predict text reading performance in healthy adults. Specifically, the SMG-VWFA x SMG-AG RSFC interaction is able to significantly predict a spectrum of reading performances. The model's prediction power was proven to be significant despite having a relatively narrow range of reading performances from the participants. These results are promising for the utilization for RSFC in predicting complex behavior such as text-reading. The analysis was limited in the scope and complexity of interactions investigated, and this may speak to the fact that we were only able to find one significant predictor amongst all the possible pairs. It is very likely that in a well-sampled study using a network-based approach, a more complex interaction of RSFC will be a more accurate predictor of text-reading performance.

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