

Individual Differences in Resting-state Brain Rhythms Uniquely Predict Second Language Learning Rate and Willingness to Communicate in Adults

Chantel S. Prat, Brianna L. Yamasaki, and Erica R. Peterson

Abstract

■ The current study used quantitative electroencephalography (qEEG) to characterize individual differences in neural rhythms at rest and to relate them to fluid reasoning ability, to first language proficiency, and to subsequent second language (L2) learning ability, with the goal of obtaining a better understanding of the neurocognitive bases of L2 aptitude. Mean spectral power, laterality, and coherence metrics were extracted across theta, alpha, beta, and gamma frequency bands obtained from eyes-closed resting-state qEEG data from 41 adults aged 18–34 years. Participants then completed 8 weeks of French training using a virtual language and cultural immersion software. Results replicate and extend previous studies showing that faster learners have higher beta power recorded over right hemisphere (RH) electrode sites, greater laterality (RH – LH/RH + LH) of alpha and beta bands, and greater coherence between

RH frontotemporal sites across all frequencies, although only coherence measures survived multiple comparisons. Increased coherence within and between RH networks was also associated with greater posttest declarative memory scores and with more accurate speech during learning. Total speech attempts, in contrast, correlated with bilaterally distributed small-world network configurations, as indexed by lower power and coherence over high-frequency (beta and gamma) bands recorded over frontotemporal networks in both hemispheres. Results from partial correlations and regression analyses suggest that the neural predictors of L2 learning rate, posttest proficiency, and total speech attempts varied in their degree of overlap with qEEG correlates of first language proficiency and fluid reasoning abilities, but that neural predictors alone explained 26–60% of the variance in L2 outcomes. ■

INTRODUCTION

The concept of a “talent” for language learning has captivated researchers, educators, and laypersons alike for centuries (e.g., Handschin & Henmon, 1930; Russell, 1858). Perhaps this is because language is one of the quintessential human abilities, or perhaps it is because many of us have attempted to learn a second language (L2) and failed. Differences in the ease with which languages can be acquired across the lifespan have been the focus of extensive research on learning and neural plasticity (e.g., Birdsong, 1999; Snow & Hoefnagel-Höhle, 1978). Despite the fact that acquiring an L2 in adulthood is difficult, large individual differences, typically referred to as L2 aptitude, exist (e.g., Dörnyei, 2009), and researchers from a variety of fields have attempted to measure and understand these differences with incremental success (see Wen, Biedroń, & Skehan, 2017, for a review).

Theoretical perspectives of L2 aptitude have historically progressed iteratively with the development of behavioral batteries for assessing it (see Wen et al., 2017; Dörnyei & Skehan, 2003, for reviews) and by extension to theories of L2 learning. One central research question

that has been addressed through such psychometric investigations is whether L2 aptitude consists of one or many aptitudes. For example, the foundational work of Carroll (e.g., Dörnyei, 2009; Carroll & Sapon, 1959) resulted in a four-factor model of L2 aptitude, which included phonemic coding ability, grammatical sensitivity, inductive language learning ability, and associative memory strength. A related theoretical question is understanding the extent to which L2 aptitude is specific to language learning or reflects a more general ability to learn complex skills or acquire knowledge (e.g., Gardner & Lambert, 1965).

Relatively recently, neuroscientists have “thrown their hat into the ring” in attempts to answer these questions. The majority of this research has measured neural changes associated with different levels of L2 proficiency (Chee, Soon, Lee, & Pallier, 2004; Mechelli et al., 2004; Perani et al., 1998), and a subset of studies have investigated neural changes longitudinally as a function of increasing exposure to an L2 (see Mamiya, Richards, Coe, Eichler, & Kuhl, 2016; Li, Legault, & Litcofsky, 2014, for a review). However, very few studies have related individual differences in brain functioning to language aptitude or to the ability to acquire an L2 in the future, adopting, in effect, a neuropsychometric approach (Chai et al., 2016; Prat, Yamasaki, Kluender, & Stocco, 2016; Qi, Han, Garel, San

Chen, & Gabrieli, 2015; Tan et al., 2011). Importantly, two of these existing studies (Chai et al., 2016; Prat et al., 2016) have measured properties of brain functioning at “rest,” and a third focused on static properties of white matter structure (Qi et al., 2015). Such research is critical, as it allows one to partially disentangle any intrinsic properties of brain functioning associated with facile learning from differences that result from the way an individual’s brain might process or respond to linguistic stimuli.

To understand the neuropsychometric properties of resting-state data obtained from quantitative electroencephalography (qEEG) measures, the current study employs an individual differences approach (Prat, 2011), relating variability in network-level brain functioning at rest and a battery of cognitive variables to the subsequent ease (or difficulty) with which one acquires an L2 in adulthood. The goals of this approach are (1) to better understand the neurocognitive basis of L2 acquisition and (2) to characterize the patterns of brain functioning associated with “good” L2 learning. Although these goals are interrelated, their implications are largely separate. The first goal is centered on the belief that comprehensive theories of L2 acquisition should be able to account for individual differences in brain functioning and their behavioral consequences (e.g., Prat, 2011). The second provides a template for what optimal functioning looks like, which can be used to target brain-based interventions (see Hanslmayr, Sauseng, Doppelmayr, Schabus, & Klimesch, 2005; Klimesch, Sauseng, & Gerloff, 2003, for examples of this approach within intelligence research).

In the first exploration of resting-state qEEG predictors of L2 aptitude, Prat and colleagues (2016) showed that the power in beta and gamma frequency bands of neural oscillations recorded primarily over right hemisphere (RH) electrode sites was the strongest predictor of subsequent L2 learning rates. Based on the correspondence between these findings and what is known about the role of the RH and first language (L1) proficiency, Prat et al. (2016) proposed that these results may reflect the known relation between L1 proficiency and L2 aptitude. Specifically, according to the RH dynamic spillover hypothesis, monolingual individuals who are more proficient in their native language have more specialized patterns of brain activation, which are more highly left-lateralized, resulting in recruitment of fewer RH resources for language processes (Prat, 2011; Prat, Mason, & Just, 2011). It is worth noting, however, that laterality differences in qEEG recorded over the scalp do not necessarily translate to ipsilateral cortical sources.

Prat and colleagues (2016) also found that individual differences in laterality of alpha power predicted L2 learning rate. Based on the correspondence between this result and previous research linking resting-state qEEG to fluid intelligence (Thatcher, North, & Biver, 2005), they proposed that this finding may highlight a more general role of fluid cognitive abilities in L2 acquisition (Sasaki, 1996; Gardner & Lambert, 1965).

The goal of the current study was to extend these previous results and our knowledge of the neurocognitive basis of L2 aptitude more broadly by exploring the degree to which qEEG indicators of L2 aptitude reflect individual differences in linguistic specific abilities (as measured by L1 proficiency) versus more general correlates of fluid reasoning (as measured by the Raven’s Advanced Progressive Matrices [RAPM]). In addition, we explored multiple facets of L2 learning to look for convergence and divergence of neural predictors. In a recent review of the neural basis of language aptitude, Biedron (2015) states that “One of the most important obstacles in examining *foreign language* aptitude is the heterogeneity of the construct” (p. 15). By leveraging what is known about the neural basis of learning, fluid reasoning, and individual differences in L1 proficiency, the current experiment investigated neural oscillations, properties of intrinsic brain functioning that are known to relate to subsequent cognitive performance (see Klimesch, 1999, for a review). Specifically, we used metrics obtained through qEEG recorded while participants sat with their eyes closed to predict subsequent L2 learning ability.

The current study employed the Operational Language and Culture Training System (OLCTS), a virtual immersion language training software that provides simultaneous training in language and sociocultural norms (Johnson, Friedland, Watson, & Surface, 2012). This software, which has been used to investigate L2 aptitude (Prat et al., 2016), was designed to enable military personnel to function safely and effectively in foreign countries by attaining functional language proficiency in very short time periods. The training is organized hierarchically around goal-based scenarios (e.g., obtaining transportation). It requires the learner to interact with intelligent avatars by speaking and by choosing socially relevant behaviors such as eye contact (or lack thereof), interruption of ongoing speech, and formality of intonation.

The current investigation extends the previous work by Prat and colleagues (2016) in several important ways. First, qEEG data were analyzed using a network-level approach, which assessed not only mean power and laterality in functional networks known to correlate with language learning (Kepinska, Pereda, Caspers, & Schiller, 2017) but also spectral coherence within and between these networks. This allows us to make further inferences about the mechanisms driving differences in power and laterality. Second, total speech attempts and speaking accuracy during L2 learning were added to L2 learning rate and posttest declarative memory as outcome measures. This allows us to assess whether procedural (speaking accuracy) and declarative (translational accuracy) outcome variables are explained by the same neural metrics. Finally, the current study involves a much larger sample size than the original, allowing us to examine which of the effects originally measured on 16 participants replicates in a group of 41 participants.

METHODS

Participants

Forty-seven healthy adults aged 18–34 years (33 women)¹ were initially recruited for participation in this study. Of these, data were analyzed from the 41 participants who completed the 8-week French training program. Partial data from 16 of these participants linking qEEG power to L2 learning rate was previously reported in a brief communication article (Prat et al., 2016). All participants were monolingual English speakers with no previous exposure to French or to any L2 before the age of 10 and reported low proficiency to any L2 exposed to at any point. All participants gave informed consent according to the standards set forth by the University of Washington institutional review board and were paid for their participation.

Materials

Behavioral Assessments of Cognitive Abilities

A battery of standardized or commonly used tests of fluid information processing (Raven's Advanced Progressive Matrices, Arthur & Day, 1994; Reading Span and Operation Span, Unsworth, Heitz, Schrock, & Engle, 2005), executive functioning (Simon Task, Stocco et al., 2017; 3-back updating task, Kane, Conway, Miura, & Colflesh, 2007; color-shape-switching task, Monsell, 2003; Continuous Performance Test, Cohen, Barch, Carter, & Servan-Schreiber, 1999; Attentional Blink task, Raymond, Shapiro, & Arnell, 1992; Broadbent & Broadbent, 1987), probabilistic learning (Probabilistic Stimulus Selection task, Frank, Seeberger, & O'Reilly, 2004), and English reading ability (Nelson-Denny Reading Test [NDRT]; Brown, Fishco, & Hanna, 1993) were used to assess cognitive abilities behaviorally. These tasks are described in more detail in Prat et al. (2016) and in the supplementary material.²

Language Training Software

The OLCTS (Johnson et al., 2012), a virtual immersion language training program, was used to provide participants with 8 weeks of French language training. The OLCTS provides immersive, goal-directed cultural and language training, including comprehension and production components (using speech recognition software), as well as sociocultural practices and pragmatic instruction. These skills are applied through goal-directed scenarios involving interactions with avatars and then tested explicitly through quizzes that incorporate all aspects of linguistic proficiency (written comprehension, verbal production, and auditory comprehension). The OLCTS is organized by “units” or “levels” that terminate with these quizzes. Participants were not allowed to advance until they obtained a minimum accuracy of 50% on each quiz. At the end of each 30-min training session, the final level was recorded. A regression line was fit to terminal-level data at each session to calculate a rate of L2 learning. For each

participant, the OLCTS records the total number of speech productions and number of “correct” speech attempts. A speech attempt is considered correct when the utterance is recognized, with the highest likelihood, from a classification model that uses utterances of both native speakers and of learners in the “correct” model and also includes a “garbage” parameter. Speaking accuracy was determined by taking the ratio of correct speech attempts to total speech attempts as measured by the software.

The French–English Translation Posttest of French Proficiency

Long-term declarative memory for items studied was assessed using a French–English translation test, which was created individually for each participant based on the materials they encountered over the 8-week session of language training. The test required participants to select the correct English translation for 50 French words or phrases they learned during training. The number of items drawn from each level was proportionate to the amount of material covered on that level.

Procedures

Participant Training and Testing

All participants initially completed two 1.5-hr testing sessions in which all behavioral measures were collected. In addition, 5 min of eyes-closed resting-state EEG were collected at 128 Hz using wireless, EPOC 16-channel Emotiv headsets, with reference channels set at DMS and CRL electrodes over the parietal lobe. The presentation order of the behavioral tests varied across participants, but EEG was always collected at the beginning of one of the behavioral sessions. Following these two sessions, all participants received sixteen 30-min language training sessions using the OLCTS over the course of 8 weeks.

qEEG Analysis

Initial EEG data were analyzed using the procedures outlined in the preliminary report (Prat et al., 2016), which were slightly modified from Doppelmayr, Klimesch, Stadler, Pöhlhuber, and Heine (2002). In short, the 5 min of resting-state data were segmented into 2-sec epochs with 50% overlap and cleaned for blinks, motion, and impedance artifacts, and the artifact-free data were analyzed using fast Fourier transform to measure average power in theta (4–7.5 Hz), alpha (8–12.5 Hz), beta (13–29.5 Hz), and low-gamma (30–40 Hz) frequency bands for each individual. Any channel that did not have at least 75 artifact-free epochs was not included in the data analysis, which resulted in the removal of 13 channels (2.2% of the data), which were treated as missing in subsequent analyses. Spectral coherence was calculated for all pairwise combinations of electrodes. As in other publications (e.g., Sauseng, Klimesch, Schabus, & Doppelmayr, 2005),

coherence $C_{x,y}(f)$ between two channels x and y at a frequency f was computed according to the formula:

$$C_{x,y}(f) = \frac{P_{x,y}(f)^2}{P_x(f) \times P_y(f)}$$

where the $P_{x,y}(f)$ is the cross-power density and the $P_x(f)$ and $P_y(f)$ are the power densities of x and y , respectively. The calculations were carried out using the default spectral analysis function in the R statistical software (R Core Team, 2013).

To reduce the dimensionality of this qEEG data in a theoretically driven way, we then collapsed the 14 qEEG channels into networks based on recent data obtained from phase synchronization during an artificial grammar learning task (Kepinska et al., 2017). The resulting five networks, as depicted in Figure 1, were (A) medial frontal consisting of AF3, AF4, F3, and F4 electrodes; (B) LH frontotemporal consisting of F7, FC5, and T7 electrodes; (C) RH frontotemporal consisting of F8, FC6, and T8 electrodes; (D) LH posterior consisting of P7 and O1 electrodes; and (E) RH posterior consisting of P8 and O2 electrodes. Mean power across each of the four frequency bands was computed over each network by averaging the results of the fast Fourier transform analysis on individual channels within each network. From these data, two laterality indices were then calculated for each of the four frequency bands by subtracting mean power in each frequency band in the LH network from the mean power in the corresponding RH network and dividing by the average of the two values (e.g., $C - B / \text{Average}(C, B)$). Mean within- and between-network spectral coherence analyses were then computed by averaging coherence within networks and between network pairs, as indicated by red arrows in Figure 1.

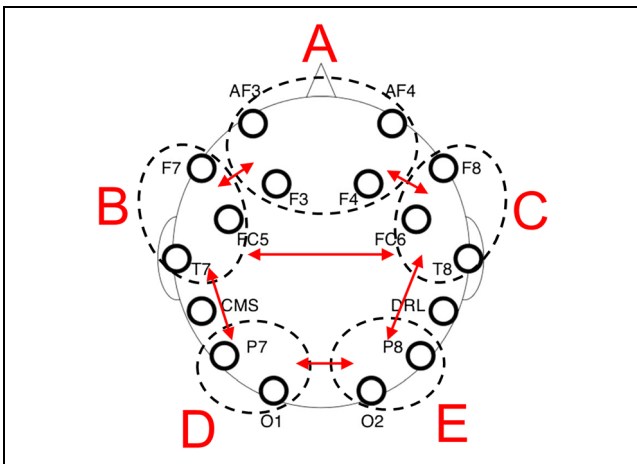


Figure 1. Schematic depiction of network-level qEEG data analysis conducted based on Kepinska et al. (2017). Letters correspond to networks labeled herein: (A) medial-frontal, (B) LH frontotemporal, (C) RH frontotemporal, (D) LH posterior, and (E) RH posterior. Red arrows indicate between-network coherence analyses that were conducted as reported in Table 1.

Group-level network coherence analysis supported our choice of networks, as all within network coherence values were significantly greater than between network values (see Table 1). False discovery rates (FDRs) were also calculated and reported for each of the analyses (Benjamini & Hochberg, 1995).

RESULTS

Individual Differences in Indicators of L2 Learning

Individual differences in the ability to acquire an L2 in adulthood were apparent in each of the four metrics of L2 learning acquired. With respect to L2 learning rate, the fastest learner progressed three and a half times as quickly through the training program as the slowest learner did (mean = 0.80, range = 0.38–1.32, $SD = 0.22$). Individual learning rates are depicted in Figure 2. A similar amount of variability was observed for proportion of correct speech attempts (mean = 0.24, range = 0.13–0.33, $SD = .05$), with even greater variability observed for total speech attempts (mean = 2025, range = 280–3586, $SD = 825$) across the 8-week session. In contrast, performance on the declarative memory posttest was much less variable (mean = 91.7%, range = 70–100%, $SD = 7.86\%$).

Correlations between the four indicators of L2 learning suggest that they were not completely independent. Specifically, accuracy on the declarative memory posttest was positively correlated with rate of L2 learning, $r_s(41) = .54, p = .001$, demonstrating that the fastest learners also retained the most information following training. A positive correlation between total speech attempts and proportion of correct speech attempts, $r_s(41) = .44, p = .004$, was also observed, showing that willingness to communicate, as indexed by total speech attempts, was positively correlated with accuracy of speech, as indexed by the percentage of these utterances recognized as correct by the software.

Cognitive Predictors of L2 Learning

L2 Learning Rate

As in our previous experiment, none of the cognitive tests correlated significantly with L2 learning rate ($ps > .05$).

Declarative Memory Posttest

Performance on the declarative memory posttest was positively correlated with L1 proficiency, as measured by the NDRT, $r_s(41) = .45, p = .001$. None of the other cognitive measures reliably correlated with declarative memory posttest scores.

Total Speech Attempts

Total speech attempts were negatively correlated with the attentional blink size, $r_s(41) = -.40, p = .010$, such

Table 1. Mean Group-level Within and Between-network Coherence Values (*SEM* in Parentheses) with Paired Sample *t* Test Comparison Values Demonstrating that All Within-network Coherence Values Were Significantly Greater than All Between-network Coherence Values

<i>Within-network Coherence</i>		<i>Between-network Coherence</i>		<i>t Test</i>
A) Medial frontal	.755 (.006)	A-B	.613 (.005)	$t(40) = 26.8, p < .001$
A) Medial frontal	.755 (.006)	A-C	.651 (.006)	$t(40) = 16.5, p < .001$
B) LH frontotemporal	.625 (.008)	B-A	.613 (.005)	$t(40) = 2.7, p = .009$
B) LH frontotemporal	.625 (.008)	B-D	.525 (.002)	$t(40) = 12.5, p < .001$
B) LH frontotemporal	.625 (.008)	B-C	.565 (.005)	$t(40) = 10.3, p < .001$
C) RH frontotemporal	.710 (.012)	C-A	.651 (.006)	$t(40) = 7.5, p < .001$
C) RH frontotemporal	.710 (.012)	C-E	.619 (.006)	$t(40) = 15.6, p < .001$
C) RH frontotemporal	.710 (.012)	C-D	.565 (.005)	$t(40) = 9.6, p < .001$
D) LH posterior	.607 (.008)	D-B	.525 (.002)	$t(37) = 9.2, p < .001$
D) LH posterior	.607 (.008)	D-E	.545 (.004)	$t(37) = 7.5, p < .001$
E) RH posterior	.742 (.007)	E-C	.619 (.006)	$t(36) = 18.0, p < .001$
E) RH posterior	.742 (.007)	E-D	.545 (.004)	$t(36) = 26.6, p < .001$

that people who spoke aloud more frequently had reliably smaller attentional blinks. Total speech attempts were also positively correlated with working memory updating accuracy as measured by total accuracy, $r_s(41) = .34, p = .031$, and distractor accuracy, $r_s(41) = .40, p = .010$, on the 3-back updating task.

Proportion of Accurate Speech

None of the cognitive tests correlated significantly with proportion of accurate speech ($ps > .05$), although verbal working memory as measured by the reading span task approached significance, $r_s(41) = .29, p = .067$.

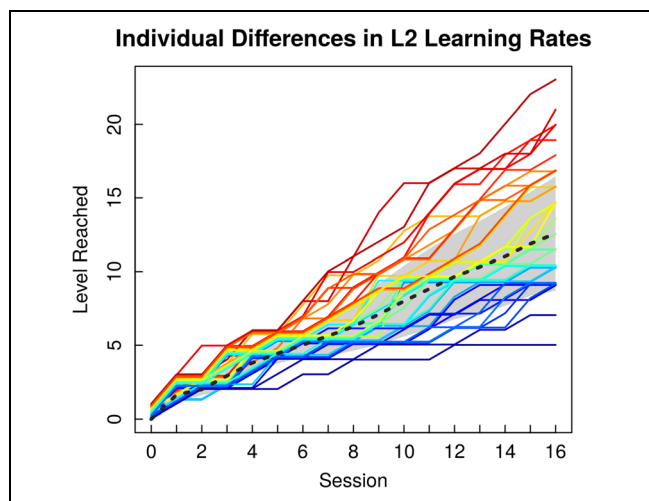


Figure 2. L2 learning rates for individual participants plotted as a function of level reached at the end of each 30-min training session (mean level depicted by dashed line, standard deviation of the mean in gray).

Relating Individual Differences in Resting-state qEEG Power to L2 Aptitude Variables

Fluid Reasoning Ability

Performance on the abbreviated RAPM did not correlate with mean power averaged across any of the five networks.

L1 Proficiency

Performance on the NDRT was correlated with alpha power in the RH in both frontotemporal, $r_s(37) = .33, p = .049$, and posterior, $r_s(37) = .34, p = .039$, networks as well as in the LH posterior network, $r_s(38) = .33, p = .046$. L1 proficiency was also correlated with mean theta power averaged over bilateral frontal, $r_s(40) = .36, p = .023$, and RH posterior, $r_s(37) = .36, p = .031$, networks.

Relating Individual Differences in Resting-state qEEG Power to L2 Learning

L2 Learning Rate

Consistent with previous research (Prat et al., 2016), mean power in the beta frequency range recorded over the RH predicted subsequent L2 learning rate. Specifically, mean beta power over the RH posterior cluster was significantly positively correlated with L2 learning rate, $r_s(37) = .39, p = .019$, and the correlation between mean beta power over the RH frontotemporal electrode cluster and L2 learning rate approached significance, $r_s(37) = .31, p = .063$. Both correlations retained or reached significance when either L1 proficiency or fluid intelligence were partialled out ($ps < .025$).

Declarative Memory Posttest

Performance on the declarative memory posttest did not correlate with qEEG power at rest ($p > .10$). This finding also replicates previous research (Prat et al., 2016).

Total Speech Attempts

Total number of speech attempts was negatively correlated with mean beta power recorded over both left frontotemporal, $r_s(40) = -.38, p = .016$, and right frontotemporal, $r_s(37) = -.41, p = .013$, sites and approached significance over the medial frontal network, $r_s(40) = -.31, p = .054$. Number of speech attempts was also negatively correlated with mean gamma power recorded over RH frontotemporal, $r_s(37) = -.41, p = .012$, and posterior, $r_s(37) = -.48, p = .003$, networks. These negative correlations retained or reached significance when either L1 proficiency or fluid intelligence were partialled out ($p < .05$).

Proportion of Accurate Speech

Proportion of accurate speech attempts did not correlate with qEEG power at rest, although a negative correlation between mean beta power in the left frontotemporal network and accurate speech approached significance, $r_s(40) = -.28, p = .077$.

None of the reported correlations between L2 variables and resting-state qEEG power remained significant when FDR corrections for multiple comparisons were applied. All bivariate correlations between the four OLCTS outcome measures and power in the five resting-state networks are listed in Table 2.

Relating Individual Differences in Resting-state qEEG Laterality to L2 Aptitude Variables

Fluid Reasoning Ability

Performance on the RAPM did not correlate with frontotemporal or posterior laterality in any power band.

L1 Proficiency

NDRT scores were positively correlated with frontotemporal laterality across theta, $r_s(37) = .36, p = .030$, and alpha, $r_s(37) = .34, p = .042$, frequency bands.

Relating Individual Differences in Resting-state qEEG Laterality to L2 Learning

L2 Learning Rate

Consistent with previous research (Prat et al., 2016), L2 learning rate was positively correlated with laterality in alpha and beta frequency bands. Specifically, L2 learning

rate was positively correlated with alpha laterality in both frontotemporal, $r_s(37) = .44, p = .006$, and posterior, $r_s(35) = .40, p = .016$, networks, whereas learning rate only correlated with laterality of beta power in posterior regions, $r_s(35) = .34, p = .046$. When controlling for L1 proficiency, only frontotemporal alpha laterality remained significant ($p = .017$), although the resulting correlation with posterior alpha laterality, $r_s(32) = .30, p = .084$, was not significantly different than the original correlation ($p = .65$). Correlations with posterior beta laterality and L2 learning rate also decreased when L1 proficiency was partialled out, $r_s(32) = .16, p = .381$, although the correlations were still not significantly different (correlation difference: $p = .48$). Similarly, when controlling for fluid intelligence, only frontotemporal alpha laterality remained significant, $r_s(34) = .40, p = .017$, although the resulting correlation with posterior alpha laterality, $r_s(32) = .33, p = .055$, was not significantly different than the original correlation ($p = .76$). Correlations with posterior beta laterality and L2 learning rate also decreased when fluid intelligence was partialled out, $r_s(32) = .17, p = .327$, although the correlations were still not significantly different ($p = .48$).

Declarative Memory Posttest

Declarative memory posttest scores were not correlated with resting-state qEEG laterality ($p > .10$).

Total Speech Attempts

Total speech attempts did not correlate with any index of power laterality at rest ($p > .17$).

Proportion of Accurate Speech

Proportion of accurate speech did not correlate with resting-state laterality; however, the correlation with laterality in frontotemporal beta power approached significance, $r_s(37) = .31, p = .067$.

None of the reported correlations between L2 variables and resting-state qEEG laterality remained significant when FDR corrections for multiple comparisons were applied. All bivariate correlations between the four OLCTS outcome measures and laterality indices are listed in Table 3.

Relating Individual Differences in Resting-state qEEG Coherence to L2 Aptitude Variables

Fluid Reasoning Ability

Performance on the RAPM was positively correlated with coherence within the RH posterior network across theta frequencies, $r_s(37) = .40, p = .014$.

Table 2. All Bivariate Correlations (Spearman's Rho) between Mean Power Obtained from Resting-state qEEG Networks and L2 Outcome Variables

<i>Network</i>	<i>L2 Learning Rate</i>	<i>Posttest Scores</i>	<i>Speech Attempts</i>	<i>Correct Speech</i>
<i>A. Medial Frontal</i>				
theta (4–7.5 Hz)	.158 (40)	.180 (40)	.107 (40)	.259 (40)
alpha (8–12.5 Hz)	.049 (40)	–.005 (40)	–.047 (40)	.084 (40)
beta (13–29.5 Hz)	.252 (40)	.066 (40)	–.307 (40)	–.027 (40)
gamma (30–40 Hz)	.179 (40)	–.023 (40)	–.304 (40)	.040 (40)
<i>B. Left Frontotemporal</i>				
theta (4–7.5 Hz)	.014 (40)	–.090 (40)	–.259 (40)	–.152 (40)
alpha (8–12.5 Hz)	.018 (40)	–.033 (40)	–.213 (40)	–.092 (40)
beta (13–29.5 Hz)	.021 (40)	.013 (40)	–.379 (40)*	–.283 (40)
gamma (30–40 Hz)	–.024 (40)	–.005 (40)	–.250 (40)	–.124 (40)
<i>C. Right Frontotemporal</i>				
theta (4–7.5 Hz)	.286 (37)	.154 (37)	–.115 (37)	.138 (37)
alpha (8–12.5 Hz)	.227 (37)	.166 (37)	–.104 (37)	.110 (37)
beta (13–29.5 Hz)	.308 (37)	.088 (37)	–.406 (37)*	–.010 (37)
gamma (30–40 Hz)	.161 (37)	–.116 (37)	–.410 (37)*	–.122 (37)
<i>D. Left Posterior</i>				
theta (4–7.5 Hz)	.235 (38)	.170 (38)	.121 (38)	.280 (38)
alpha (8–12.5 Hz)	.062 (38)	.089 (38)	.116 (38)	.275 (38)
beta (13–29.5 Hz)	.132 (38)	.086 (38)	–.260 (38)	.061 (38)
gamma (30–40 Hz)	.029 (38)	.064 (38)	–.205 (38)	.017 (38)
<i>E. Right Posterior</i>				
theta (4–7.5 Hz)	.286 (37)	.173 (37)	.028 (37)	.216 (37)
alpha (8–12.5 Hz)	.154 (37)	.100 (37)	.028 (37)	.226 (37)
beta (13–29.5 Hz)	.385 (37)*	.179 (37)	–.288 (37)	–.011 (37)
gamma (30–40 Hz)	.129 (37)	.093 (37)	–.481 (37)**	–.216 (37)

ns are in parentheses.

* $p < .05$.

** $p < .01$.

L1 Proficiency

Performance on the NDRT was positively correlated with coherence within medial frontal network over theta, $r_s(41) = .32, p = .045$, and alpha, $r_s(41) = .31, p = .048$, frequencies and negatively correlated with coherence between left and right posterior networks over the theta frequency band, $r_s(41) = -.33, p = .035$.

Relating Individual Differences in Resting-state qEEG Coherence to L2 Learning

L2 Learning Rate

Rate of L2 learning was positively correlated with mean coherence within the right frontotemporal network across all power bands, $r_s(41) = .35, p = .026$. This was driven by

Table 3. All Bivariate Correlations (Spearman's Rho) Between Laterality Indices Obtained from Mean Power Averaged across Resting-state qEEG Networks and L2 Outcome Variables

	<i>L2 Learning Rate</i>	<i>Posttest Scores</i>	<i>Speech Attempts</i>	<i>Correct Speech</i>
<i>Frontal</i>				
theta (4–7.5 Hz)	.242 (37)	.219 (37)	.227 (37)	.243 (37)
alpha (8–12.5 Hz)	.440 (37)**	.245 (37)	.184 (37)	.211 (37)
beta (13–29.5 Hz)	.119 (37)	–.029 (37)	.126 (37)	.305 (37)
gamma (30–40 Hz)	.053 (37)	–.250 (37)	–.082 (37)	.077 (37)
<i>Posterior</i>				
theta (4–7.5 Hz)	.208 (35)	–.044 (35)	–.058 (35)	–.051 (35)
alpha (8–12.5 Hz)	.404 (35)*	.139 (35)	–.215 (35)	–.061 (35)
beta (13–29.5 Hz)	.339 (35)*	.107 (35)	–.107 (35)	–.012 (35)
gamma (30–40 Hz)	.014 (35)	–.042 (35)	–.204 (35)	–.129 (35)

ns are in parentheses.

* $p < .05$.

** $p < .01$.

strong positive correlations between learning rate and right frontotemporal coherence in theta, $r_s(41) = .46$, $p = .003$, and alpha, $r_s(41) = .38$, $p = .014$, frequency ranges. Conversely, rate of L2 learning was negatively correlated with coherence within the left posterior network across all power bands, $r_s(38) = -.39$, $p = .016$. In particular, coherence across alpha, $r_s(38) = -.35$, $p = .029$, and beta, $r_s(38) = -.36$, $p = .025$, frequency bands was significantly negatively related to L2 learning rate. These correlations remained significant when controlling for L1 proficiency and fluid intelligence ($ps < .05$).

Declarative Memory Posttest

Similar to rate of L2 learning, accuracy on the declarative memory posttest was positively correlated with mean coherence within the right frontotemporal network across all power bands, $r_s(41) = .48$, $p = .001$. This was reflected by strong positive correlations between posttest score and right frontotemporal coherence in theta, $r_s(41) = .54$, $p < .001$; alpha, $r_s(41) = .50$, $p = .001$; and beta, $r_s(41) = .40$, $p = .010$, frequency ranges. In addition, mean coherence between right frontotemporal and right posterior regions across all power bands significantly predicted declarative memory posttest scores, $r_s(41) = .37$, $p = .016$. This was driven by correlations over theta, $r_s(41) = .38$, $p = .013$, and alpha, $r_s(41) = .39$, $p = .013$, frequency ranges. Coherence over the theta frequency band between right frontotemporal and medial–frontal networks was also positively correlated with posttest

performance, $r_s(41) = .35$, $p = .027$. When controlling for L1 proficiency or fluid reasoning abilities, the correlations remained significant ($ps < .03$).

Total Speech Attempts

Total speech attempts were reliably negatively correlated with gamma coherence within the left frontotemporal network, $r_s(41) = -.49$, $p = .001$. On the contrary, mean coherence across frequencies in the left posterior network was positively correlated with total speech attempts, $r_s(38) = .33$, $p = .045$, driven primarily by strong positive correlations with alpha coherence, $r_s(38) = .46$, $p = .004$, and more moderate correlations with beta coherence, $r_s(38) = .34$, $p = .035$. When controlling for L1 proficiency, these correlations remained marginally significant ($ps < .053$). When controlling for fluid intelligence, the correlation with left frontotemporal gamma coherence remained highly significant ($p = .001$), whereas the correlation with left posterior coherence across all channels dropped below significance, $r_s(35) = .31$, $p = .060$, but was not significantly lower than the original ($p = .93$).

Proportion of Accurate Speech

Proportion of accurate speech was also correlated with higher coherence in RH networks, averaged across all power bands between RH frontotemporal and posterior networks, $r_s(41) = .32$, $p = .041$. Although this trend was observed for all frequency bands below gamma ($ps < .10$), it was significant only over the beta frequency band,

$r_s(41) = .34, p = .029$, when ranges were considered separately. These correlations dropped below significance when either L1 proficiency or fluid reasoning abilities were factored out ($ps < .10$), but the resulting correlations were not significantly different than the originals ($ps > .70$).

Positive correlations between declarative memory and right frontotemporal coherence and negative correlations between total speech attempts and gamma coherence between left frontotemporal networks remained significant after FDR corrections for multiple comparisons were applied. All correlations between the four OLCTS outcome measures and coherence metrics are listed in Table 4.

Regression Analyses

L2 Learning Rate

When the six predictors of L2 learning rate (right posterior mean beta power, frontotemporal and posterior alpha laterality, posterior beta laterality, mean within right frontotemporal coherence across all bands, and mean within left posterior coherence across all bands) were entered into a simultaneous regression analysis, the model was significant, $F(6, 25) = 3.89, p = .007$, and explained 48% of the variance in L2 learning rate, with a Bayesian Information Criteria (BIC) of 98.35. Only right posterior beta power ($b = .33, t = 2.17, p = .04$) and frontotemporal alpha laterality ($b = .36, t = 2.12, p = .044$) were significant predictors. By comparison, when L1 language proficiency and fluid reasoning were entered along with the qEEG variables into the model, the significance was approximately the same, $F(8, 23) = 3.21, p = .013$, and explained 53% of the variance in L2 learning rate, with a BIC of 102.37. Right posterior beta power remained the strongest predictor, although it was not significant in the full model ($b = .29, t = 1.83, p = .08$). Both models showed very strong evidence of fitting the data better than the null model (BIC = 122.77; model probabilities = 99.99% for both the EEG-only and EEG plus L1 proficiency and fluid reasoning model). The probability that the EEG-only model explained more variance in L2 learning rate than the EEG plus behavioral model was 88.20%. However, given that this represents only “positive” evidence for a difference, the data suggest that the two models fit the data similarly well (Wagenmakers, 2007; Raftery, 1995).

Declarative Memory Posttest

When the three predictors of declarative posttest scores (mean within right frontotemporal network and between right frontotemporal and posterior network coherence across all frequency ranges, and mean between right frontotemporal and medial frontal theta coherence) were entered into a simultaneous regression analysis, the

model was significant, $F(3, 37) = 4.39, p = .010$, and explained 26% of the variance, with a BIC of 121.42. However, only RH frontotemporal to posterior coherence approached significance ($b = .335, t = 1.83, p = .076$) as a predictor. By comparison, when L1 proficiency and fluid reasoning were entered along with the three qEEG variables into the model, the significance was increased, $F(5, 35) = 6.37, p < .001$, and explained 48% of the variance in L2 learning rate, with a BIC of 114.80. Only L1 proficiency explained significant variance in this model ($b = .45, t = 3.59, p = .001$). When compared with a null model (BIC = 122.77), the only model to demonstrate strong evidence for a better fit to the data than the null model was the EEG plus L1 proficiency and fluid reasoning model (model probability = 98.17%).

Total Speech Attempts

When the six predictors of total speech attempts (mean left and right frontotemporal beta power, mean right frontotemporal and posterior gamma power, mean within left frontotemporal gamma coherence, and mean within left posterior coherence across all bands) were entered into a simultaneous regression analysis, the model was highly significant, $F(6, 25) = 6.34, p < .001$, and explained 60% of the variance, with a BIC of 520.73. Mean within left posterior coherence across all frequency bands ($b = .41, t = 2.88, p = .008$) and mean right posterior gamma power ($b = -.53, t = -2.52, p = .018$) were significant predictors. By comparison, when L1 proficiency and fluid intelligence were entered along with the six qEEG variables into the model, the model remained highly significant, $F(8, 23) = 5.35, p = .001$, and explained 65% of the variance, with a BIC of 523.62. Again, however, only mean within left posterior coherence across all frequencies ($b = .36, t = 2.55, p = .018$) and mean right posterior gamma power ($b = -.47, t = -2.22, p = .036$) remained significant when the variables competed for variance. There was very strong evidence that both the EEG-only and the EEG plus L1 proficiency and fluid reasoning models explained significantly more variance in total speech attempts than the null model (BIC = 673.45; model probabilities = 100.00% for both the EEG-only and the EEG, L1 proficiency, and fluid reasoning model). Again, there was only positive evidence to suggest that the EEG-only model fit the data better than the EEG plus behavioral model (model probability = 80.97%), which suggests that both models fit the data similarly well.

Proportion of Correct Speech

Because there was only one significant correlation between proportion of correct speech and resting-state qEEG, we did not run regression analyses on this outcome variable.

Table 4. All Bivariate Correlations (Spearman's Rho) between Network Coherence Indices and L2 Outcome Variables

<i>Network Coherence</i>	<i>L2 Learning Rate</i>	<i>Posttest Scores</i>	<i>Speech Attempts</i>	<i>Correct Speech</i>
<i>Within Medial Frontal</i>				
theta (4–7.5 Hz)	–.026 (41)	–.019 (41)	–.064 (41)	–.271 (41)
alpha (8–12.5 Hz)	.032 (41)	.001 (41)	–.100 (41)	–.103 (41)
beta (13–29.5 Hz)	–.107 (41)	.010 (41)	–.044 (41)	–.166 (41)
gamma (30–40 Hz)	–.108 (41)	–.005 (41)	–.145 (41)	–.236 (41)
All	–.035 (41)	.021 (41)	–.083 (41)	–.236 (41)
<i>Within Left Frontotemporal</i>				
theta (4–7.5 Hz)	.213 (41)	.242 (41)	–.122 (41)	–.196 (41)
alpha (8–12.5 Hz)	.078 (41)	.091 (41)	–.180 (41)	–.076 (41)
beta (13–29.5 Hz)	.046 (41)	.003 (41)	–.243 (41)	–.145 (41)
gamma (30–40 Hz)	–.033 (41)	–.154 (41)	–.492 (41)**	–.284 (41)
All	.066 (41)	.094 (41)	–.230 (41)	–.142 (41)
<i>Within Left Posterior</i>				
theta (4–7.5 Hz)	–.238 (38)	.008 (38)	.229 (38)	.159 (38)
alpha (8–12.5 Hz)	–.354 (38)*	–.070 (38)	.455 (38)**	.251 (38)
beta (13–29.5 Hz)	–.363 (38)*	–.061 (38)	.342 (38)*	.090 (38)
gamma (30–40 Hz)	–.188 (38)	.103 (38)	–.066 (38)	.001 (38)
All	–.388 (38)*	–.107 (38)	.327 (38)*	.120 (38)
<i>Within Right Frontotemporal</i>				
theta (4–7.5 Hz)	.458 (41)**	.542 (41)**	–.003 (41)	.098 (41)
alpha (8–12.5 Hz)	.380 (41)*	.504 (41)**	–.092 (41)	.113 (41)
beta (13–29.5 Hz)	.261 (41)	.398 (41)**	–.049 (41)	.125 (41)
gamma (30–40 Hz)	.248 (41)	.261 (41)	–.240 (41)	–.137 (41)
All	.348 (41)*	.484 (41)**	–.066 (41)	.114 (41)
<i>Within Right Posterior</i>				
theta (4–7.5 Hz)	.034 (37)	.123 (37)	.019 (37)	.206 (37)
alpha (8–12.5 Hz)	.155 (37)	.272 (37)	.269 (37)	.097 (37)
beta (13–29.5 Hz)	.132 (37)	.287 (37)	–.062 (37)	.031 (37)
gamma (30–40 Hz)	.131 (37)	.261 (37)	–.314 (37)	–.046 (37)
All	.153 (37)	.298 (37)	–.087 (37)	.037 (37)
<i>Left Frontotemporal to Right Frontotemporal</i>				
theta (4–7.5 Hz)	.063 (41)	.117 (41)	–.018 (41)	.064 (41)
alpha (8–12.5 Hz)	–.029 (41)	.081 (41)	–.119 (41)	.089 (41)
beta (13–29.5 Hz)	–.005 (41)	.139 (41)	–.083 (41)	–.034 (41)
gamma (30–40 Hz)	–.046 (41)	.144 (41)	–.302 (41)	–.088 (41)
All	.026 (41)	.182 (41)	–.102 (41)	.048 (41)

Table 4. (continued)

<i>Network Coherence</i>	<i>L2 Learning Rate</i>	<i>Posttest Scores</i>	<i>Speech Attempts</i>	<i>Correct Speech</i>
<i>Left Posterior to Right Posterior</i>				
theta (4–7.5 Hz)	–.091 (41)	–.082 (41)	–.090 (41)	–.078 (41)
alpha (8–12.5 Hz)	–.154 (41)	–.074 (41)	.162 (41)	.064 (41)
beta (13–29.5 Hz)	–.128 (41)	–.033 (41)	.035 (41)	–.185 (41)
gamma (30–40 Hz)	–.129 (41)	.023 (41)	–.116 (41)	–.202 (41)
All	–.108 (41)	–.022 (41)	–.008 (41)	–.126 (41)
<i>Left Frontotemporal to Medial Frontal</i>				
theta (4–7.5 Hz)	.046 (41)	.076 (41)	–.011 (41)	–.041 (41)
alpha (8–12.5 Hz)	–.074 (41)	.010 (41)	–.140 (41)	.077 (41)
beta (13–29.5 Hz)	–.130 (41)	.011 (41)	–.167 (41)	–.107 (41)
gamma (30–40 Hz)	–.150 (41)	–.014 (41)	–.271 (41)	–.237 (41)
All	–.050 (41)	.017 (41)	–.181 (41)	–.095 (41)
<i>Right Frontotemporal to Medial Frontal</i>				
theta (4–7.5 Hz)	.231 (41)	.345 (41)*	–.149 (41)	–.061 (41)
alpha (8–12.5 Hz)	.057 (41)	.264 (41)	–.172 (41)	.079 (41)
beta (13–29.5 Hz)	.090 (41)	.253 (41)	–.230 (41)	–.088 (41)
gamma (30–40 Hz)	.084 (41)	.286 (41)	–.163 (41)	.073 (41)
All	.073 (41)	.262 (41)	–.219 (41)	–.077 (41)
<i>Left Frontotemporal to Left Posterior</i>				
theta (4–7.5 Hz)	–.040 (41)	–.072 (41)	.041 (41)	.122 (41)
alpha (8–12.5 Hz)	–.183 (41)	–.016 (41)	.086 (41)	.124 (41)
beta (13–29.5 Hz)	–.230 (41)	–.104 (41)	.037 (41)	–.016 (41)
gamma (30–40 Hz)	–.195 (41)	–.155 (41)	–.128 (41)	–.098 (41)
All	–.220 (41)	–.096 (41)	.076 (41)	.089 (41)
<i>Right Frontotemporal to Right Posterior</i>				
theta (4–7.5 Hz)	.263 (41)	.384 (41)*	.069 (41)	.290 (41)
alpha (8–12.5 Hz)	.292 (41)	.386 (41)*	–.059 (41)	.273 (41)
beta (13–29.5 Hz)	.077 (41)	.278 (41)	.074 (41)	.342 (41)*
gamma (30–40 Hz)	.051 (41)	.170 (41)	–.117 (41)	.133 (41)
All	.187 (41)	.374 (41)*	.013 (41)	.320 (41)*

ns are in parentheses.

* $p < .05$.

** $p < .01$.

DISCUSSION

The results reported herein provide extended evidence that characteristics of intrinsic brain functioning, as measured by resting-state qEEG, can be used to predict individual differences in subsequent L2 acquisition in adulthood. Results from the current experiment replicated and extended our original report (Prat et al., 2016) by demonstrating again that mean beta power recorded over RH regions and laterality of frontotemporal alpha and posterior beta power (as indexed by RH – LH/average of the two) were associated with faster L2 learning. The current experiment provided further evidence about the mechanisms underpinning these differences by showing that learning rate, declarative knowledge, and speaking accuracy were also correlated with greater coherence within and between RH networks. With respect to learning rate and memory performance, this increased coherence was most prevalent in theta and alpha frequency ranges, which have been widely demonstrated to reflect memory and general cognitive processes (Klimesch, 1999). Using a neuropsychometric approach, the results of the current study also showed that combined neural metrics explained 48% of the variance in subsequent L2 learning rate, which is comparable to that explained by standardized behavioral measures such as the MLAT (Carroll, 1958). In addition, the current results provide neural evidence supporting the hypothesis that L2 aptitude is a multifaceted construct, involving a combination of general and language-specific abilities. These results are linked to their theoretical implications in greater detail in subsequent sections.

Relating qEEG Predictors of L2 Learning to L1 Proficiency and Fluid Reasoning Abilities

One of the motivations of the current experiment was to explore the overlap between neural predictors of L2 learning and neural correlates of L1 proficiency. Some overlap between these two variables was observed, particularly with respect to alpha and theta laterality recorded over the frontotemporal networks, which correlated both with L1 proficiency and with L2 learning rate. However, when L1 proficiency was partialled out of the correlation between L2 learning rate and laterality, the resulting correlations did not significantly change. Thus, although individual differences in L1 proficiency and L2 outcome measures shared some resting-state qEEG features, the relation between L2 learning rate and qEEG laterality was not explained by L1 proficiency.

Another hypothesis explored herein is that the relation between intrinsic brain functioning and L2 aptitude is explained, in part, by domain general cognitive mechanisms such as fluid reasoning. Interestingly, the correlations between our abbreviated RAPM and resting-state qEEG were confined to increased theta coherence within the RH posterior network, which did not overlap with any of the

other L2 aptitude predictors. This may be because shortening the RAPM reduced our power to detect individual differences in fluid reasoning abilities. It is worth noting again that alpha laterality has been correlated with fluid intelligence (Thatcher et al., 2005), so this remains an area of interest for future investigation. Along these lines, when fluid intelligence was partialled out of the relation between L2 learning rate and alpha and beta laterality, the correlation between posterior alpha and beta laterality decreased, although not significantly so. Taken together, these results suggest that the relation between L2 learning and qEEG characterizations of intrinsic brain functioning at rest is not significantly explained by fluid reasoning abilities.

Perhaps the strongest piece of evidence about the roles of L1 proficiency and fluid reasoning abilities in L2 aptitude can be gleaned from the regression analysis data. Specifically, when NDRT and RAPM scores were added to the qEEG predictors, there was no evidence that the resulting models predicted L2 learning rate or total speaking attempts better than the qEEG models alone. In fact, positive evidence suggested that the qEEG alone models explained the data better. This pattern of results, when combined with the lack of behavioral correlations and lack of significant changes in partial correlations, suggests that neither L1 proficiency (as measured by NDRT) nor fluid reasoning abilities (as measured by abbreviated RAPM) explain the association between resting-state brain functioning and individual differences in L2 learning outcomes.

In contrast, regression analyses conducted on the declarative memory posttest suggested that only the model that included L1 proficiency, fluid reasoning, and qEEG indicators explained the data significantly. In addition, when behavioral and brain metrics were entered simultaneously, L1 proficiency was the only significant predictor of posttest performance. These analyses provide specific evidence that L1 proficiency and increased RH coherence contribute uniquely to ultimate posttest proficiency obtained and that L1 proficiency explains more of the variance than RH functioning. Taken together, results from these analyses provide preliminary evidence about the relation between fluid reasoning abilities, L1 proficiency, and resting-state qEEG as predictors of various facets of L2 aptitude. As a second step, the cognitive implications of the current set of results are discussed in light of what is known about the neurocognitive bases of neural oscillations.

Leveraging Neural Oscillations to Understand the Cognitive Bases of L2 Learning

In the current study, we operationalized individual differences in L2 language learning in four ways: (1) rate of L2 learning, which corresponds to the most basic definition of aptitude (e.g., Carroll, 1958); (2) long-term declarative memory for vocabulary learned, which corresponds to the amount of crystallized information retained across

learning, (3) total speech attempts produced, which reflects a willingness to engage with the software aloud, and (4) the percentage of speech utterances correctly recognized by the software, which reflects combined declarative (knowing what to say) and procedural (knowing how to pronounce it) skills.

Relating Beta Power and Laterality to L2 Learning Rate

Consistent with our previous study, increased beta power in RH posterior regions and increased laterality over these regions correlated with faster L2 learning, although only the later survived multiple corrections. Beta frequency bands have become increasingly implicated in online linguistic processes (see Weiss & Mueller, 2012, for a review) and seem to be particularly important for maintaining or binding information that unfolds over time in memory. For example, experiments measuring online memory encoding have shown that increased power in beta (12–20 Hz) was associated with the encoding of novel auditory stimuli (Haenschel, Baldeweg, Croft, Whittington, & Gruzelier, 2000). In addition, qEEG recordings obtained intracranially from the anterior parahippocampal regions have shown evidence for increased beta (19–25 Hz) power and synchronization as a function of increasing working memory task demands (Axmacher, Schmitz, Wagner, Elger, & Fell, 2008). In a recent review of cortical plasticity changes associated with short-term L2 learning, Li and colleagues (2014) summarized evidence suggesting that increases in RH hippocampal volumes accompany L2 learning in the laboratory setting.

Despite the increasing amount of evidence implicating beta frequencies to online language processing, it can be difficult to understand how characteristics of beta at rest might predict subsequent language learning. One critical link comes from a study that used independent component analysis to define multiple resting-state networks and to correlate them with resting-state qEEG characteristics (Mantini, Perrucci, Del Gratta, Romani, & Corbetta, 2007). They identified six resting-state networks, and the strongest correlation between beta power and these networks was observed for Resting-State Network 4, which consisted primarily of bilateral temporal networks proposed to be involved in auditory and phonological systems. Taken together, the existing research suggests that power and synchronization recorded over the RH posterior network in beta frequencies may relate to systems involved in either memory encoding and maintenance broadly construed or more specifically to auditory/phonological encoding processes. We see this as an important area for future exploration.

Relating Beta Power to Total Speech Attempts

It is worth noting that the relation between beta power and the willingness to engage verbally with the software, as indexed by total speech attempts, was nonoverlapping

with the predictors of L2 learning rate. Specifically, lower beta power in bilateral frontotemporal regions (with no laterality effects) was correlated with an increased number of speech attempts. Taken together, this may reflect a difference in the importance of frontotemporal versus posterior beta networks, a difference in the nature of the two outcome measures (which were not correlated with one another), or some combination of the two. Below, we discuss a third option, centered on the interaction between high- and low-frequency qEEG bands, hemispheres, and network configuration.

Individual Differences in LH and RH Network Configuration Differentially Predict L2 Learning Outcomes

The network coherence analyses discussed for the first time herein contribute critically to our understanding of the nature of the individual differences in resting-state qEEG reported previously (Prat et al., 2016). With one exception discussed subsequently, increased coherence within and between RH networks was associated with better L2 learning outcomes whereas decreased coherence within LH was associated with better L2 learning outcomes (see Figure 3). Specifically, increased coherence across all power bands within the RH frontotemporal network was predictive both of rate of L2 learning and of ultimate declarative memory proficiency level achieved, and increased coherence of all power bands between RH frontotemporal and posterior networks was positively correlated with both posttest proficiency and total speaking accuracy measures. Although none of these measures reflects a “pure” index of L2 learning aptitude, their shared reliance on declarative memory performance, combined with the fact that these effects were often largest in alpha and theta frequency bands, suggests that the availability of large-scale, undifferentiated networks may promote more facile initial L2 learning.

The fact that these results were significant when averaging across power bands is also consistent with previous research showing that increased white matter organization in the RH corresponds to better L2 learning (e.g., Mamiya et al., 2016; Qi et al., 2015). Qi and colleagues (2015) suggested that their findings, linking the quality of the superior and inferior longitudinal fasciculi in the RH to subsequent Mandarin learning success, may be related to the particular auditory and visuospatial demands of Mandarin, which are both tonal and logographic. However, Mamiya and colleagues (2016) found similar results in native Chinese learners of English. The fact that the current study involved native English learners of French provides further evidence that the relevance of the RH for L2 learning may not be specific to the perceptual demands of the language. In addition, despite the convergence between our findings and structural brain research, it is important to note that, without sufficient scalp coverage to assess source localization, it is unclear whether

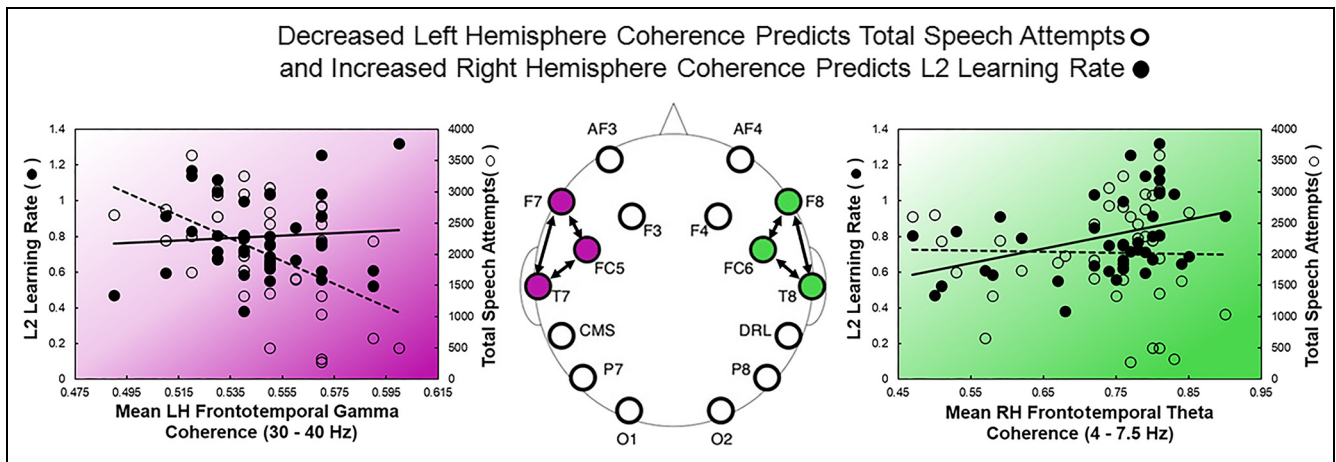


Figure 3. Scatterplots depicting individual differences in rate of L2 learning (filled circles) and total speech attempts (open circles) as a function of LH coherence over gamma bands (in purple) and RH coherence over theta bands (in green). Electrode locations are displayed in center.

the qEEG coherence recorded over the RH reflects large-scale networks that are generated in the RH. We see this as an important next step for this research.

In contrast, lower coherence recorded over LH frontotemporal networks in the gamma frequency band (which is known to reflect local cortical firing patterns) was strongly associated with a higher willingness to communicate. In addition, lower coherence across all frequency bands within the LH posterior network was correlated with faster rates of L2 learning. Only one L2 learning outcome (L2 learning rate) was associated with both higher RH coherence and lower LH coherence. Thus, these differences may reflect fundamental distinctions in the neural computations reflected by the various L2 outcome tasks.

Relating LH Posterior Coherence to L2 Aptitude

Perhaps the most puzzling findings in the current study show that decreased coherence in the LH posterior network across all frequency bands was predictive of an increased rate of L2 learning but a decreased number of total speech attempts (the one exception to the LH/RH coherence distinction). One might suppose that this reflects the fact that speech acts take time and that people who voluntarily engage in more speech acts move more slowly through the software than those who don't. Although the correlation between the two variables does trend in that direction, $r_s(41) = -.26, p = .38$, it is not significant. These results are even more perplexing when viewed in light of a recent study investigating resting-state connectivity using fMRI and L2 aptitude (Chai et al., 2016). Specifically, this study, which also investigated native English speakers learning French, showed that increased connectivity between the left visual word form area (a posterior region) and the superior temporal gyrus correlated with faster subsequent L2 reading rate. Thus, our results may suggest that increased lexical access through reading pathways is associated with a greater

willingness to engage verbally with the software; however, it seems as though facility with L2 lexical access should also enable individuals to move through the software more rapidly. As discussed in the next section, a better understanding of the nature of individual differences in total speech attempts is necessary to gain traction on this puzzle.

Individual Differences in Network-level Functioning and Speaking Behaviors

Among the most novel findings of the current experiment are those that address the neurocognitive correlates of learners' willingness to engage verbally with the software (total speech attempts). Such individual differences have been characterized in the literature as "willingness to communicate" (Burgoon, 1976; MacIntyre, 2007) and are difficult to measure in canonical classroom or immersion environments. It is unclear whether existing research, which has focused on individuals' willingness to engage verbally with other live speakers, can be applied to our language training paradigm, which involves interacting with computers. One possible link is that all language learners were in the same room with another person (the experimenter) seated at a different table. It is worth noting that there are several portions of the learning experience where speaking aloud is optional and that doing so required learners to produce foreign sounds in the presence of the experimenter. Thus, it is plausible that some of the key factors that have been related to willingness to communicate (e.g., positive self-confidence, low communication apprehension, high motivation) may drive differences in total speech attempts, whereas it is less likely that other variables (international attitudes) drive these differences (Öz, Demirezen, & Pourfeiz, 2015; Fallah, 2014; Yashima, Zenuk-Nishide, & Shimizu, 2004; Yashima, 2002).

Our data suggest that this willingness to speak was largely correlated with the presence of small-world

networks (or focal representations) as indexed by lower power in higher-frequency ranges (gamma and beta), thought to reflect more focal network coupling, over bilateral frontotemporal and RH posterior regions and by lower coherence between LH frontotemporal regions over gamma frequencies. These predictors of total speech attempts were completely nonoverlapping with the other L2 outcome variables, suggesting that if total speech attempts index social cognition in some way, the neural indicators of these skills are not overlapping with those associated with L2 learning rate, posttest declarative memory, or even with speaking accuracy, which was positively correlated with total speech attempts. In fact, each of these outcome measures was associated with greater coherence in RH networks. Taken together, these findings limit our ability to consider the role of social motivation in RH contributions to L2 learning. However, our data do provide novel characterizations of individual differences in willingness to communicate aloud in experimental settings.

It is critical to note here that total speech attempts were predicted by two cognitive variables, attentional blink size and working memory updating accuracy. Although these two variables are considerably different in nature, they both deal with the ability to encode serially presented information in memory. With respect to the attentional blink in particular, recent work in our lab has shown that bilingual language experience correlates with the size of attentional blink observed, such that bilingual individuals who exhibit more balanced use of both of their languages on a daily basis (or more frequent use of their less dominant language) were also shown to have smaller attentional blinks (Yamasaki, Stocco, & Prat, 2018). The data reported herein suggests that this relation may be driven, in part, by individual differences in willingness to communicate, which may be underpinned by differences in executive attention. We see this as an important area for future investigation, as willingness to communicate has been largely viewed as a social/personality variable rather than a cognitive one. Because willingness to communicate relates to speaking proficiency in our current data and more broadly to L2 proficiency in the literature (Knell & Chi, 2012), understanding its neurocognitive underpinnings is critical to understanding individual differences in L2 learning.

Summary

The results reported herein replicate and extend previous research using qEEG (Prat et al., 2016), resting-state fMRI (Chai et al., 2016), and structural connectivity (Mamiya et al., 2016; Qi et al., 2015) metrics of intrinsic network-level brain functioning to predict variance in the ability to acquire an L2 in adulthood. Taken together, our qEEG indicators explained 48% of the variance in rate of L2 learning, 26% of the variance in declarative posttest

vocabulary knowledge, and 60% of the variance in total speech attempts. We also provided evidence that patterns of network connectivity recorded over the left hemisphere (LH) and RH differentially predict L2 learning outcomes and share little variance with correlates of L1 proficiency or fluid reasoning abilities.

Interpretation of these results and their generalizability are subject to several limitations, however. The first is to clarify that we are talking about laterality patterns as recorded over the scalp, which may or may not directly reflect differences in the functioning of the two hemispheres. Although this is an important limitation, links between our research and patterns of structural connectivity in the RH (e.g., Mamiya et al., 2016; Qi et al., 2015) and changes in RH gray matter following short periods of L2 learning (as discussed in Li et al., 2014) provide some evidence that the effects we are measuring may be tied to differences in brain structure. A second limitation is that our results come from a brief, 8-week exposure to an L2. Although similar, and sometimes shorter, training periods are common in L2 aptitude research (see Li et al., 2014), they do limit the likelihood that learners will reach advanced proficiency. A third limitation is that the language training protocol used herein involves a computer software that includes both language and culture training modules. Thus, it is unclear whether these results will generalize to classroom learning, to natural immersion environments, or to longer learning periods that result in greater proficiency. Nonetheless, the use of the OLCTS allowed us to ensure that all learners were exposed to the same training environment and enabled us to collect data on voluntary speech acts and the accuracy of these acts, which were uniquely correlated with qEEG indicators at rest. In addition, it is unclear whether the predictors we have identified are specific to language learning or represent some more general facility with learning and memory that could be applied to multiple complex tasks. In fact, existing work on alpha and intelligence and beta and memory suggests the latter or at least some combination of the two. Finally, although a number of recent experiments have investigated changes in qEEG signals during artificial language learning (Kepinska et al., 2017; de Diego-Balaguer, Fuentemilla, & Rodriguez-Fornells, 2011), further research is needed to link the patterns of brain activity at rest described herein with patterns of brain activity associated with language aptitude during active learning. We see this as an exciting avenue for future research.

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Reprint requests should be sent to Chantel S. Prat, Department of Psychology, University of Washington, Box 351525, Seattle, WA 98195-1525, or via e-mail: csprat@uw.edu.

Notes

1. Although there were unequal numbers of men and women included in this study, the groups did not differ in any of the L2 learning variables or qEEG indices (all p s > .24).
2. Supplementary material for this paper can be retrieved from <https://figshare.com/s/b99fc1dc3cd3c4634695>.

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