



Contents lists available at ScienceDirect

Brain & Language

journal homepage: www.elsevier.com/locate/b&l

Short Communication

Resting-state qEEG predicts rate of second language learning in adults



Chantel S. Prat*, Brianna L. Yamasaki, Reina A. Kluender, Andrea Stocco

University of Washington, Department of Psychology and Institute for Learning & Brain Sciences, United States

ARTICLE INFO

Article history:

Received 29 July 2015
 Revised 18 March 2016
 Accepted 10 April 2016

Keywords:

Second language aptitude
 Second language acquisition
 EEG
 Neuroplasticity
 Individual differences
 Bilingualism
 Working memory capacity

ABSTRACT

Understanding the neurobiological basis of individual differences in second language acquisition (SLA) is important for research on bilingualism, learning, and neural plasticity. The current study used quantitative electroencephalography (qEEG) to predict SLA in college-aged individuals. Baseline, eyes-closed resting-state qEEG was used to predict language learning rate during eight weeks of French exposure using an immersive, virtual scenario software. Individual qEEG indices predicted up to 60% of the variability in SLA, whereas behavioral indices of fluid intelligence, executive functioning, and working-memory capacity were not correlated with learning rate. Specifically, power in beta and low-gamma frequency ranges over right temporoparietal regions were strongly positively correlated with SLA. These results highlight the utility of resting-state EEG for studying the neurobiological basis of SLA in a relatively construct-free, paradigm-independent manner.

Published by Elsevier Inc.

1. Introduction

Learning a second language in adulthood is dramatically more difficult than doing so as a child. For example, large individual differences in SLA exist (e.g., Dörnyei, 2009), with only a small portion of adult learners reaching native-like fluency. Such differences are likely underpinned, in part, by factors related to neural plasticity (see Wong, Morgan-Short, Ettlinger, & Zheng, 2012 for discussion). Due to this fact, investigations of second language acquisition (SLA) in adulthood have become a cornerstone of research on human neural plasticity. Thus, understanding the nature of individual differences in SLA is critical for both research on second language acquisition itself, and also more generally for research on human learning and neural plasticity. In addition to the centrality of this research for basic science, being able to identify which individuals will achieve second language fluency with ease or difficulty has important broader applications for education and industry.

In a recent review, Biedroń (2015) highlights the need for further neuroscientific research to inform theories of second language “aptitude,” a construct traditionally referring to behavioral indices that predict the ease with which an individual will be able to acquire a second language. The review by Biedroń discusses the likelihood that heterogeneity of the construct of second language aptitude has limited the impact of research investigating its neural

basis (Biedroń, 2015, pp. 15–160). With the current experiment, we show that one way in which neuroscientific research can inform theories of language aptitude is to investigate stable aspects of brain functioning in a paradigm-free manner and relate the indices obtained to second language aptitude.

While existing research on the neurobiological basis of second language aptitude has provided promising results, the majority of this research has focused on understanding the neural correlates of acoustic or phonological processes (e.g., Chandrasekaran, Kraus, & Wong, 2012; Golestani, Molko, Dehaene, LeBihan, & Pallier, 2007; Golestani & Zatorre, 2004; Hu et al., 2013; Reiterer, Hu, Sumathi, & Singh, 2013). However, recent research has shown that phonological processes explain a rather small, sometimes insignificant (Linck et al., 2013), portion of the variance in SLA.

In fact, an increasing number of contemporary studies have highlighted the importance of general cognitive mechanisms such as implicit or procedural learning (e.g., Linck et al., 2013; Morgan-Short, Faretta-Stutenberg, Brill-Schuetz, Carpenter, & Wong, 2014) and working memory capacity (e.g., Juffs & Harrington, 2011; Miyake & Friedman, 1998) for predicting second language learning. Unfortunately, very little research to date has related aspects of neural functioning known to underlie such general cognitive abilities with second language aptitude (see Chee, Soon, Lee, & Pallier, 2004, for one example).

Neuroscientific research has been instrumental, however, in informing theories about the relation between general cognitive abilities such as working memory capacity and *native* language abilities (see Prat, 2011 for a review). This body of functional

* Corresponding author at: University of Washington, Box 35152, Seattle, WA 98195-1525, United States.

E-mail address: csprat@uw.edu (C.S. Prat).

magnetic resonance imaging (fMRI) and electroencephalography (EEG) research has highlighted the importance of network-level characterizations of brain function. Specifically, neural efficiency (Maxwell, Fenwick, Fenton, & Dollimore, 1974; Prat, Keller, & Just, 2007) and neural synchronization (Prat & Just, 2011; Prat et al., 2007) have been identified as stable characteristics of more-skilled, or higher-capacity native language comprehenders.

Perhaps the earliest and most commonly used neural indices of general cognitive abilities are quantitative EEG (qEEG) measures. Nearly 50 years of research have shown that various qEEG indices extracted from eyes-closed resting-state EEG data are stable and highly accurate predictors of performance on a variety of cognitive tests (e.g., Doppelmayr, Klimesch, Stadler, Poellhuber, & Heine, 2002; Giannitrapani, 1969). More recently, research comparing qEEG indices in monozygotic and dizygotic twins has shown that qEEG profiles are highly heritable, and also correlate with indices of brain structure such as grey and white matter volumes (Smit, Boomsma, Schnack, Hulshoff Pol, & de Geus, 2012). Thus, qEEG is an ideal method for relating stable properties of brain functioning to SLA.

One common form of qEEG analysis involves converting electrophysiological recordings from the time domain to the frequency domain, and measuring the distribution of power across different frequencies over various electrode locations (Gudmundsson, Runarsson, Sigurdsson, Eiriksdottir, & Johnsen, 2007). Power estimates are then averaged across predetermined intervals that correspond to the frequency bands of cognitively relevant brain activity (Başar, Başar-Eroglu, Karakaş, & Schürmann, 2001). While a considerable amount of research has gone into understanding the neurocognitive implications of such frequency bands (see Ward, 2003 for review), much work is yet to be done. It seems plausible that different frequencies serve unique network-level functions (for instance in establishing local versus long-distance coherence); however, the precise role that each frequency band plays in complex cognitive processes remains an active area of investigation.

A few studies to date have looked specifically at online qEEG power distributions during linguistic tasks (see Weiss & Mueller, 2003, 2012 for reviews). These studies have implicated beta (13–30 Hz) and theta (4–8 Hz) rhythms in linguistic processing. This is not particularly surprising, as both frequency bands have been implicated more broadly in memory encoding and retrieval processes (e.g., Hanslmayr, Staudigl, & Fellner, 2012; Klimesch, Doppelmayr, Schimke, & Ripper, 1997; Weiss & Mueller, 2003, 2012; Weiss & Rappelsberger, 2000). To the best of our knowledge, however, very little research has related static (or resting state) qEEG indices to linguistic ability (see Maxwell et al., 1974 for one exception), or to second language aptitude.

The goal of this study was to extend previous findings showing that stable, network-level properties of brain functioning relate strongly to general intelligence (Giannitrapani, 1969) and to native language abilities (Prat & Just, 2011; Prat et al., 2007), by using qEEG to predict success of second language learning in adulthood. To do so, we recorded 5 min. of eyes-closed resting-state EEG from healthy monolingual adults, in addition to a psychometric battery that included measures of working memory capacity, nonverbal reasoning, and executive functioning. Subsequently, participants were exposed to French using the Operational Language and Culture Training System (OLCTS), a language training program which uses an immersive, goal-directed virtual reality software designed to provide military personnel with rapid acquisition of functional fluency in a second language. The OLCTS is organized hierarchically according to different goals and scenarios (e.g., clearing customs and getting transportation). Within each goal, the material is presented in a scaffolded manner, moving from explicit translation through interactions with progressively fewer hints. Feedback is

given continuously, based on speech production, and auditory and written comprehension, with more points received for completing scenarios with fewer hints required. Behavioral metrics and qEEG indices were used to predict the rate at which individuals acquired an L2 by moving through the levels of the OLCTS.

2. Results

2.1. Individual differences in language learning

Consistent with previous research, large variability was observed in final language proficiency level achieved, with the fastest learner progressing more than twice as quickly through the training program than the slowest learner (*range* = level 8–19, *mean* = level 13.25, *sd* = 3.8). Individual learning curves are depicted in Fig. 1.

Learning was best explained by a linear function in all participants, with R^2 values for individual participant's data ranging from 0.93 to 0.99. With intercepts fixed at the origin, beta values (or learning slopes) extracted for each participant were used to characterize learning rate (*range* = 0.58–1.24, *mean* = 0.88, *sd* = 0.21).

All individuals performed well on individually tailored comprehension tests which included only the materials covered by that individual (*mean* = 94%, *sd* = 7%). Furthermore, no correlation was observed between final level achieved and final comprehension score of the material. This is not particularly surprising because (as described in the methods), the OLCTS intermittently tested individuals on comprehension, production, and memory of materials covered, and participants were not allowed to advance past a level until a minimum proficiency was achieved. Taken together, these results suggest that individual differences in language learning rate were related to second language aptitude, rather than to differences in criteria for comprehension used to advance through the training.

2.2. Behavioral indices of cognitive ability and L2 learning rates

None of the correlations between behavioral measures collected and language learning rate reached significance (all $ps > 0.10$). These correlations and their uncorrected p values are listed in the supplementary materials.

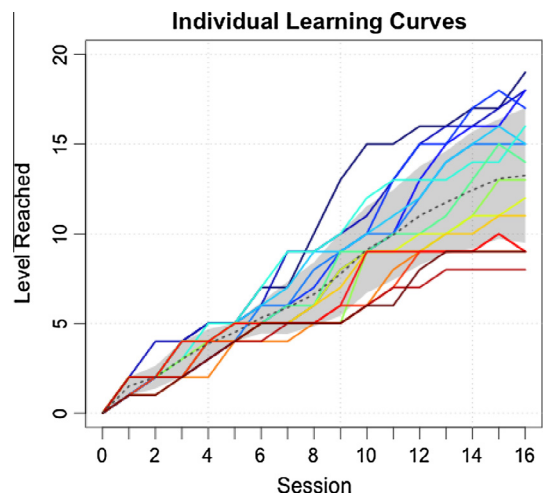


Fig. 1. Learning curves for individual subjects plotted as a function of level reached at the end of each 30 min training session (mean level depicted by dashed line, standard deviation of the mean in grey).

2.3. Resting-state qEEG and L2 learning rates

Resting-state qEEG indices were robustly correlated with language learning rate, explaining up to 60% of the variance observed (see Table 1). This value was calculated from the R^2 values, i.e., the squared Pearson product-moment correlation coefficient (not the Spearman's r), which is an accurate indication of the percentage of variance in the language rate explained by resting EEG power. The most predictive frequency band was low-beta (13–14.5 Hz), with significant positive correlations between low-beta power and L2 learning rates ranging from $r = 0.60$ – 0.77 over the right hemisphere (RH) homologues of left hemisphere (LH) frontal and posterior temporal language regions (F8 and T8) as well as over the parietal lobe (P8). Positive correlations between mid-beta (15–17.5 Hz, $r = 0.52$ – 0.71), high-beta (18–29.5 Hz, $r = 0.52$ – 0.56), low-gamma (30–40 Hz, $r = 0.52$ – 0.7), and L2 learning rate were observed over more distributed regions including bilateral frontal (AF3, F7, F8 and FC6) and RH temporo-parietal regions (T8 and P8). The distribution and magnitude of these positive correlations is depicted in Fig. 2, along with a scatterplot of the individual data from three frequency ranges over the right temporal lobe.

Power in the theta frequency band (4–7.5 Hz) was negatively correlated with L2 learning rate ($r = -0.58$) in the left parietal lobe (P7) only.

2.4. Laterality effects

Based on previous neural efficiency findings suggesting that less linguistically skilled *native* language speakers use more RH than do more linguistically skilled individuals (Prat, Long, and Baynes, 2007; Prat, Mason, & Just, 2011), laterality indices were computed over each frequency range using the seven pairs of homologous electrodes (see methods section). More lateralized patterns of brain activation were predictive of better SLA. This was manifest by positive correlations between laterality indices for alpha power

($r = 0.54$ – 0.58) over frontal (FC5/FC6) and temporal (T7/T8) regions as well as for low-beta power ($r = 0.57$) over the temporal regions (T7/T8), as listed in Table 2.

3. Discussion

Our results demonstrate that stable properties of network-level brain functioning at rest, as measured by qEEG, were robust and reliable predictors of subsequent individual differences in second language learning. The best of these single variables, right hemisphere low-beta power, explained 60% of the variability in final language level achieved after eight weeks of training. Although beta frequency ranges have previously been shown to relate to online language and memory processes (Hanslmayr et al., 2012; Weiss & Mueller, 2012), to the best of our knowledge, no research to date has related resting-state beta power to subsequent language aptitude. Because qEEG was not measured during or after L2 learning, it is not yet clear how these results relate to the related work of McLaughlin, Osterhout and colleagues, who have shown that electrophysiological measures are sensitive to changes in neural organization following L2 exposure (McLaughlin, Osterhout, & Kim, 2004) and that such changes are related to L2 proficiency (Tanner, McLaughlin, Herschensohn, & Osterhout, 2013). We see this as an important area for future SLA research.

Consistent with previous research in the field of intelligence (Thatcher, North, & Biver, 2005), we also found that more lateralized distributions of alpha power was correlated with faster language learning. These results are also consistent with previous individual differences research showing that more lateral patterns of brain activation are correlated with increased linguistic skill in first language (L1) comprehenders (Prat et al., 2011). Interestingly, previous research has also shown that second language (L2) representations are more variable than are L1 representations, and include the RH more frequently (e.g., Dehaene et al., 1997). Additionally, a recent investigation of second language learning showed

Table 1
Correlations between raw resting-state qEEG and final level achieved.

Frequency band (Hz)	Electrode	Location	N	r	p
(A) Low-beta (13–14.5 Hz)	F8	RH frontal	16	0.596	0.015
	T8	RH temporal	16	0.745	0.001*
	P8	RH parietal	16	0.774	0.000*
(B) Mid-beta (15–17.5 Hz)	F7	LH frontal	16	0.554	0.026
	F8	RH frontal	16	0.536	0.032
	FC6	RH frontal	15	0.567	0.028
	T8	RH temporal	16	0.644	0.007
	P8	RH parietal	16	0.705	0.002*
	O1	LH occipital	15	0.522	0.046
	O2	RH occipital	12	0.699	0.011
	T8	RH temporal	16	0.644	0.007
	P8	RH parietal	16	0.705	0.002*
(C) High-beta (18–29.5 Hz)	FC6	RH frontal	15	0.529	0.043
	F8	RH frontal	16	0.557	0.025
	T8	RH temporal	16	0.540	0.031
	P8	RH parietal	16	0.521	0.038
(D) Low-gamma (30–40 Hz)	AF3	LH frontal	16	0.526	0.036
	F4	RH frontal	15	0.517	0.048
	F7	LH frontal	16	0.585	0.017
	F8	RH frontal	16	0.596	0.015
	FC6	RH frontal	16	0.632	0.012
	T8	RH temporal	16	0.695	0.003*
	P8	RH parietal	16	0.583	0.018
	O1	LH occipital	15	0.519	0.048
	O2	RH occipital	12	0.621	0.031
(E) Theta (4–7.5 Hz)	P7	LH parietal	16	−0.581	0.018

* Indicates that values are significant after FDR correction.

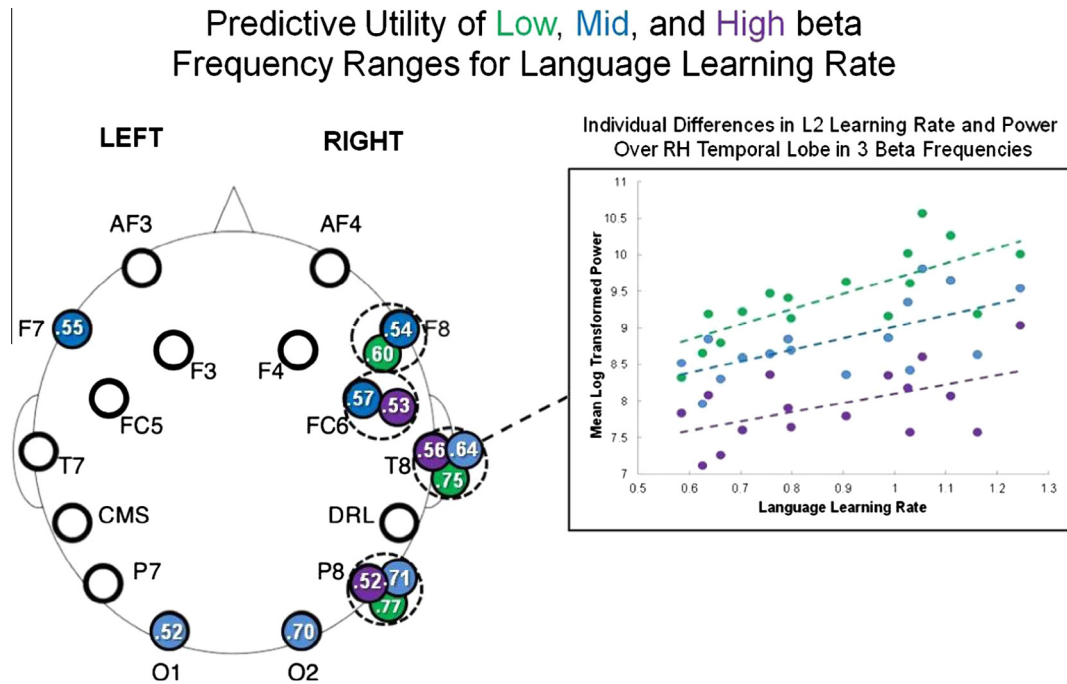


Fig. 2. Pearson's r correlation values between low-beta (13–14.5 Hz) in green, upper-beta (15–17.5 Hz) in blue, and low-gamma (30–40 Hz) in purple.

Table 2
Correlations between qEEG laterality and final level achieved.

Electrodes	Location	Frequency band (Hz)	N	$r(16)$	p
FC5/FC6	Frontal	Alpha (8–12.5 Hz)	15	0.577	0.024
T7/T8	Temporal	Alpha (8–12.5 Hz)	16	0.536	0.032
		Low-beta (13–14.5 Hz)	16	0.574	0.020

that white matter organization in the RH (but not the LH) predicted the ability of native English speakers to acquire Mandarin in adulthood (Qi, Han, Garel, San Chen, & Gabrieli, 2015).

Taken together, our qEEG results suggest that power in RH electrodes, and laterality coefficients derived from them, correlated with L2 learning rates. Note that the qEEG indices reported herein are measured at the scalp, with no source localization algorithms applied. Thus, this data in isolation doesn't warrant inferences about lateralized neural generators. However, in light of the previous individual differences results using functional (Prat et al., 2011) and structural (Qi et al., 2015) neuroimaging, it does seem plausible that variability in RH functioning relates to L2 learning rate. This is not to say that the RH plays a bigger role in L2 learning than does the LH. In fact, a recent review of structural changes associated with L2 learning showed that increases in grey matter density with L2 learning were bilaterally distributed, and that changes in LH density were most frequently associated with L2 proficiency (Li, Legault, & Litcofsky, 2014). Additionally, a meta-analysis by Hull and Vaid (2007) showed that in late L2 learners, greater LH involvement was associated with poorer L2 proficiency. It remains to be seen, then, whether the results described herein are specific to the role of the RH in L2 learning *rate*, or whether they reflect some more stable index of language processing more generally (e.g., more efficient L1 processes). A third possibility, supported by the intelligence literature, is that these results reflect a general neural efficiency that is not language specific. We see this as an interesting avenue for future research.

The data presented in this report are not without limitations. First, the sample size was relatively small, with only 16 individuals completing the language training (75% of which were female).

Thus, the lack of significant correlations between behavioral indices and language learning rates may simply reflect a lack of power. Additionally, it is possible that the significant qEEG results described herein may not generalize to the larger population. However, the fact that many of the relations between qEEG and SLA described herein are consistent with previous research (such as the phenomena described above) bolster our confidence in the fidelity of these results.

Another limitation of this study is that the amount of language training administered was relatively small (eight hours total training distributed across 16, 30-min sessions). By comparison, the research of Ando and colleagues relating working memory capacity to second language learning (Ando et al., 1992 as translated and described in Miyake & Friedman, 1998) involved 20 h of classroom instruction. It is not clear, however, how to compare the amount of learning that occurs during one hour of classroom based curriculum to that which occurs in one hour of interaction with the OLCTS. The OLCTS provides an immersive and individualized training experience, and was specifically designed with the goal of getting individuals in the armed forces functionally proficient in a second language over a short period of time. Additionally, other research on SLA has focused on concentrated language learning over even shorter periods of time (e.g., Qi et al., 2015). Nonetheless, further exploration will be needed to see whether these results are specific to initial language learning phases, or whether the predictive utility of the qEEG indices recorded will be sustained over longer periods of training. Future research should also explore whether or not the same predictors are relevant for qualitatively different types of training such as that provided in a canonical L2 classroom.

Finally, the critical dependent variable predicted by qEEG in the current experiment was rate of language learning, which, in itself, does not provide much information about the quality of language learning attained. The fact that comprehension test scores did not correlate with either qEEG or behavioral measures is likely a reflection of the fact that there was almost no variability in final comprehension of the material covered (with a mean score of 94%). These results suggest that all learners mastered the material covered in the training levels they completed. It is also worth

noting that in order to pass a level, language learners needed to pass quizzes that involved speech production and comprehension components as well as multiple-choice questions. If we had given everyone the same, comprehensive French test at the end of training, instead of tailoring comprehension to the materials covered by each individual, it is likely that much larger individual differences would have been observed, and that such differences would relate to the same indices of qEEG that predicted rate of learning. Our future research will explore a richer investigation of the quality of second language skills attained by faster- and slower-learners (e.g., syntactic parsing, phonological processing skills, vocabulary size) and how they may differentially relate to qEEG predictors.

Despite these limitations, the potential power of this approach can be seen by comparing the predictive utility of qEEG with those obtained from standard measures of complex reasoning ability and working memory capacity, which were not significantly related to second language learning with the sample size tested herein. In contrast, the best qEEG predictors were correlated with language level achieved with $r_s > 0.77$, with $p_s < 0.001$. Thus, our results show that qEEG indices collected from resting-state data provide a powerful, paradigm-free tool for predicting second language learning. Because qEEG power spectra are known to be genetically based (Smit et al., 2012) but experientially modifiable (see Gruzeliier, 2014 for review), we believe this research has important implications not only for studying second language aptitude, but also for developing paradigms to modify it.

4. Methods

4.1. Participants

Nineteen healthy young adults (18–31 yrs) were initially recruited as part of a larger study investigating how various language and cognitive training protocols shape the brain and behavior. Of these, 16 participants (12 female) completed the eight-week language training program, and only their data are reported herein. All participants were monolingual English speakers, with no exposure to a second language before high school, and with low proficiency in any language learned after high school. Additionally, any individual with exposure to French was excluded from participation. All individuals gave informed consent in accordance with the standards set forth by the University of Washington Institutional Review Board and were paid for their participation.

4.2. Psychometric measures

A battery of psychometric assessments was given before language training. These assessments consisted of ten computerized and paper-and-pencil measures of cognitive, reasoning, and first language reading abilities. In addition, a paper-and-pencil French-English Translation test was given to each subject following language training. Descriptions of each task or a reference to such are provided below. One to two variable values were entered for each participant, for each task, corresponding to the measure most typically used to index individual differences in that task.

4.2.1. Measures of general reasoning ability

4.2.1.1. *Raven's Advanced Progressive Matrices (RAPM)*. The RAPM is a timed test of nonverbal reasoning abilities. In this task, participants choose the best option, among 8 alternatives, that completes a pattern displayed across a matrix of items. A shortened 18-item version of this task (sRAPM) was used in this study. Using the item difficulty ratings reported by Arthur and Day (1994), the original 36 questions were split into two 18-item tests of matched difficulty. Participants were given 20 min to complete the sRAPM.

Performance was measured as the proportion of correctly solved problems.

4.2.2. Measures of executive functioning

4.2.2.1. *Response-Interference Task*. The Response-Interference Task is a nonverbal measure of susceptibility to stimulus-response interference. In this task participants respond with left and right button presses to visually presented shapes (e.g., circle = right, square = left). 75% of the trials are congruent, with shapes appearing on the same side of the screen as the correct response (e.g., circle on RIGHT side of the screen), and the remaining 25% of the trials are incongruent, with shapes appearing on the opposite side as the correct response (e.g., circle on LEFT side of screen). Interference management was computed by subtracting response times for congruent trials from incongruent trials (for correct responses only).

4.2.2.2. *3-back updating task*. The 3-back task is a variant of the canonical n -back test of updating believed to measure working memory abilities. In this task participants are presented with a series of letters to which they are to respond "Same" (if the letter presented was the same as the letter presented 3 items ago) or "Different" (if the letter presented was different than the letter presented 3 items ago). Overall percent accuracy and accuracy to distractor trials (trials in which a letter was presented 1–2 items away from the target) were calculated separately and both entered as variables of interest for this task.

4.2.2.3. *Color-shape switching task*. The Color-Shape Switch task is a task-switching paradigm that measures mental set-shifting abilities. In this task, participants are presented with blue and orange circles and squares. Contingent on the location of the stimulus (top or bottom of screen), participants either respond to whether the stimulus is a circle or square (when the stimulus is displayed on the top of the screen) or whether the stimulus is orange or blue (when the stimulus is displayed on the bottom of the screen). Switching ability was measured by subtracting response times from trials in which the task repeated from those in which the task switched, for correct trials only.

4.2.2.4. *A-X continuous performance test of goal maintenance (AX-CPT)*. A shortened version of the traditional AX-CPT task (Cohen, Barch, Carter, & Servan-Schreiber, 1999) was used in this study. In this task, participants are presented with a series of letters to which they must respond to according to two task rules: (1) respond "Target" when an X is presented after an A and (2) respond "Non-Target" for all other situations. Goal maintenance was measured by subtracting reaction times for trials that contained a target that was not preceded by an A (BX trials) from those in which A was not followed by a target (AY trials).

4.2.2.5. *The Probabilistic Stimulus Selection Task of implicit learning*. The Probabilistic Stimulus Selection Task measures individual differences in learning from positive and negative feedback in a repeated-choice decision-making task (for methods see Frank, Seeberger, & O'reilly, 2004). Sensitivity to the most frequently rewarding stimulus (Choose Accuracy) and sensitivity to the least frequently rewarding stimulus (Avoid Accuracy) were entered as indices of implicit statistical learning.

4.2.2.6. *Attentional Blink task*. The Attentional Blink task examines the temporal limitations of perceptual attention. In this rapid serial visual presentation task, participants are presented with a series of letters within which two target numbers are embedded. Participants are instructed to recall the two target numbers, in order, after each trial. The lag between the onset of the first target

number and the onset of the second target number was varied. A participant's "attentional blink" was measured by the difference between their conditional accuracies (i.e., mean accuracy for the second target on the trials in which the first target was also successfully recalled) when the lag between the two targets was within the "blink window" (100–500 ms) versus outside of that window (<100 ms or >500 ms).

4.2.2.7. Stop-signal response inhibition task. The Stop Signal task as described by Logan (1994) was used to measure indices of response inhibition. For each participant, response inhibition was calculated as the last moment in time after a subject has initiated a response that they were able to then inhibit that response.

4.2.2.8. Complex working memory span tasks. Both the computerized Operation and Reading Span tasks were employed as described in Unsworth, Heitz, Schrock, & Engle, 2005. Span scores were used for both tasks.

4.2.3. Measures of language proficiency

4.2.3.1. Nelson-Denny Test of L1 reading ability. The Nelson-Denny Reading Test is a timed multiple-choice English reading assessment normed for college levels. The 38 question passage comprehension portion of this test was used in the current study. Brown, Fishco, and Hanna (1993) provides a detailed description of the methods for this test. Normed percentiles for college readers were calculated based on raw scores and used to indicate reading comprehension ability.

4.2.3.2. The French-English Translation test of French proficiency. French-English Translation multiple-choice tests were created individually for each participant based on the total amount of materials they had encountered over the course of eight-weeks of language training. Participants were instructed to indicate the correct English translation for 50 French words or phrases previously encountered during their training. The number of items drawn from each level were proportional to the amount of material covered on that level. Accuracy (total items correct/50) was used to indicate performance on the French-English translation test.

4.2.3.3. French language learning rate. The OLCTS (Johnson, Friedland, Watson & Surface, 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 customs training including comprehension and production components (with speech recognition software), as well as socio-cultural practices such as pragmatics. These skills are applied through goal-directed virtual reality scenarios, and then tested explicitly through quizzes that incorporate all aspects of linguistic proficiency (written, verbal production, and auditory comprehension). At the end of each 30-minute training session, the final level reached for each participant was recorded. Learning rate was indexed by fitting a line to the data points from 16 training sessions, and using the slope of the line to indicate learning rate.

4.3. Procedures

After signing informed consent, five minutes of eyes-closed resting-state EEG were collected from all participants using wireless EPOC 16-channel headsets (Emotiv, Australia) at a sampling rate of 128 Hz. Three hours of psychometric testing were then collected across two tests sessions. The tests described above were collected in varying order across participants. Subsequently, all participants completed sixteen 30-min sessions of language training (using the OCLTS) over the course of eight weeks. Participants

were allowed to move through the training at their own pace, but were not allowed to advance to the next level until they had passed the corresponding quizzes on that level with an accuracy of 50% or higher.

4.4. qEEG analysis

EEG data were analyzed using the procedures described in Doppelmayr et al. (2002), with minor variations to fit our equipment. For the purposes of this experiment, power analyses were chosen over coherence analyses, due to their established link with grey matter densities (Smit et al., 2012). The 5-minute recording was first segmented into 2-second epochs with a 1-second overlap. Epochs where eyeblinks or significant motion artifacts (as recorded by the Emotiv built-in eyelid muscle sensors and gyroscope) occurred were discarded, and only channels with >75 artifact-free epochs per individual were included in the final analysis. The mean log power spectrum between 1.5 and 40 Hz was calculated by first computing each epoch's power spectrum using the Fast Fourier Transform, log-transforming it, and then averaging the resulting power spectra across all epochs. To reduce spectral leakage, a Hanning window was applied to each epoch before computing the corresponding Fourier transform. The mean log power was then separately calculated across 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 channel and in each participant. Delta (<4 Hz) and high-gamma (>40 Hz) frequencies were not analyzed due to susceptibility to artifact.

To better understand how these results link to existing literature, two follow-up analyses were conducted. First, Beta power calculated separately across three frequency ranges: low-beta (13–14.5 Hz), mid-beta (15–17.5 Hz), and high-beta (18–29.5 Hz). Second, eight laterality coefficients were computed by taking the mean power in each frequency band in the left hemisphere (LH) and subtracting it from the homologous region in the right hemisphere (RH), then dividing this difference by the average power in both channels e.g., (low-beta power in T8 – low-beta power in T7)/average (low-beta power in T7 and T8). To correct for multiple comparisons in the EEG data, the False Discovery Rate procedure (Benjamini & Hochberg, 1995) was applied, using a corrected threshold $q < 0.05$, which corresponded to an uncorrected threshold of $t p < 0.007$.

Acknowledgments

This research was funded by a grant from the Office of Naval Research (ONRBA13-003) entitled "Training the Mind and Brain: Investigating Individual Differences in the Ability to Learn and Benefit Cognitively from Language Training." We would like to thank Justin Abernethy, Roy Seo, and Jose Ceballos for their feedback on earlier drafts of the manuscript.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.bandl.2016.04.007>.

References

- Ando, J., Fukunaga, N., Kurahashi, J., Suto, T., Nakano, T., & Kage, M. (1992). A comparative study on the two EFL teaching methods: The communicative and the grammatical approach. *Japanese Journal of Educational Psychology*, 40, 247–256 (in Japanese).
- Arthur, W., & Day, D. V. (1994). Development of a short form for the Raven Advanced Progressive Matrices Test. *Educational and Psychological Measurement*, 54(2), 394–403.

- Başar, E., Başar-Eroglu, C., Karakaş, S., & Schürmann, M. (2001). Gamma, alpha, delta, and theta oscillations govern cognitive processes. *International Journal of Psychophysiology*, 39(2), 241–248.
- Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society. Series B (Methodological)*, 289–300.
- Biedroń, A. (2015). Neurology of foreign language aptitude. *Studies in Second Language Learning and Teaching*, V-1, 13–40.
- Brown, J. I., Fishco, V. V., & Hanna, G. (1993). *Nelson-denny reading test: Manual for scoring and interpretation forms G & H*. Rolling Meadows, IL: Riverside Publishing.
- Chandrasekaran, B., Kraus, N., & Wong, P. C. (2012). Human inferior colliculus activity relates to individual differences in spoken language learning. *Journal of Neurophysiology*, 107(5), 1325–1336.
- Chee, M. W., Soon, C. S., Lee, H. L., & Pallier, C. (2004). Left insula activation: A marker for language attainment in bilinguals. *Proceedings of the National Academy of Sciences of the United States of America*, 101(42), 15265–15270.
- Cohen, J. D., Barch, D. M., Carter, C., & Servan-Schreiber, D. (1999). Context-processing deficits in schizophrenia: Converging evidence from three theoretically motivated cognitive tasks. *Journal of Abnormal Psychology*, 108(1), 120–133.
- Dehaene, S., Dupoux, E., Mehler, J., Cohen, L., Paulesu, E., Perani, D., ... Le Bihan, D. (1997). Anatomical variability in the cortical representation of first and second language. *NeuroReport*, 8(17), 3809–3815.
- Doppelmayr, M., Klimesch, W., Stadler, W., Poellhuber, D., & Heine, C. (2002). EEG alpha power and intelligence. *Intelligence*, 30(3), 289–302.
- Dörnyei, Z. (2009). *The psychology of second language acquisition*. Oxford: Oxford University Press.
- Frank, M. J., Seeberger, L. C., & O'reilly, R. C. (2004). By carrot or by stick: Cognitive reinforcement learning in parkinsonism. *Science*, 306(5703), 1940–1943.
- Giannitrapani, D. (1969). EEG average frequency and intelligence. *Electroencephalography and Clinical Neurophysiology*, 27(5), 480–486.
- Golestani, N., Molko, N., Dehaene, S., LeBihan, D., & Pallier, C. (2007). Brain structure predicts the learning of foreign speech sounds. *Cerebral Cortex*, 17(3), 575–582. <http://dx.doi.org/10.1093/cercor/bhk001>.
- Golestani, N., & Zatorre, R. J. (2004). Learning new sounds of speech: Reallocation of neural substrates. *Neuroimage*, 21(2), 494–506.
- Gruzelier, J. H. (2014). EEG-neurofeedback for optimising performance. I: A review of cognitive and affective outcome in healthy participants. *Neuroscience & Biobehavioral Reviews*, 44, 124–141.
- Gudmundsson, S., Runarsson, T. P., Sigurdsson, S., Eiriksdottir, G., & Johnsen, K. (2007). Reliability of quantitative EEG features. *Clinical Neurophysiology*, 118(10), 2162–2171.
- Hanslmayr, S., Staudigl, T., & Fellner, M. C. (2012). Oscillatory power decreases and long-term memory: The information via desynchronization hypothesis. *Frontiers in Human Neuroscience*, 6.
- Hu, X., Ackermann, H., Martin, J. A., Erb, M., Winkler, S., & Reiterer, S. M. (2013). Language aptitude for pronunciation in advanced second language (L2) learners: Behavioural predictors and neural substrates. *Brain and Language*, 127(3), 366–376.
- Hull, R., & Vaid, J. (2007). Bilingual language lateralization: A meta-analytic tale of two hemispheres. *Neuropsychologia*, 45(9), 1987–2008.
- Johnson, W. L., Friedland, L., Watson, A., & Surface, E. (2012). The art and science of developing intercultural competence. In Durlach & Lesgold (Eds.), *Adaptive technologies for training and education* (pp. 261).
- Juffs, A., & Harrington, M. (2011). Aspects of working memory in L2 learning. *Language Teaching*, 44(02), 137–166.
- Klimesch, W., Doppelmayr, M., Schimke, H., & Ripper, B. (1997). Theta synchronization and alpha desynchronization in a memory task. *Psychophysiology*, 34(2), 169–176.
- Li, P., Legault, J., & Litcofsky, K. A. (2014). Neuroplasticity as a function of second language learning: Anatomical changes in the human brain. *Cortex*, 58, 301–324.
- Linck, J. A., Hughes, M. M., Campbell, S. G., Silbert, N. H., Tare, M., Jackson, S. R., ... Doughty, C. J. (2013). Hi-LAB: A new measure of aptitude for high-level language proficiency. *Language Learning*, 63(3), 530–566.
- Logan, G. D. (1994). On the ability to inhibit thought and action: A users' guide to the stop signal paradigm. In D. Dagenbach & T. H. Carr (Eds.), *Inhibitory processes in attention, memory, and language* (pp. 189–239). San Diego, CA: Academic Press.
- Maxwell, A. E., Fenwick, P. B., Fenton, G. W., & Dollimore, J. (1974). Reading ability and brain function: A simple statistical model. *Psychological Medicine*, 4(3), 274–280.
- McLaughlin, J., Osterhout, L., & Kim, A. (2004). Neural correlates of second-language word learning: Minimal instruction produces rapid change. *Nature Neuroscience*, 7(7), 703–704.
- Miyake, A., & Friedman, N. P. (1998). Individual differences in second language proficiency: Working memory as language aptitude. In A. F. Healy & L. E. Bourne, Jr. (Eds.), *Foreign language learning: Psycholinguistic studies on training and retention* (pp. 339–364). New Jersey: Lawrence Erlbaum Associates, Inc., Publishers.
- Morgan-Short, K., Faretta-Stutenberg, M., Brill-Schuetz, K. A., Carpenter, H., & Wong, P. (2014). Declarative and procedural memory as individual differences in second language acquisition. *Bilingualism: Language and Cognition*, 17(01), 56–72.
- Prat, C. S. (2011). The brain basis of individual differences in language comprehension abilities. *Language and Linguistic Compass*, 5(9), 635–649.
- Prat, C. S., & Just, M. A. (2011). Exploring the cortical dynamics underpinning individual differences in sentence comprehension. *Cerebral Cortex*, 21, 1747–1760.
- Prat, C. S., Keller, T. A., & Just, M. A. (2007). Individual differences in sentence comprehension: An fMRI investigation of syntactic and lexical processing demands. *Journal of Cognitive Neuroscience*, 19(12), 1950–1963.
- Prat, C. S., Long, D. L., & Baynes, K. (2007). The representation of discourse in the two hemispheres: An individual differences investigation. *Brain and Language*, 100(3), 283–294.
- Prat, C. S., Mason, R. A., & Just, M. A. (2011). Individual differences in the neural basis of causal inferencing. *Brain and Language*, 116, 1–13.
- Qi, Z., Han, M., Garel, K., San Chen, E., & Gabrieli, J. D. (2015). White-matter structure in the right hemisphere predicts Mandarin Chinese learning success. *Journal of Neurolinguistics*, 33, 14–28.
- Reiterer, S. M., Hu, X., Sumathi, T. A., & Singh, N. C. (2013). Are you a good mimic? Neuro-acoustic signatures for speech imitation ability. *Frontiers in Psychology*, 4.
- Smit, D. J., Boomsma, D. I., Schnack, H. G., Hulshoff Pol, H. E., & de Geus, E. J. (2012). Individual differences in EEG spectral power reflect genetic variance in gray and white matter volumes. *Twin Research and Human Genetics*, 15(03), 384–392.
- Tanner, D., McLaughlin, J., Herschensohn, J., & Osterhout, L. (2013). Individual differences reveal stages of L2 grammatical acquisition: ERP evidence. *Bilingualism: Language and Cognition*, 16(02), 367–382.
- Thatcher, R. W., North, D., & Biver, C. (2005). EEG and intelligence: Relations between EEG coherence, EEG phase delay and power. *Clinical Neurophysiology*, 116(9), 2129–2141.
- Unsworth, N., Heitz, R. P., Schrock, J. C., & Engle, R. W. (2005). An automated version of the operation span task. *Behavior Research Methods*, 37(3), 498–505.
- Ward, L. M. (2003). Synchronous neural oscillations and cognitive processes. *Trends in Cognitive Sciences*, 7(12), 553–559.
- Weiss, S., & Mueller, H. M. (2003). The contribution of EEG coherence to the investigation of language. *Brain and Language*, 85(2), 325–343.
- Weiss, S., & Mueller, H. M. (2012). "Too many betas do not spoil the broth": The role of beta brain oscillations in language processing. *Frontiers in Psychology*, 3.
- Weiss, S., & Rappelsberger, P. (2000). Long-range EEG synchronization during word encoding correlates with successful memory performance. *Cognitive Brain Research*, 9(3), 299–312. [http://dx.doi.org/10.1016/S0926-6410\(00\)00011-2](http://dx.doi.org/10.1016/S0926-6410(00)00011-2).
- Wong, P. C., Morgan-Short, K., Ettliger, M., & Zheng, J. (2012). Linking neurogenetics and individual differences in language learning: The dopamine hypothesis. *Cortex*, 48(9), 1091–1102.