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Resting state EEG network modularity predicts literacy skills in L1 Chinese but not in L2 English

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ABSTRACT

EEG network modularity, as a proxy for cognitive plasticity, has been proposed to be a more reliable neural marker than power and coherence in predicting learning outcomes. The present study examined the associations between resting state EEG network modularity and both L1 Chinese and L2 English literacy skills among 90 Hong Kong first to fifth graders. The modularity indices of different frequency bands were highly correlated with one another. An exploratory factor analysis, performed to extract a general modularity index, explained 77.1% of the total variance. The modularity index was positively associated with Chinese word reading, Chinese phonological awareness, Chinese morphological awareness, and Chinese reading comprehension but was not significantly correlated with English word reading or English morphological awareness. Findings suggest that resting state EEG network modularity is likely to serve as a reasonable, reliable, and cost-effective neural marker of the development of first language but not second language literacy skills.

1. Introduction

Literacy skills are very important in modern society. Poor literacy skills may lead to unfavorable consequences for academic achievement, career success, and psychological well-being. Hence, identifying neural markers which facilitate or predict literacy skills has high practical significance in developmental cognitive neuroscience. Theoretically, identifying neural markers associated with literacy skills may help to determine which neural processes are involved in language development and reading disability. Many previous studies have focused on examining neural markers of literacy skills measured while an individual is performing a task, such as a Chinese character or word decision (Lo, McBride, Ho, & Maurer, 2019; Lui, Lo, Maurer, Ho, & McBride, 2020; Tong et al., 2016; Zhao, Maurer, He, & Weng, 2019), a one-back color repetition detection task (Zhao et al., 2014), and a word-symbol one-back task (Maurer et al., 2006). In contrast, relatively few studies have examined the neural markers identified when an individual is in a resting state.

Theoretically, spontaneous neural activity during rest has been suggested to be a hallmark of the internal state of the brain (Sadaghiani, Hesselmann, Friston, & Kleinschmidt, 2010); spontaneous neural activity captures some fundamental neurobiological characteristics of the neural system. These fundamental properties of the brain influence how the brain processes external information and generates behaviors (Sadaghiani et al., 2010) and have been found to be associated with various cognitive abilities. The present study assessed neural modularity, i.e., the extent to which the brain is functionally organized into segregated modules (Gallen & D'Esposito, 2019); we also examined the associations of neural modularity with first and second language literacy skills. It has been suggested that resting state network modularity is a proxy for cognitive plasticity, which is highly predictive for learning outcomes in various cognitive domains (Gallen & D'Esposito, 2019). Cognitive mechanisms underlying language learning are modular in nature (Sparks & Ganschow, 1993). As a result, we expected that the network modularity assessed using resting state EEG paradigms should be predictive of literacy skill development.

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Table 1
Summary of findings of 15 studies examining the relationships between resting state EEG power and language abilities.

Study	Sample size	Age (years)	Delta	Theta	Alpha	Beta	Gamma
1. Arns et al., 2007	38	8–16	negative	negative	no diff.	negative	
2. Babiloni et al., 2012	37	11	no diff.	no diff.	positive	no diff.	no diff.
3. Benasich et al., 2008	63	1.33, 2, 3	no diff.	no diff.	no diff.	no diff.	positive
4. Clarke et al., 2002	60	8–12	negative	negative	positive	positive	
5. Colon et al., 1979	93	7–11	no diff.	negative	positive		
6. Duffy et al., 1980	18	9–11		negative	negative		
7. Garcia et al., 1989	22	8–11			no diff.	positive	
8. Gou et al., 2011	40	1.33, 2, 3	no diff.	no diff.	no diff.	no diff.	positive
9. Harmony et al., 1995	49	9–12	negative	negative	positive	negative	
10. Papagiannopoulou & Lagopoulos, 2016	40	8.33	no diff.	negative	no diff.	no diff.	
11.P inkerton et al., 1989	32	8–9	negative	negative	negative	negative	
12. Rumsey et al., 1989	29	22	no diff.	no diff.	no diff.	no diff.	
13. Schiavone et al., 2014	62	2.93	positive	no diff.	negative	no diff.	
14. Sklar et al., 1972	25	7–18	positive	negative	positive	negative	
15. Tierney et al., 2014	99	14–15	no diff.	no diff.	no diff.	no diff.	negative

Note. For age of the participants, study 3 and study 8 were longitudinal studies with three waves. Study 2, 10, 12, 13 reported only the average age of the participants. For the frequency bands, "positive" indicates a positive relationship between resting state power and language abilities or lower power in participants with reading disabilities; "negative" indicates a negative relationship between resting state power and language abilities or higher power in participants with reading disabilities; "no diff." indicates not significant association was found between resting state power and language abilities or no significant difference was found between participants with reading disabilities and the control group.

1.1. Introduction to the resting state EEG paradigm

Resting state electroencephalography (EEG) measures the neural activity of an "idling" brain, which means that the participant does not engage in an active task during the EEG recording. Spontaneous neural activity at rest is thought to reflect baseline perceptual and cognitive processing, which may allow the examination of fundamental neurobiological characteristics of the neural system that are not associated with particular task-related strategies (Fraga González et al., 2016; Papagiannopoulou & Lagopoulos, 2016). Resting state EEG, which examines the dynamics of spontaneous neural activity, has also been suggested to provide meaningful information about long-range communication across brain areas and the underlying architecture of functional brain networks (Fraga González et al., 2018). In addition, resting state EEG is a cost-effective method to identify neural markers that could predict various human behaviors. EEG paradigms using reading-related tasks usually require a lot of trials for each experimental condition in order to achieve good reliability, while a resting state paradigm typically lasts for between 2 (e.g. Arns, Peters, Breteler, & Verhoeven, 2007), 3 (e.g. Benasich, Gou, Choudhury, & Harris, 2008; Gou, Choudhury, & Benasich, 2011; Papagiannopoulou & Lagopoulos, 2016) and 5 min (e.g. Babiloni et al., 2012). A short EEG paradigm is particularly useful for infants and children who have difficulty in sitting still for a long time and performing complex cognitive tasks.

Typical analyses for resting state EEG usually involve spectral power and coherence analyses. Power spectrum is obtained by transforming the EEG signals from the time domain into the frequency domain, i.e., frequency analysis, which is usually performed using the Fourier transformation. Coherence is basically the covariation of power spectra of two EEG signals. Coherence values lie between 0 and 1, and a high coherence value between two EEG channels suggests high cooperation and synchronization between underlying brain regions. EEG power alone does not provide any coupling information, while the coherence between two sites has been interpreted as evidence of a functional connection between the underlying cortical areas (Marosi et al., 1995). EEG power and coherence measures of different frequency bands have been linked to different cognitive processes. For example, high and low alpha power may represent inhibitory and excitatory cognitive processes respectively (Klimesch, Sauseng, & Hanslmayr, 2007). Gamma power has been linked to various higher-level cognitive processes such as attention, memory, and language (Benasich et al., 2008). For coherence, theta coherence has been linked to language-related mnemonic processes (e.g., Weiss, Mueller, & Rappelsberger, 2000), alpha coherence has been linked to sensory processing (e.g., Weiss & Rappelsberger, 1998), and beta and gamma coherence have been linked to semantic and syntactic processing (e.g., Weiss & Rappelsberger, 1998; also see Weiss & Mueller, 2003 for a review). Research findings about the relations among EEG power, coherence and language development, however, are not very consistent across studies.

1.2. Relations among resting state EEG Power, Coherence, and language abilities

As shown in Table 1, research findings among the fifteen studies examining the relationships between resting state EEG power and language abilities that we could identify and review yielded mixed results. These mixed findings basically occurred across all frequency bands, including delta, theta, alpha, beta, and gamma. Perhaps the frequency band with the most inconsistent findings is the alpha band. Among the 15 studies, 5 of them found lower resting alpha power in children with reading disabilities as compared to typically developing children (Babiloni et al., 2012; Clarke, Barry, McCarthy, & Selikowitz, 2002; Colon, Notermans, Weerd, & Kap, 1979; Harmony et al., 1995; Sklar, Hanley, & Simmons, 1972), 3 of them found the opposite result pattern, with higher resting alpha power in children with reading disabilities as compared to typically developing children (Duffy, Denckla, Bartels, & Sandini, 1980; Pinkerton, Watson, & McClelland, 1989; Schiavone et al., 2014), and 7 of them found no difference in resting alpha power between children with reading disabilities and typically developing children (Arns et al., 2007; Benasich et al., 2008; Garcia, Portellano, Cabanyes, & Gonzalex, 1989; Gou et al., 2011; Papagiannopoulou & Lagopoulos, 2016; Rumsey, Coppola, Denckla, Hamburger, & Kruesi, 1989; Tierney, Strait, & Kraus, 2014).

Findings regarding the relation between resting state EEG coherence and language abilities were also mixed. Sklar et al. (1972) found higher intra-hemispheric alpha coherence and lower inter-hemispheric theta and beta coherence in children (7–18 years old) with dyslexia as compared to children in a control group. Shiota, Koeda, and Takeshita (2000), however, found both higher intra-hemispheric alpha coherence and inter-hemispheric alpha and beta coherence in children with dyslexia than in typically developing children (7–14 years old). In another study comparing the resting state EEG coherence between two attention-deficit/ hyperactivity disorder combined types (AD/HD), with or without comorbid reading disabilities (RD), Barry, Clarke, McCarthy, and Selikowitz (2009) showed that the AD/HD group (8–12 years old) with reading disabilities showed lower intra-hemispheric delta coherence in the left hemisphere and lower alpha coherence across hemispheres while there were no significant inter-hemispheric differences between the two AD/HD groups for all frequency bands. In addition, Marosi et al. (1995) have found a frequency-dependent effect such that children (7–11.2 years old) with poor reading and writing ability in general showed higher coherence in the delta, theta, and beta bands but lower coherence in the alpha band compared with children with good reading and writing abilities. Arns et al. (2007), however, found that children (8–16.3 years old) with dyslexia showed increased EEG coherence in the frontal, central, and temporal regions for all frequency bands as compared to the control children. In one training study with Quadrato Motor Training (QMT), Ben-Soussan et al. (2014) showed that the participants (mean age = 30 years) with dyslexia had higher inter-hemispheric alpha coherence than the controls (mean age = 27 years) both before and after training and there were no training effects on the Magnetoencephalography (MEG) coherence for either participants with dyslexia or controls. However, in another training study with neurofeedback training (NFT), Nazari, Mosanezhad, Hashemi, and Jahan (2012) found an interesting change toward normalization of EEG coherence for various frequency bands for 6 children (8–10 years old) with dyslexia. In particular, the lower than normal delta coherence was increased to near normal and the higher than normal theta and beta coherences were decreased to near normal after the NFT training.

There is consensus that the heterogeneous findings of the associations among EEG power, coherence, and language abilities were probably caused by differences in the ages of the participants, degrees of language disability, and methodological differences in EEG data collection and analysis (Babiloni et al., 2012; Schiavone et al., 2014; Weiss & Mueller, 2003). For example, Tierney et al. (2014) proposed that resting gamma power follows a maturational trajectory that peaks at age 4 and decreases thereafter, and this explains why both Benasich et al. (2008) and Gou et al. (2011) found a positive relationship between resting gamma power and language abilities in preschoolers while they found a negative relationship between resting gamma power and language abilities in adolescents. It is unclear whether the differences in participants and methodology can account for all the mixed findings. Nevertheless, a reliable neural marker that is not sensitive to the subtle methodological differences and can predict language abilities across populations, such as network modularity (Gallen & D'Esposito, 2019), is practically valuable.

1.3. Graph analysis and network modularity

Graph analysis is a relatively new technique in analyzing resting state EEG data; it allows modeling of the whole brain functional connectivity network based on graph theory. Graph theory is a mathematical approach which uses graphs to represent networks and examines the network properties. A graphical representation of the brain network consists of a set of individual units called nodes and the connections between nodes called edges. Various indices can be computed to quantify the network properties, indicating efficiency of the neural network such as the global and local efficiency of information transfer (see Bullmore & Sporns, 2009 for a review). There have been a few attempts to perform graph analysis on resting state EEG data and to examine the relationships between network properties and language abilities. Dimitriadis et al. (2013) performed graph analysis, specifically a detrended fluctuation analysis (DFA), on resting state MEG data obtained from 23 children with reading difficulties and 27 typically developing children (7–14 years old): Reading impaired children showed reduced global efficiency in all frequency bands and reduced local efficiency in the beta band when compared with the control group. Fraga González et al., 2016 performed graph analysis, specifically a minimum spanning tree (MST) analysis, on resting state EEG data obtained from 29 third-grade children with dyslexia (mean age = 8.46 years) and 15 third-grade control children (mean age = 8.75 years). Children with and without dyslexia did not differ significantly in the power and functional connectivity; children with dyslexia, however, showed lower leaf fraction and higher diameter for the theta band, suggesting a less integrated network organization and less efficient communication between network nodes in children with dyslexia compared to controls. In a follow up study, Fraga González et al. (2018) performed again the MST analysis on resting state EEG data obtained from 28 participants with dyslexia (mean age = 23.14 years) and 36 typically reading adults (mean age = 22.22 years). Participants with dyslexia were found to show more interconnected nodes than typical readers, reflecting reduced presence of specialized sub-networks in participants with dyslexia compared to typically reading adults.

Network modularity is one of the indices characterizing the brain network properties which can be used to quantify the extent to which the brain sub-networks, or modules, are segregated from other sub-networks. A neural network has high modularity if it has many connections within its modules and has sparser connections between the modules. Network modularity has been proposed to represent cognitive plasticity. Hence, network modularity is presumed to be positively associated with learning outcomes because a highly modular network (1) has many connections within modules which allow faster processing and reduce network wiring costs and hence are more adaptable to changing external demands in learning a new task and (2) has few between module connections, so that each module is relatively independent from other modules which leads to increased flexibility in learning (see Gallen & D'Esposito, 2019 for a review). Network modularity can not only be computed from functional magnetic resonance imaging (fMRI) data but also from EEG data. For example, Chennu et al. (2017) examined EEG network modularity on patients (5–73 years old) with a disorder of consciousness and found that patients with higher modularity showed more positive clinical outcomes one year later. Gallen and D'Esposito (2019) have also suggested that network modularity is a more reliable neural marker than other types of brain measurements such as regional brain volume and EEG power since the relationship between network modularity and training-related cognitive control gains were reliably observed (1) across a variety of populations, ranging from patients to healthy individuals with different educational backgrounds; (2) across several different interventions such as therapies, physical fitness interventions, and cognitive training; and (3) across studies adopting different methodologies in modeling the neural network and optimizing the modularity. If network modularity is a reliable neural marker in predicting cognitive plasticity and learning outcomes, it should be positively associated with language abilities too. However, to the best of our knowledge, there have been few, if any, studies that have examined the relationships between network modularity and language abilities.

1.4. Factors influencing first and second language development

The question concerning what factors influence first language (L1) and second language (L2) development has been widely studied. For example, cognitive factors such as intelligence and working memory are associated with both L1 and L2 reading performance (Geva & Ryan, 1993). However, compared to L1, cognitive factors explain only a small portion of variance in L2 reading performance (Geva & Siegel, 2000). This is probably because, apart from cognitive factors, L2 language learning is also affected by affective, social, and environmental factors. Gardner, Lalonde, and Moorcroft (1985) found that participants with higher integrative motivation learned L2 French vocabulary words in a paired associate learning paradigm better than did those with lower integrative motivation. In addition, anxiety is also a crucial factor influencing second language acquisition (for a review, see Horwitz, Horwitz, & Cope, 1986). Finally, the resources available to children, the amount of exposure to a second language, and the richness of the second language learning environment are also significant predictors of L2 learning outcomes (Palfreyman, 2006; Paradis, 2011). Given this, if network modularity is measuring cognitive plasticity, it should influence language learning and should be associated with the learning outcomes of L1 to a larger extent than with that of L2.

1.5. The present study

The present study was part of a large-scale longitudinal twin study conducted in Hong Kong examining both neural and genetic factors underlying early literacy development. The present study examined the relations between resting state EEG neural network modularity and literacy skills in both Chinese (the first language, L1) and English (the second language, L2). Participants were 90 pairs of Chinese twins from grades 1 to 5 who studied in Hong Kong. To conform to the independent observation assumption in the general linear model, only one child's data from each twin pair was selected for the analyses. EEG activity was recorded for 3 min while the children were asked to keep their eyes open without performing any tasks. Among the 15 EEG resting state studies reviewed in Tables 1, 5 of them adopted an eyes-open design, 6 of them adopted an eyes-closed design and 4 of them adopted both. We chose the former design because asking children to keep their eyes open while fixated on a fixation cross may result in less eye movement artifacts than asking them to keep their eyes closed. A whole brain neural network modularity index was then computed for each individual and for each frequency band. As there were few previous studies about EEG network modularity and it was not clear from previous research what the functional roles of the network modularity of different frequency bands are, we first explored the associations among the network modularity indices across frequency bands. In cases in which the correlations among the network modularity indices were high, common network modularity factors were extracted by performing an exploratory factor analysis. After that, the network modularity was correlated with the literacy skills in both the first and second languages.

The literacy skills for both L1 Chinese and L2 English were assessed using behavioral tasks. For English, only basic word reading ability and morphological awareness were assessed. For Chinese, apart from word reading ability and morphological awareness, phonological awareness and reading comprehension were also assessed. It was hypothesized that the neural network modularity would be positively associated with Chinese reading performance and literacy skills since a higher neural network modularity indicates larger cognitive plasticity and better learning outcomes. For English, we did not have specific predictions. On the one hand, larger cognitive plasticity should lead to better learning outcomes in general and, hence, better English reading performance and literacy skills. On the other hand, in addition to cognitive plasticity, second language acquisition is also affected by affective, social, and environmental factors; hence, it was less clear to what extent neural network modularity would correlate with second language literacy skills.

2. Method

2.1. Participants

Ninety-nine pairs of Chinese twins from grades 1 to 5 participated in the current study. Nine pairs were ultimately excluded from the analyses because both children in each pair yield less than 1-minute data after EEG pre-processing. To conform to the independent observation assumption in the general linear model, only one child's data from each twin pair was selected for the analyses based on the data quality. The 90 children, including 33 males and 57 females, ranged between 6.58 and 12.42 years old ($M = 8.17$, $SD = 0.99$). All the participants were native Cantonese speakers, not previously diagnosed as having developmental dyslexia, and had normal or corrected to normal visual ability. Informed consent was obtained in written form from the parents. The study protocol was approved by the Survey and Behavioral Research Ethics Committee of the Chinese University of Hong Kong (Ref. CUHK8/CRF/13G/2300035) and the Joint Chinese University of Hong Kong-New Territories East Cluster Clinical Research Ethics Committee (Ref. 2017.479).

2.2. Procedure

Children completed a behavioral session and an EEG testing session, on average, held within 2 months of each other. They completed the behavioral measures either in their homes or their primary schools. For the EEG session, they were individually tested in a sound-attenuated lab in the Department of Psychology of the Chinese University of Hong Kong. The EEG activity was collected using the HydroCel GSN EGI 128-channel system (EGI net station, Electrical Geodesics Inc., Eugene, Oregon).

2.3. Behavioral measures

2.3.1. Chinese word reading (CWR)

The children were given items adapted from The Hong Kong Test of Specific Learning Difficulties in Reading and Writing (Ho, Chan, Tsang, & Lee, 2000), which includes 150 two-character words. The items were arranged in order of increasing difficulty. The task was stopped when the child failed to read 15 consecutive items. The total number of words they read correctly served as the indicator of their word reading performance.

2.3.2. Chinese phonological awareness (CPA)

Phonological awareness was tested using a task which included both syllable deletion and onset deletion items (Yang, McBride, Ho, & Chung, 2019). For the syllable deletion section, the children were asked to take away one syllable from three-syllable phrases (e.g., dai6 mun4 hau2 without mun4 would be dai6 hau2). This part consisted of 4 practice items and 19 testing items. Half of the items were real words and half consisted of nonsense syllables that conformed to the phonological constraints of Cantonese. In the onset phoneme deletion section, the children were asked to take away the initial phoneme of the Cantonese words. For example, tsa1 without the initial sound would be a1. This part consisted of 4 practice items and 22 test items. One point was given for each correct item and the maximum possible score was 41.

2.3.3. Chinese morphological awareness (CMA)

In the Morphological Construction Test (e.g., McBride-Chang, Shu, Zhou, Wat, & Wagner, 2003), for the first 27 items, scenarios were orally presented in three-sentence stories. One example is: "If we see a web weaved by a spider, we call that a spider web (zi1 zyu1 mong5). What should we call if we see a web weaved by an ant?" The correct answer, in this case, is ant web (maa5 ngai5 mong5). Thus, children were asked to actively construct new compounds for newly presented objects or concepts based on previously acquired morphemes. For the remaining 19 items, children were not given scenarios anymore. One point was given for each correct answer and the maximum possible score was 46.

2.3.4. Chinese reading comprehension (CRC)

In this task, children were asked to read in silence a total of three narrative or expository passages. The passage lengths varied between 67 and 130 Chinese characters. For each passage, children were asked to answer questions in either the multiple choice or open-ended format. Two practice items were given to the participants before the testing ones. One point was awarded for each correct answer to each multiple-choice question and, at maximum, two points for each open-ended question which contained one or two main ideas. The full marks for this task were 24 points.

2.3.5. English word reading (EWR)

The English word-reading task was adopted from Tong and McBride-Chang (2010). It taps English word-reading skills for both Chinese-speaking children learning English as a second language and English–Chinese bilingual children studying English as a first language. Fifty items were arranged according to children's reading levels as well as the complexities of the word meanings and phoneme combinations. A stopping rule was applied if children read four consecutive words incorrectly. The total number of words they read correctly served as the indicator of their word reading performance.

2.3.6. English morphological awareness (EMA)

We assessed English compounding awareness with two sections including morpheme compounding and compounding production (McBride-Chang, Wagner, Muse, Chow, & Shu, 2005). In the first section, children were first presented with the definition of a real compound word and then asked to create a novel compound word using the same pattern, e.g., a dishwasher is a machine that you use to wash dishes. What should we call the machine that we use to wash spoons? (spoonwasher). There were 15 items in this section and one point was awarded to each correct answer. For the compounding production section, children were asked to create a word for an object or concept orally without given examples in English, e.g., what do we call a monster that only eats pizza? (pizza-eating monster). This section contained 5 items and each response was scored as ranging from 0 to 4. The possible maximum score of this test was 35.

2.3.7. Nonverbal IQ (NVIQ)

Nonverbal IQ were assessed by the Raven's Standard Progressive Matrices (Raven, Court, & Raven, 1976). There were 60 items in this standardized measure, with five sets (Sets A to E) of 12 items each. Following the test user manual, participants who were less than 8.5 years old at the time of testing were administered the short form with 36 items (Sets A to C) while older participants were given the full version. For each item, children were presented a geometric matrix with a missing piece and were required to select a piece out of six to eight choices to best complete the matrix. One point was awarded to each correct response. The maximum score was 60.

2.3.8. Verbal working memory (WM)

Backward digit span test was used to assess children' verbal working memory. For each trial, a random sequence of one-syllable Cantonese digits was played via a MP3 player at a rate of one digit per second. Children were required to recall orally the sequence of digits in the reverse order. There were 16 trials of 8 different lengths for the digit sequence ranging from 2 to 9 (2 trials for each). The trials were presented in the order of increasing sequence length starting with a two-digit sequence. One practice trial of two-digit sequence was given before the actual test. The task was stopped when the children answered 2 consecutive trials incorrectly. One point was awarded to each correctly backward recalled trial. The maximum score of this task was 16.

2.4. Eyes-open resting-state paradigm

In the EEG session, children participated in a three-minute eyes-open resting-state paradigm in which their EEG activity was recorded while they were asked to keep their eyes open and fixate on a fixation cross presented on a computer for three minutes without performing any tasks. They were seated at a distance of 80 cm from the stimuli presentation computer monitor and were also asked to sit as still as possible.

2.5. EEG recording and preprocessing

EEG was recorded using the HydroCel GSN EGI 128-channel system (EGI net station, Electrical Geodesics Inc., Eugene, Oregon) at a sampling rate of 500 Hz and with the Cz electrode as the online reference. A 0.1 Hz high-pass filter was applied for the acquisition. Electrode impedance levels were set at less than 50 kΩ. Preprocessing steps were carried out using EEGLAB v14.1.2 (Delorme & Makeig, 2004). The first 10 s and the last 10 s of the continuous EEG data were firstly removed to exclude noisy data caused by body movements of the children at the beginning and the end of the paradigm. The data were then down-sampled to 100 Hz to facilitate subsequent independent component analyses to produce better decomposition by cutting off unnecessary high-frequency information. An independent component analysis (ICA) was then performed on the continuous EEG data with an optimization algorithm - CUDAICA (Raimondo, Kamienkowski, Sigman, & Slezak, 2012). Components related to eye movement artifacts were then removed using ADJUST (Mognon, Jovicich, Bruzzone, & Buiatti, 2011). After that, the continuous EEG data were filtered with a 40 Hz low-pass filter and then divided into adjacent intervals of four seconds. Finally, epochs with absolute voltage values larger than 100 μV at any electrodes were removed. Nine pairs of twins with less than 1-minute of data (15 epochs) after these preprocessing steps were excluded from further analyses.

2.6. EEG modularity analysis

A modularity analysis was performed for the following frequency bands (Babiloni et al., 2012): delta1 (0.5–2 Hz), delta2 (2–4 Hz), theta (4–6 Hz), alpha1 (6–8 Hz), alpha2 (8–10 Hz), alpha3 (10–12 Hz), beta1 (12–20 Hz), beta2 (20–30 Hz), and gamma (30–40 Hz). For each frequency band, cross-channel phase coherence analyses, implemented in EEGLab, were performed for all pairwise combinations of the 128 channels resulting in a 128 by 128 phase coherence matrix. For each frequency band, the corresponding phase coherence matrix was then used as input for computing a whole brain neural network modularity index using the heuristic Louvain algorithm (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008). The algorithm aims at extracting the network structure with the highest network modularity through optimizing the modularity iteratively. The modularity of the extracted network is computed as the ratio between the density of connections within modules and that between modules. Following Chennu et al. (2017), the algorithm was repeatedly run 50 times to minimize the randomness of the iteration processes and then the outputs across the 50 runs were averaged to be the final neural network modularity index.

2.7. Statistical analyses

To conform to the independent observation assumption in the general linear model, only one child's data from each twin pair was selected for the analyses. For each twin pair, the child who attained more epochs than his or her co-twin after EEG pre-processing was selected. The relations among network modularity index of the nine frequency bands were first examined by performing correlation analyses. As the correlations were very high, an exploratory factor analysis was performed to extract a general factor underlying the modularity index. The effects of age and gender on the network modularity factor were then examined by performing a correlation analysis and an independent-sample *t*-test, respectively. Partial correlations between the general modularity factor and both the L1 Chinese and L2 English literacy skills after controlling for age and gender were finally obtained. Age was statistically controlled because age was highly associated with the literacy skills while gender was statistically controlled because a large gender difference in the network modularity was observed. In addition, generalized least squares regression models, with the second set of children included, were also performed to examine whether the same results can be replicated if the paired structure of the twin data was considered in the analysis. Finally, although the main purpose of the current study was not to examine the EEG power, EEG power analyses were performed and the results are reported in the Appendix.

3. Results

3.1. Descriptive and reliability

To conform to the independent observation assumption in the

Table 2
Descriptive results and reliability for age and all behavioral literacy skills.

Variable	Valid N	Reliability	Mean (SD)	Range	Maximum possible
Age	90	–	8.17 (0.99)	6.58–12.42	–
NVIQ	90	0.67	26.79 (8.62)	11–51	60
WM	90	0.95	4.83 (1.93)	1–11	16
CWR	90	0.99	75.46 (33.2)	5–130	150
CPA	89	0.99	26.9 (9.8)	7–41	41
CMA	89	0.88	22.4 (6.9)	0–39	46
CRC	90	0.82	9.6 (5.1)	0–21	24
EWR	90	0.99	19.6 (15.6)	0–50	50
EMA	90	0.82	15.5 (6.3)	0–31	35

Note. NVIQ = nonverbal intelligence; WM = verbal working memory; CWR = Chinese word reading; CPA = Chinese phonological awareness; CMA = Chinese morphological awareness; CRC = Chinese reading comprehension; EWR = English word reading; EMA = English morphological awareness.

general linear model, only one child's data from each twin pair was selected for the subsequent analyses. Means, standard deviations, ranges, and reliability coefficients for the tasks undertaken in the present study are shown in Table 2. Generally, the reliabilities of the measures were acceptable with reliability coefficients ranging from 0.67 to 0.99.

3.2. Correlations between network modularity and literacy skills

Correlational analyses were first performed in the network modularity index of different frequency bands. As shown in Table 3, all the correlations were significant and higher than 0.5, *r*s(88) greater than 0.8, *p*s less than 0.001. As all the correlations in the network modularity index of different frequency bands were very high, an exploratory factor analysis was performed to extract a general network modularity factor across frequency bands. The general network modularity factor explained 77.1% of the total variance. Table 4 shows the component matrix of the factor solution.

The effects of age and gender on the general network modularity factor were then examined by performing a correlation analysis and an independent-sample *t*-test, respectively. Age was not significantly correlated with the general network modularity factor, $r(88) = 0.081$, $p = .448$. In contrast, a large gender difference in the general network modularity factor was found with females (M = 0.27, SE = 0.13) showing a significantly larger network modularity than males ($M = -0.46$, $SE = 0.16$), $t(88) = 3.53$, $p < .001$. Since a large gender difference in the network modularity was found and age was highly associated with the literacy skills ($rs > 0.3$, $ps < 0.003$), partial correlation analyses were performed to examine whether the general network modularity factor was associated with both L1 Chinese and L2 English literacy skills, statistically controlling for age and gender. To rule out the potential influences from higher level cognitive processes, a second set of partial correlation analyses was also performed by additionally controlling for nonverbal IQ and verbal working memory. Table 5 shows the results of both the zero-order correlation and the partial correlation analyses.

As shown in Table 5, for zero order correlation analyses, network modularity was only significantly and positively associated with Chinese phonological awareness and Chinese reading comprehension. For partial correlation analyses, network modularity was significantly positively associated with Chinese word reading, $r(88) = 0.216$, $p = .043$, Chinese phonological awareness, $r(87) = 0.328$, $p = .002$, Chinese morphological awareness (marginally significant), $r(87) = 0.209$, $p = .052$, and Chinese reading comprehension performance, $r(88) = 0.340$, $p = .001$, suggesting that higher network modularity was associated with better performance in Chinese reading and literacy skills. For English, network modularity was not significantly correlated with word reading performance, $r(88) = 0.132$, $p = .222$ or morphological awareness, $r(88) = 0.106$, $p = .326$. Fig. 1 shows the scatter plots of all the partial correlations, statistically controlling for age and gender. The results of the second set of partial correlation analyses which additionally controlled for nonverbal IQ and verbal working memory were

Table 4
Component Matrix of the exploratory factor analysis.

	General Network Modularity Factor
1. delta1	0.803
2. delta2	0.880
3. theta	0.926
4. alpha1	0.933
5. alpha2	0.845
6. alpha3	0.848
7. beta1	0.932
8. beta2	0.882
9. gamma	0.846

Note. The general network modularity factor explained 77.1% of the total variance.

Table 5
Partial correlations between the general modularity factor and the literacy skills.

Measure	N	Zero Order		Partial 1		Partial 2	
		r	*p-value*	*r*	*p-value*	*R*	*p-value*
CWR	90	0.169	0.112	0.216*	0.043	0.261*	0.015
CPA	89	0.243*	0.022	0.328**	0.002	0.339**	0.001
CMA	89	0.189	0.077	0.209	0.052	0.218*	0.045
CRC	90	0.228*	0.031	0.340**	0.001	0.344**	0.001
EWR	90	0.138	0.194	0.132	0.222	0.141	0.196
EMA	90	0.075	0.484	0.106	0.326	0.098	0.368

Note. *$p < .05$, **$p < .01$. CWR = Chinese word reading; CPA = Chinese phonological awareness; CMA = Chinese morphological awareness; CRC = Chinese reading comprehension; EWR = English word reading; EMA = English morphological awareness. The first partial correlation analysis (partial 1) controlled for only age and gender. The second partial correlation analysis (partial 2) controlled additionally for nonverbal IQ and verbal working memory.

Table 3
Correlations among the network modularity index of different frequency bands.

	V1	V2	V3	V4	V5	V6	V7	V8	V9
1. delta1	–	0.93	0.77	0.70	0.57	0.60	0.69	0.57	0.54
2. delta2		–	0.87	0.78	0.63	0.64	0.77	0.69	0.65
3. theta			–	0.90	0.72	0.72	0.82	0.76	0.73
4. alpha1				–	0.80	0.78	0.87	0.78	0.75
5. alpha2					–	0.88	0.75	0.67	0.65
6. alpha3						–	0.78	0.68	0.62
7. beta1							–	0.86	0.80
8. beta2								–	0.94
9. gamma									–

Note. Sample size = 90. All the correlations were larger than 0.5 and significant with *p*-values smaller than 0.001.

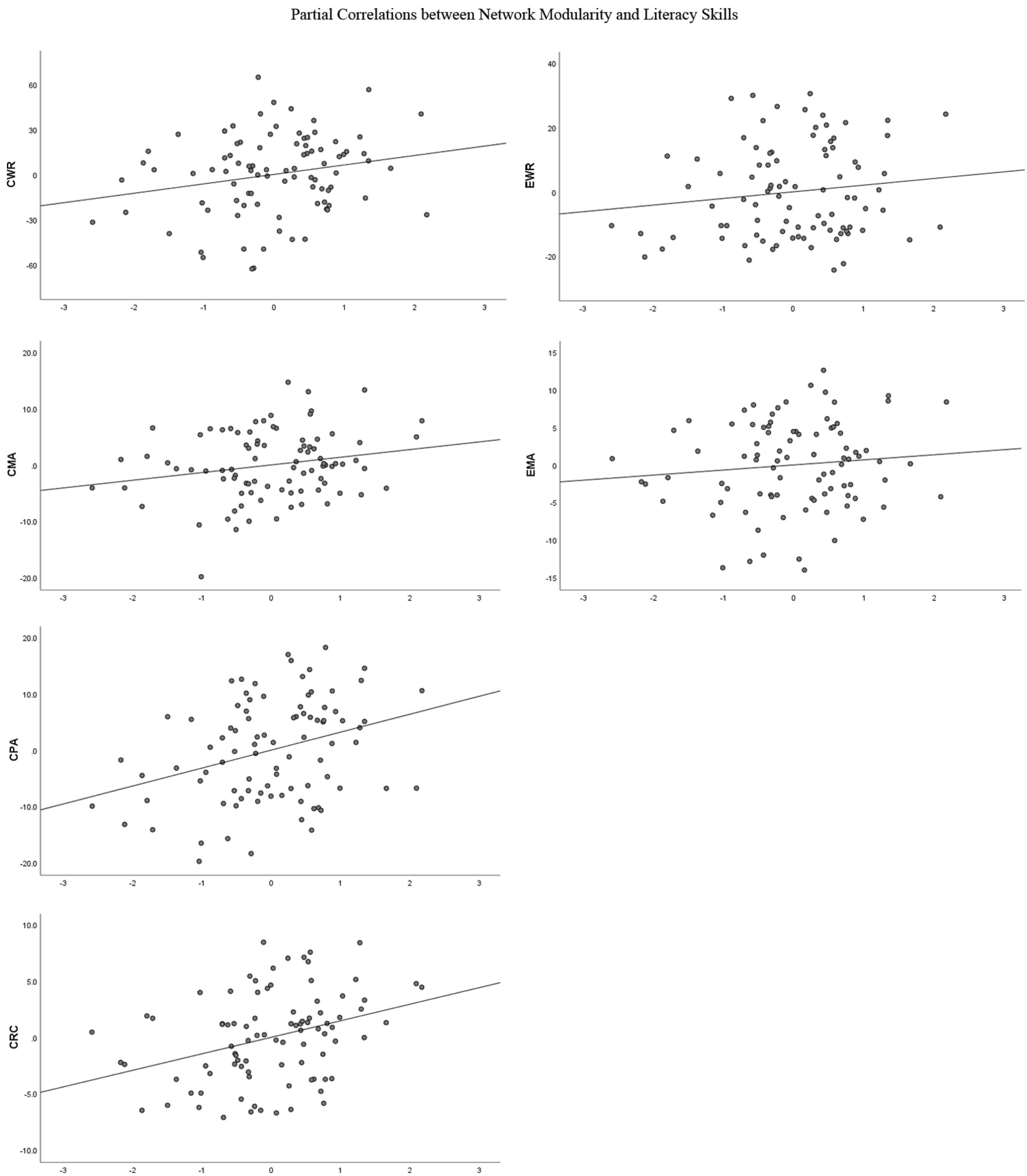

Fig. 1. Scatter plots of the partial correlations between the general network modularity index and both L1 Chinese and L2 English literacy skills.

qualitatively the same as the first set of partial correlation analyses, suggesting that the observed associations between network modularity and L1 Chinese literacy skills were unlikely to have been attributable to higher level cognitive processes.

3.3. Generalized least squares regression with the co-twin

Although the sample size of the second set of children was smaller (60 vs. 90) and the data quality was poorer (average epochs 27.6 vs. 33.9) in comparison to the first set of children, we examined whether the same results could be replicated with this second set of children included. Generalized least squares (GLS) regressions were performed, regressing the L1 Chinese and L2 English literacy skills on the network modularity and the controlled variables (age, gender, nonverbal IQ, and verbal work memory), with the co-twin included in the model (Model 2 suggested by Carlin, Gurrin, Sterne, Morley, & Dwyer, 2005). This

Table 6
Generalized least squares regression with the co-twin.

DV	CWR			CPA			CMA			CRC		
IV	*B*	*t*	*p*	*B*	*t*	*p*	*B*	*t*	*p*	*B*	*t*	*p*
Gender	−9.05	−1.87	0.064	−4.9	−3.12	0.002	−2.2	−1.89	0.060	−2.2	−3.05	0.003
Age	1.40	6.80	0.000	0.13	2.00	0.047	0.21	4.24	0.000	0.19	6.48	0.000
IQ	−0.50	−1.70	0.091	0.23	2.41	0.017	0.08	1.12	0.262	0.06	1.49	0.137
WM	3.49	3.11	0.002	0.88	2.40	0.018	0.45	1.66	0.099	0.44	2.66	0.009
Mod$_{(W)}$	−0.47	−0.10	0.915	2.0	1.37	0.174	0.39	0.37	0.712	0.35	0.55	0.586
Mod$_{(B)}$	7.59	2.90	0.004	2.0	2.39	0.018	1.5	2.40	0.018	1.2	3.05	0.003
	EWR						**EMA**					
	B	***t***	***p***				***B***	***t***	***p***			
Gender	−0.37	−0.15	0.883				−1.9	−1.89	0.061			
Age	0.41	3.80	0.000				0.07	1.65	0.102			
IQ	0.35	2.25	0.026				0.19	2.97	0.004			
WM	0.50	0.85	0.400				0.44	1.83	0.069			
Mod$_{(W)}$	−0.53	−0.23	0.819				1.2	1.24	0.219			
Mod$_{(B)}$	2.5	1.80	0.074				1.1	1.89	0.061			

Note. CWR = Chinese word reading; CPA = Chinese phonological awareness; CMA = Chinese morphological awareness; CRC = Chinese reading comprehension; EWR = English word reading; EMA = English morphological awareness; IQ = nonverbal IQ; WM = verbal working memory; Mod$_{(w)}$ = within-pair coefficient for network modularity; Mod$_{(B)}$ = between-pair coefficient for network modularity.

Table A1
Partial correlations between the EEG ERSP and the literacy skills.

Frequency	Region	CWR	CPA	CMA	CRC	EWR	EMA
Delta	Frontal	0.004	0.189	0.032	0.084	0.122	0.011
	Central	0.026	0.198	0.042	0.028	0.208	0.058
	Temporal	0.083	0.106	0.076	0.153	0.215*	0.059
	Parietal	−0.057	0.163	−0.029	0.139	0.073	−0.002
	Occipital	−0.130	0.180	0.017	0.023	0.030	0.054
Theta	Frontal	0.060	0.288*	0.004	0.236*	0.087	0.002
	Central	0.043	0.273*	−0.071	0.111	0.171	−0.029
	Temporal	0.057	0.129	−0.053	0.149	0.113	−0.037
	Parietal	0.047	0.153	−0.013	0.197	0.109	0.041
	Occipital	0.015	0.198	0.128	0.142	0.085	0.141
Alpha	Frontal	0.025	0.174	−0.016	0.163	0.058	0.020
	Central	0.035	0.230*	0.071	0.180	0.186	0.110
	Temporal	0.018	0.186	0.005	0.149	0.207	0.090
	Parietal	0.019	0.184	0.012	0.183	0.137	0.102
	Occipital	0.028	0.161	0.095	0.163	0.051	0.076
Beta	Frontal	0.087	0.209	0.099	0.188	0.059	0.078
	central	−0.015	0.163	0.034	0.118	0.103	−0.001
	temporal	0.089	0.130	0.001	0.144	0.110	0.001
	parietal	−0.016	0.152	−0.046	0.093	0.078	0.024
	occipital	0.023	0.127	−0.044	0.085	0.073	0.022
Gamma	frontal	0.116	0.040	0.010	0.090	−0.054	0.009
	central	−0.072	0.005	−0.108	0.061	0.014	−0.070
	temporal	0.032	0.038	−0.092	0.027	0.050	−0.017
	parietal	−0.067	0.136	−0.152	0.030	0.040	−0.081
	occipital	0.059	0.058	−0.054	−0.041	0.006	−0.017

Note. *$p < .05$, **$p < .01$. CWR = Chinese word reading; CPA = Chinese phonological awareness; CMA = Chinese morphological awareness; CRC = Chinese reading comprehension; EWR = English word reading; EMA = English morphological awareness.

approach was recommended because it took into account the paired structure of the twin data. As shown in Table 6, the between-pair coefficient for network modularity was significant for all L1 Chinese literacy skills, suggesting that network modularity tends to be positively associated with L1 Chinese literacy skills even taking into consideration the paired structure of the twin data in the model.

4. Discussion

The present study examined the associations between neural network modularity computed from resting state EEG activity and both L1 Chinese and L2 English literacy skills of grade 1 to grade 5 Chinese children. The neural network modularity indices of different frequency bands were highly correlated with each other. The general neural network modularity index extracted among the indices of various frequency bands through an exploratory factor analysis was also significantly and moderately correlated with the Chinese language measures, including Chinese word reading, Chinese phonological awareness, Chinese morphological awareness, and Chinese reading comprehension. The correlations showed that higher network modularity was associated with better performance in Chinese reading and literacy skills. On the other hand, the general neural network modularity index was not significantly correlated with either English word reading or English morphological awareness.

4.1. Resting state EEG network modularity as a proxy for cognitive plasticity

The present study found that the whole brain network modularity computed from resting state EEG data was positively associated with various L1 Chinese literacy skills including word reading, phonological awareness, morphological awareness (marginally significant), and reading comprehension. These findings provide support for the theoretical argument that neural network modularity represents cognitive plasticity (Gallen & D'Esposito, 2019). Although the EEG data were collected at the scalp level, the phase coherence estimates of phase relationships should be partially invariant to volume conduction (Chennu et al., 2017; Fraga González et al., 2018); hence, the modularity index computed based on the phase coherence matrix should be a valid indicator for brain network modularity. A neural network with high modularity has many connections within modules which allow for faster processing (Coltheart, 1999) and reduce network wiring costs (Clune, Mouret, & Lipson, 2013). Meanwhile, a high modularity neural network also has few connections between modules which results in a neural network with relatively independent modules and so increases the flexibility in learning (Ellefsen, Mouret, & Clune, 2015). The higher modular organization of the neural network and larger cognitive plasticity, in turn, lead to better learning outcomes in various cognitive domains, including the Chinese language acquisition assessed in the current study. This was consistent with previous behavioral studies suggesting a positive association between L1 Chinese literacy skills and different cognitive abilities including visual spatial skill (e.g., Lin, Sun, & Zhang, 2016; Liu, Chen, & Chung, 2015; McBride-Chang, Chow, Zhong, Burgess, & Hayward, 2005) and executive functioning (Zhang, 2016). In addition, high cognitive plasticity should be beneficial in general for different cognitive domains, consistent with the current findings showing that neural network modularity was associated with L1 Chinese language skills in different processing levels.

4.2. Cognitive plasticity predicts only L1 Chinese language skills

As Chinese is the first language of the children in the current study, the current findings suggest that first language acquisition is closely related to individual cognitive plasticity. The lack of significant correlations between network modularity and English word reading performance and morphological awareness suggests that second language learning may not benefit a lot from the highly modular neural system. This seems to support the claim that the modular systems of the brain may fail or function inefficiently in second language learning (Sparks & Ganschow, 1993). Another possible explanation is that second language learning may also be affected by affective factors such as motivation (Gardner et al., 1985) and anxiety (Horwitz et al., 1986), as well as social factors such as resources available to children (Palfreyman, 2006; Paradis, 2011). In Hong Kong, all children learn English in school from an early age, but families and schools differ tremendously in terms of how they value learning this language and the resources they have available for facilitating such learning.

Another possible explanation for the neural network modularity being positively associated with L1 Chinese language skills but not L2 English language skills, however, is that Chinese and English are quite different in the properties of the writing system. In a behavioral study, Tavassoli (2002) showed that spatial memory was marginally better for Chinese characters and words in native Chinese speakers than for English words in native English speakers (Experiment 1), and spatial memory for symbols was better in native Chinese speakers than in native English speakers (Experiment 2). Chinese characters are more visually complex than English words and with a greater grapheme inventory size than English with about 5000 commonly used characters (Lee, 2000). In addition, the orthography-phonology association is relatively arbitrary in Chinese. Perhaps Chinese skills are more related to cognitive plasticity than English language skills due to these differences in the writing system. The data from the current study are not able to differentiate these two different accounts of the results. It is also possible that both factors play a role in influencing the associations between language and cognition. Future research can examine the association between neural network modularity and the development of various L1 languages to provide additional information.

4.3. Resting state EEG network modularity as a reliable neural marker

The current findings also provide support for the suggestion that neural network modularity is a reliable neural marker (Gallen & D'Esposito, 2019). The present study has shown that it can be used to predict L1 Chinese reading acquisition for typically developing children across the primary school grades. In contrast to the inconsistent findings of the previous resting state EEG power studies (as shown in Table 1), the current findings were consistent with studies by Fraga González et al. (2016) and Fraga González et al. (2018), which performed graph analysis on resting state EEG data and found a less integrated network organization and reduced presence of specialized sub-networks in children and adults with dyslexia as compared to typically reading children and adults, respectively. The clear theoretical interpretation for the neural network modularity in terms of cognitive plasticity is intriguing and provides theoretical evidence supporting the reliability and validity of the neural network modularity as a neural marker in predicting learning outcomes across cognitive domains.

Compared to EEG power and coherence, which were shown to be frequency dependent, network modularity appears to be relatively frequency independent. The general neural modularity index extracted was able to account for 77.1% of the total variance of the neural modularity indices across frequency bands ranging from delta (0.5–4 Hz) to gamma (30–40 Hz). This is consistent with findings from a previous study (Joudaki, Salehi, Jalili, & Knyazava, 2012) showing that the relationships between various graph metrics of EEG data, including network modularity and network size, were highly similar across frequency bands. This implies that the cognitive plasticity measured by the neural network modularity is frequency independent and probably relatively general across cognitive domains. As a result, the positive associations between network modularity and learning outcomes have been reliably observed across studies examining different cognitive domains (Gallen & D'Esposito, 2019). Meanwhile, it is a cost-effective neural marker which can be assessed using a short (e.g., 3 min in the current study) and simple EEG paradigm. Taken together, resting state EEG network modularity is practically valuable as a reliable, valid, and cost-effective neural marker in predicting learning outcomes in various cognitive domains.

It is also worth noting that the sample size of the current study was relatively large in comparison to previous studies examining the relationships between resting state EEG power and language abilities. The sample size of the 15 studies, summarized in Table 1, ranged from 18 to 99 with a mean sample size of 47. Therefore, the sample size of the current study with 99 pairs of twins was more than double the mean sample size of previous studies. In addition, the current study was conducted on a twin sample which allowed us to select the child with higher quality of EEG data from each twin pair. Taken together, the current study has found evidence from a relatively large sample with good data quality supporting an intriguing possibility that resting state EEG network modularity can serve as a reliable neural marker to predict literacy skills in the first language of Chinese. Future research, however, is needed to attempt to replicate the findings in different samples who are learning to read in a different first language.

4.4. Limitations

There are, however, two limitations to note for the present study. First, correlation does not imply causation. The correlations found between neural network modularity and Chinese reading performance may not guarantee that higher neural network modularity is the cause of better literacy development. Future studies should assess both the neural network modularity and reading performance longitudinally and examine these relations in the development of both. Second, there were fewer English reading measures included in the current study than the Chinese reading measures. In addition, more robust effects were found for Chinese phonological awareness and Chinese reading comprehension which were not assessed in English. Therefore, one should be cautious in interpreting the non-significant associations between neural network modularity and L2 English language acquisition. Nevertheless, the present study underscores ways in which behavioral and neural measures can be considered together to understand cognitive development fully.

4.5. Conclusion

The current study found that the whole brain network modularity index computed based on resting state EEG data, collected from Chinese primary school children, was positively associated with L1 Chinese literacy measures, including word reading, phonological awareness, morphological awareness, and reading comprehension but not L2 English word reading and morphological awareness. The neural network modularity appeared to be frequency independent and associated with Chinese reading performance at both the word level and text level, suggesting that it may represent the general cognitive plasticity of an individual. It was associated with L1 Chinese measures but not L2 English measures, perhaps at least in part because L2 literacy acquisition tends to be more affected by affective and social factors. It is also possible that Chinese and English literacy skills have differential properties that influence this association. Nevertheless, the current findings were highly consistent with previous behavioral studies showing stronger cognitive correlations for L1 Chinese than L2 English and previous graph analysis studies showing reduced presence of specialized sub-networks in children and adults with dyslexia. Taken together, the present study has suggested that resting state EEG network modularity is a potentially reliable and valid neural marker in predicting L1 Chinese literacy development.

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Authors Contributions

K. Lui developed the study concept, while all authors contributed to the design of the study. C. McBride and C. Ho acquired the funding and supervised the project. K. Lui and J. Lo analyzed the data with input from U. Maurer. K. Lui drafted the manuscript. All authors revised the manuscript and approved the final version of the manuscript for submission.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. EEG power analyses

EEG data from individual trials were submitted to time–frequency analysis using fixed-window Fast Fourier Transforms (FFTs) implemented in EEGLab. The estimates of the event-related spectral perturbation (ERSP in decibel, Makeig, 1993) were then averaged across trials for the following frequency bands: delta (0.5–4 Hz), theta (4–6 Hz), alpha (6–12 Hz), beta (12–30 Hz), and gamma (30–40 Hz) and for the following regions of interest: frontal area (Fp1, Fp2, AF3, AF4, AF7, AF8, AFZ, F1, F2, F3, F4, F5, F6, F7, F8, Fz), central area (C1, C2, C3, C4), temporal area (T7, T8, T9, T10), parietal area (P1, P2, P3, P4, P5, P6, P7, P8, Pz) and occipital area (O1, O2, OZ). The partial correlations, statistically controlling for age and gender, of EEG ERSP with Chinese and English literacy skills were then examined. As shown in Table A1, only 5 out of 150 correlations were significant. It can be concluded that there were in general no associations between EEG ERSP and literacy skills.

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