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Bilinguals have more complex EEG brain signals in occipital regions than monolinguals

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ABSTRACT

Brain signal complexity increases with development and is associated with better cognitive outcomes in older age. Research has also shown that bilinguals are able to stave off cognitive decline for longer periods of time than monolinguals, but no studies to date have examined whether bilinguals have more complex brain signals than monolinguals. Here we explored the hypothesis that bilingualism leads to greater brain signal complexity by examining multiscale entropy (MSE) in monolingual and bilingual young adults while EEG was recorded during a task-switching paradigm. Results revealed that bilinguals had greater brain signal complexity than monolinguals in occipital regions. Furthermore, bilinguals performed better with increasing occipital brain signal complexity, whereas monolinguals relied on coupling with frontal regions to demonstrate gains in performance. These findings are discussed in terms of how a lifetime of experience with a second language leads to more automatic and efficient processing of stimuli and how these adaptations could contribute to the prevention of cognitive decline in older age.

1. Introduction

Complex signal variability in physiological data appearing in the form of unpredictable random signal fluctuations is commonly regarded as "noise" and every attempt is made to reduce or remove it from the dataset prior to analysis. Recent advances in neuroscience, however, suggest that signal variability contains important information about the dynamics and complexity of neural networks.[1] To illustrate this point, Pincus et al. (1991) offer an example of heart rate variability. Person 1's heart rate fluctuates according to the following series: 70, 90, 70, 90, 70, 90, 70, 90, 70, 90, 70, 90, 70, 90, 70, 90, …while person 2's heart rate fluctuates according to the following series: 90, 70, 70, 90, 90, 90, 70, 70, 90, 90, 70, 90, 70, 70, 90, 70, …Person 1's heart rate is completely predictable and alternates between 70 and 90 beats/min, while person 2's heart rate fluctuates randomly between 70 and 90 beats per minute with equal probability of either rate. Based on means and standard deviations alone, one is not able to distinguish between these two series; both series have a mean value of 80 beats/minute and a standard deviation of 10. Similarly, rank order statistics such as median does not distinguish between the series either. However, the randomness of the series from person 2 indexes greater *complexity/entropy*, and is indicative of a healthier heart (Pincus et al., 1991).

Changes in brain signal complexity are also associated with normal development, such that complexity follows an inverted U-shaped curve and becomes greater from childhood to young adulthood (Lippé et al., 2009; McIntosh et al., 2008; Mišić et al., 2010), then decreases in the elderly (Garrett et al., 2010; Garrett et al., 2013). Increases in neural signal complexity are also associated with greater information processing capacity (Deco et al., 2011; Ghosh et al., 2008; Beharelle et al., 2012) and knowledge representations (Heisz et al., 2012; Mišić et al., 2010). For example, Heisz et al. (2012) showed that electroencephalographic (EEG) signals to familiar faces were more complex than those to novel faces because the complex signals contained richer representations than simpler ones. Importantly, the human cortex consists of neural networks that rapidly emerge and dissipate (Bressler and Kelso, 2001), and greater signal complexity is associated with the ability to switch between brain states more readily (Deco et al., 2011; Beharelle et al., 2012). For example, Deco et al. (2011) suggested that random fluctuations in brain signals (i.e., complexity) allow for neural networks to be spontaneously trained. This training in turn enhances the underlying strength of those connections and leads to brain microstates. Given that complexity is thought to be the ability of the brain to explore these different states, and that certain states (i.e., networks) are revisited and strengthened, it becomes easier for the brain to readily switch between them. The present

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[1] This idea was put forth more than 50 years ago in a review by Pinneo (1966) but was forgotten until recently.

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study explored the possibility bilingual language use is an experience that fosters greater neural complexity and leads to the ability to more readily switch between brain states.

Learning and regularly using a second language is an intense experience that has the potential to lead to a domain-general cognitive adaptation (review in Bialystok, 2017). This adaptation is thought to be driven by the overlap of the cognitive control and language control networks (reviews in Abutalebi and Green, 2016; Pliatsikas and Luk, 2016), but the precise mechanisms are not known. Critically, both language representations compete for neural resources and remain simultaneously active (review in Kroll et al., 2012), so a control mechanism is required to select the target language and switch between languages appropriately. Given that increased brain signal complexity is associated with the ability to switch brain states more readily, it might also be the case that bilinguals have increased brain signal complexity compared to monolinguals as a result of practice switching between languages.

No studies to date have examined how bilingualism affects the complexity of the brain signal on domain-general cognitive outcomes. This is an important avenue to pursue given that something about the bilingual experience leads to brain reorganization that staves off cognitive decline in the elderly, including Alzheimer's disease (reviews in Bak and Alladi, 2014; Gold, 2015; Guzmán-Vélez and Tranel, 2015). It has also been shown that healthy controls have greater brain signal complexity than Alzheimer's disease patients in occipital and parietal regions (Abásolo et al., 2006; Escudero et al., 2006; Park et al., 2007). Thus, examination of brain signal complexity of monolinguals and bilinguals in these regions might contribute to our understanding of how bilingualism reorganizes the brain. A few studies have examined complexity of neural signals in monolinguals and bilinguals (e.g., Pérez et al., 2015), but these complexity differences were found during linguistic processing. In order to ascertain whether bilingualism is associated with domain-general changes in brain signal complexity, a non-verbal cognitive task must be employed. Thus, we examined brain signal complexity during a non-verbal task-switching paradigm. Given that young adults are at peak cognitive performance and that some studies have shown that bilinguals outperform monolinguals during task-switching (e.g., Prior and Macwhinney, 2010; Wiseheart et al., 2016) whereas others have not (e.g., Paap and Greenberg, 2013), we did not expect to see behavioral differences between groups. However, in the absence of a behavioral difference, examining brain signal complexity and its relation to behavior could reveal a difference in strategy.

Brain signal complexity can be examined through various methods. In fMRI research, a common approach is to examine the standard deviation of the BOLD signal response, and this has been associated with multiple positive developmental outcomes (review in Garrett et al., 2013). In EEG, measures of *entropy* have increased in popularity in recent years. As explained above, regular (and less variable) time-series have low entropy values whereas irregular (and more variable) time-series have high entropy values. Thus, standard deviation of the EEG signal provides one measure of entropy. A problem with this approach is evident from the Pincus et al. (1991) heart rate example, namely, that equal standard deviation does not necessarily mean equal complexity. Furthermore, simple entropy calculations demonstrate that noisy signals have greater signal entropy/complexity. *Approximate entropy* (Pincus et al., 1991) solved this issue by finding a way to calculate entropy that could distinguish meaningful complexity from noise. Following this, *sample entropy* (Richman and Moorman, 2000) was created to account for the over-estimation of regularity evident in approximate entropy. Multiscale entropy (MSE) is an extension of a sample entropy analysis that examines the complexity of physiological data at *multiple timescales*, ranging from fine to coarse scales (Costa et al., 2002, 2005). Fine grain scales collapse across fewer time points while coarse grain scales collapse across more time. Greater entropy in coarse-grained time scales is thought to represent more distributed networks, whereas finer scales are thought to represent more local networks (Vakorin et al., 2011). Importantly, MSE analysis is able to distinguish meaningful complexity from random noise (Costa et al., 2005).

The present study explored the relation between brain signal complexity and bilingualism by recording EEG while young adult monolinguals and bilinguals performed an executive function task-switching paradigm.

2. Method

2.1. Participants and procedure

Twenty monolingual and 20 bilingual participants were recruited from York University's psychology participant pool. All participants had normal or corrected-to-normal vision and all procedures complied with university ethics guidelines.

The Language and Social Background Questionnaire (LSBQ; Anderson et al., 2017) was used to assess L2 proficiency in speaking and understanding. Participants were asked to estimate their proficiency in each on this scale from 0 (no proficiency) to 100 (native).

The Shipley-2 Institute of Living Scale Verbal and Blocks (Shipley et al., 2009) was used to assess English receptive vocabulary and non-verbal intelligence. Shipley measures were converted to standardized scores ($\mu = 100$, $SD = 15$).

After obtaining informed consent, participants completed the three background measures followed by the bivalency effect task (Grundy et al., 2013, Grundy and Shedden, 2014a, 2014b; Grundy and Keyvani Chahi, 2017; Meier et al., 2009; Woodward et al., 2003) while simultaneous EEG was recorded. The experiment lasted approximately 90 min.

2.2. Materials and apparatus

The task was presented using E-prime 2.0 (Psychology Software Tools, Inc., version 2.0.10.353) on a 19 inch CRT monitor, with a refresh rate set to 75 Hz. EEG was acquired via a 64-channel Biosemi ActiveTwo system. Four additional electrodes (two at the outer canthi and two just below the eyes) were used to track eye-movements and blinks, and two additional electrodes (common mode sense active electrode and a driven right leg passive electrode) were used to ground the system (www.biosemi.com/faq/cms&drl.htm). The continuous signal was acquired via open passband from DC to 150 Hz and digitized at 512 Hz. Offline signal processing was done with EEGLAB (v11.0.2.1b) and ERPLAB (v5.0.0.0) plugins for MATLAB (v7.14, 2012, Mathworks, Natick, MA). A bandpass filter at 0.1–30 Hz was applied and the signal was re-referenced to the common average. A 200 ms baseline was used and epochs from −200 to 800 were extracted. Trials indicative of muscle tension or drift were removed prior to conducting the eye artifact detection procedure using a simple voltage threshold of 400 microvolts. Horizontal eye-movements and eye blinks were detected and corrected using Independent Components Analysis (Makeig et al., 1996).

We focused on midline electrode sites Fz, Cz, Pz, and Oz for four reasons. First, it is common practice for EEG studies to examine midline electrodes Fz, Cz, Pz, and Oz to explore a general shift from anterior to posterior, and dozens of studies, including task switching studies (e.g., Hsieh and Cheng, 2006; Hsieh and Liu, 2008; Lenartowicz et al., 2010; Lorist et al., 2000; Nicholson et al., 2005), language processing studies (e.g., Gunter et al., 1995; Niznikiewicz et al., 1999; Verhoef et al., 2010) and conflict resolution studies (e.g., Bruin et al., 2001; Dimoska et al., 2006; Gajewski et al., 2008; Neuhaus et al., 2007) use this approach. Second, for ERPs during the bivalency effect task, midline electrode Fz is close to a cluster that captures the main cognitive processes associated with task effects (Grundy et al., 2013; Grundy and Shedden, 2014b). Third, bilinguals show delayed symptoms of Alzheimer's compared to monolinguals (reviews in Gold, 2015; Guzmán-Vélez and Tranel, 2015), and previous studies have shown that healthy controls have greater entropy than Alzheimer's disease patients in parietal and occipital sites surrounding (i.e., flanking) electrodes Pz (i.e., P3 & P4) and Oz (i.e., O1 & O2) (Abásolo et al., 2006; Escudero et al., 2006; Park et al., 2007). EEG

has poor spatial resolution and the electrodes examined from the Alzheimer's disease studies were just to the left and right of midline electrodes Fz, Pz and Oz; we had no a priori expectations with respect to laterality based on the previous Alzheimer's literature and the bivalency task effects at the midline. Cz was chosen because it falls between Pz and Fz. Fourth, based on previous work, there is a general shift from reliance on frontal to reliance on posterior brain region recruitment during non-linguistic processing for bilinguals than monolinguals (Grant et al., 2014; Grundy et al., 2017a). For these reasons in conjunction with the abundance of research using midline sites as representative of processing from anterior to posterior, we chose Fz, Cz, Pz, and Oz. However, to support these findings and test the robustness of the effects, we ran an additional analysis that clustered groups of electrodes around these areas (see results for details).

2.3. Bivalency task

Participants completed a task-switching paradigm using the bivalency task in which they had to decide on the color of shapes (red vs. blue), the parity of digits (odd vs. even), and the case of letters (lowercase vs. uppercase). The task is illustrated in Fig. 1. There were four blocks with 216 trials (72 for each task) in each presented in the following order: practice, pure, conflict, pure. The practice block and the pure blocks consisted of switching between the three univalent trial types (i.e., color, parity, case); the conflict block was similar but also included occasional bivalent trials for case decisions (24 of 72 case decisions). For bivalent trials, the letter stimuli were colored blue or red, and participants were instructed to ignore the color and simply judge the case. Critically, the irrelevant color always cued the opposite response to the correct decision, creating conflict. Research with this paradigm has shown that response times to bivalent trials are slowest, followed by univalent trials in conflict blocks, then by univalent trials in pure blocks (Grundy et al., 2013; Grundy and Shedden, 2014a, 2014b; Meier et al., 2009; Woodward et al., 2003).

2.4. Brain signal complexity: multiscale entropy (MSE) analysis

Fig. 2 illustrates how MSE is calculated, and a video tutorial on how to perform MSE analysis on EEG data is available from Heisz and McIntosh (2013). To calculate sample entropy at each timescale for EEG data, start with the first data point (x) in the time series. A criterion length m is then set ($m = 2$ in the present study) that defines a number of consecutive data points in the EEG signal (for a discussion of how to choose the MSE parameters, see Lake et al., 2002). For length $m = 2$ (starting with x and $x + 1$), sum the number of times that two consecutive data points occur within a pre-specified amplitude range ($r = 0.5$ in the present study) across time in the EEG waveform. Next, sum the number of times that three ($m + 1$) consecutive data points (starting with x, $x + 1$, and $x + 2$) occur within the amplitude range across time in the EEG waveform. This procedure is repeated for each data point in the time series (i.e., starting at $x + 1$, then starting at $x + 2$, then starting at $x + 3$, etc.; see Fig. 2) and all two-component matches and all three-component matches in the entire data series are summed together. Sample entropy is the natural logarithm of the ratio of two-component to three-component matches.

MSE timescales are calculated by "downsampling" the original data series by averaging consecutive data points to create a new data point that creates a coarser scale (see Fig. 2). This is done n times (in our study $n = 20$) and sample entropy is re-calculated at each timescale. This creates a series of fine to coarse grained entropy scales. Finer-grained scales are linked to local networks and coarser-grained scales are linked to distributed networks (Vakorin et al., 2011).

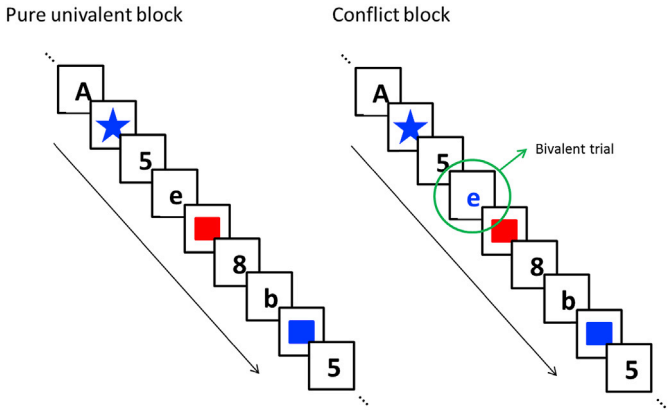

Fig. 1. The task-switching paradigm based on the bivalency task used in the present study.

3. Results

3.1. Background and behavioral measures

Table 1 presents background information by group. One-way ANOVAs revealed that groups were similar on age, SES, vocabulary, and non-verbal intelligence (all Fs < 1) but differed on second-language proficiency scores (all ps < 0.001).

Table 2 presents accuracy and RT data by group for the bivalency task. Two-way mixed measures ANOVAs for group (monolingual, bilingual) and trial type (univalent trials in pure blocks, univalent trials in conflict blocks, bivalent trials in conflict blocks) were run separately on accuracy and RT data. For accuracy, the ANOVA revealed a main effect of trial type, $F(2, 76) = 25.18$, $p < 0.001$, $\eta_p^2 = 0.40$, in which participants were less accurate on bivalent trials than univalent trials either in pure, $F(1, 39) = 26.4$, $p < 0.001$, $\eta_p^2 = 0.40$, or conflict blocks, $F(1, 39) = 24.8$, $p < 0.001$, $\eta_p^2 = 0.39$), with no difference between the two types of univalent trials, $F(1, 39) = 1.71$, $p = 0.20$, $\eta_p^2 = 0.04$. There was no effect of group, $F(1, 38) = 2.93$, $p = 0.10$, $\eta_p^2 = 0.07$, or interaction of group and trial type, $F(2, 76) = 0.97$, $p = 0.38$, $\eta_p^2 = 0.03$.

For RT, there was a main effect of trial type, $F(2, 76) = 115.51$, $p < 0.001$, $\eta_p^2 = 0.75$, because participants were faster on univalent trials in pure blocks than conflict blocks, $F(1, 39) = 54.9$, $p < 0.001$, $\eta_p^2 = 0.59$, and faster on univalent trials in conflict blocks than bivalent trials in conflict blocks, $F(1, 39) = 103.0$, $p < 0.001$, $\eta_p^2 = 0.72$. There was no effect of group, $F(1, 38) = 0.11$, $p = 0.75$, $\eta_p^2 = 0.003$, or interaction of group and trial type, $F(2, 76) = 0.36$, $p = 0.70$, $\eta_p^2 = 0.01$.

For both accuracy and RT, therefore, performance was poorest on bivalent trials and best on univalent trials in pure blocks, with intermediate performance on univalent trials in conflict blocks. There were no behavioral differences or interactions involving language group.

3.2. Overall MSE group differences

Fig. 3 illustrates MSE differences by group. A 4-way repeated-measures ANOVA[2] was performed with trial type (univalent trials in pure blocks, univalent trials in conflict blocks, bivalent trials in conflict blocks), location (Fz, Cz, Pz, Oz), and scale factor (fine scales 1–6, medium scales 7–14, coarse scales 15–20) as within-subjects variables, and group as a between-subjects variable. There was a significant interaction between location, scale factor, and group, $F(6, 228) = 2.40$, $p = 0.03$, $\eta_p^2 = 0.06$. No other effects involving the factor group reached significance (Fs < 2).

To understand the interaction, separate group by scale factor ANOVAs were run for each location. There were no significant effects a Fz, Cz, or Pz, Fs < 1, but at Oz there was a significant interaction between

[2] Previous research suggests that entropy varies as a function of RT and accuracy (McIntosh et al., 2008), so we also ran an ANCOVA using RT and accuracy as covariates. The outcomes involving language group did not change so only the ANOVA is reported here.

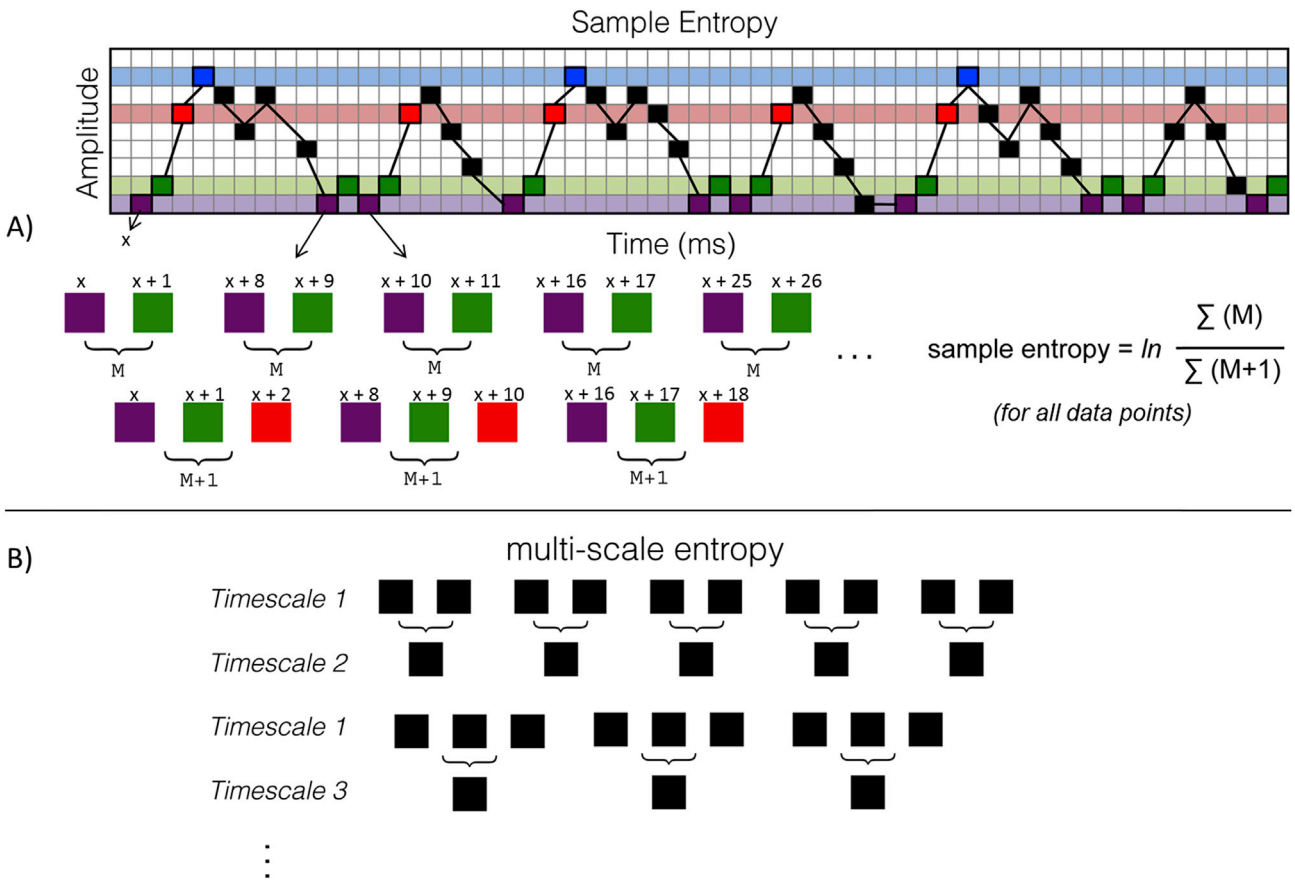

Fig. 2. Calculation of sample entropy and multiscale entropy using EEG brain signal. Panel A shows how to calculate sample entropy at each timescale. A criterion length m (2 in the present study) defines a number of consecutive data points in the EEG signal. For length m = 2 (starting with x and x+1), sum the number of times that two consecutive data points occur within a pre-specified amplitude range (r = 0.5 in the present study) across time in the EEG waveform. Next, sum the number of times that three (m + 1) consecutive data points (starting with x, x+1, and x+2) occur within the amplitude range across time in the EEG waveform. This procedure is repeated for each data point in the time series (i.e., starting at x+1, then starting at x+2, then starting at x+3, etc.) and all two-component matches and all three-component matches in the entire data series are summed together. Sample entropy is the natural logarithm of the ratio of two-component to three-component matches. Panel B represents downsampling of the original EEG data so that multiple fine to coarse timescales are created. This is done by averaging consecutive data points to create a new data point that corresponds to a coarser scale. This is done n times (in our study n = 20) and sample entropy is re-calculated at each timescale. This creates a series of fine to coarse grained entropy scales. This figure was inspired by Fig. 1 from Heisz et al. (2012).

Table 1
Means and standard deviations of background measures by group.

	Monolinguals (n = 20)	Bilinguals (n = 20)
Age	19.4 (1.6)	19.0 (1.5)
Parent's Education	3.2 (0.6)	3.4 (1.3)
Shipley Verbal	100.0 (8.6)	99.2 (6.9)
Shipley Non-verbal IQ	97.7 (11.6)	98.2 (12.2)
L1 proficiency out of 100 (speaking/understanding)	97.5 (4.7)	95.6 (7.9)
L2 proficiency out of 100 (speaking/understanding)	10.9 (16.0)	84.9 (13.9)

Table 2
Means and standard deviations for accuracy and RT in bivalency task by group.

	Monolinguals	Bilinguals
Accuracy		
Univalent in pure blocks	0.94 (0.04)	0.93 (0.05)
Univalent in conflict blocks	0.93 (0.04)	0.92 (0.04)
Bivalent in conflict blocks	0.82 (0.15)	0.80 (0.16)
RT		
Univalent in pure blocks	686 (114)	685 (105)
Univalent in conflict blocks	734 (120)	752 (113)
Bivalent in conflict blocks	876 (163)	895 (145)

scale factor and group, $F(2, 76) = 4.27$, $p = 0.02$, $\eta_p^2 = 0.10$. This is explained by the significant planned linear contrast, $F(1, 38) = 4.67$, $p = 0.04$, $\eta_p^2 = 0.11$, showing greatest to least group differences from coarse to fine grained scales (i.e. coarse > medium > fine). Thus, bilinguals showed greater brain signal complexity than monolinguals especially in coarse-grained timescales. Monolinguals did not show greater signal complexity than bilinguals in any region.

To support these findings and test the robustness of the effects,[3] we ran an additional analysis that clustered groups of electrodes around these areas. We extracted MSE values for the electrodes surrounding Fz, Cz, Pz, and Oz – F3, F1, Fz, F2, F4 for frontal, C3, C1, Cz, C2, C4 for central, P3, P1, Pz, P2, P4 for parietal, and O1, Oz, O2 for occipital. This analysis revealed a significant main effect of group, $F(1, 38) = 9.36$, $p = 0.004$, $\eta_p^2 = 0.20$, and this was qualified by a significant interaction between location and group, $F(3, 114) = 2.76$, $p = 0.04$, $\eta_p^2 = 0.07$. The interaction is explained by the finding that bilinguals had greater signal complexity in occipital electrode locations (see Fig. 4), $F(1, 38) = 8.81$, $p = 0.005$, $\eta_p^2 = 0.19$, but no other locations (all Fs < 1).

No other group effects emerged. Error bars represent standard errors.

3.3. Occipital MSE and RT correlations

The effect of these brain differences on performance was examined

[3] We thank an anonymous reviewer for the suggestion that we should determine if our results were robust after examining a greater number of electrodes.

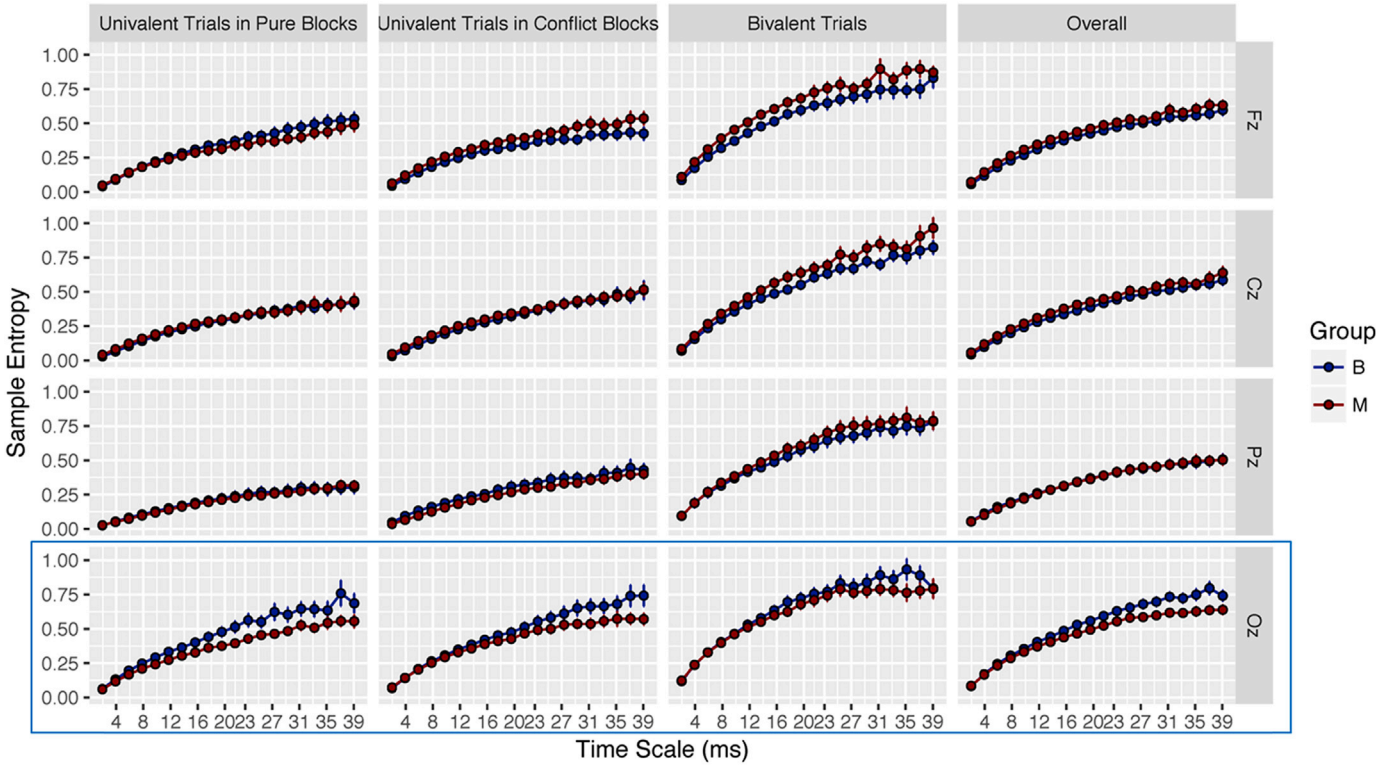

Fig. 3. Multiscale entropy for monolinguals (M) and bilinguals (B). Bilinguals showed greater sample entropy than monolinguals across all trial types in occipital regions (Oz), especially at coarse time scales. Time scales 1–20 were converted to ms by dividing each timescale by the sampling rate (512 Hz) and then multiplying the resulting number by 1000 ms. Error bars represent standard errors.

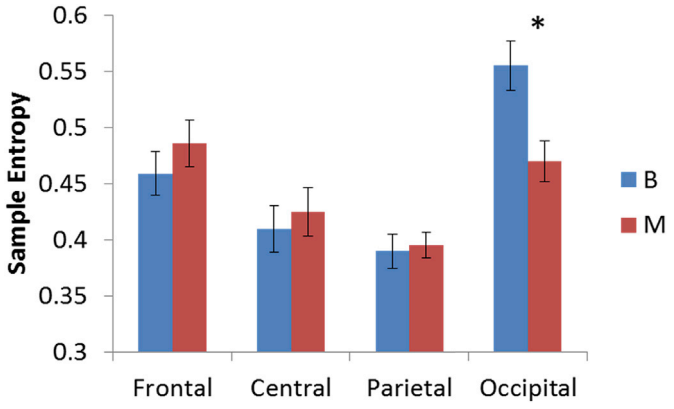

Fig. 4. Electrode cluster analysis for MSE values between monolinguals (M) and bilinguals (B). Bilinguals showed higher MSE values than monolinguals in occipital electrode locations.

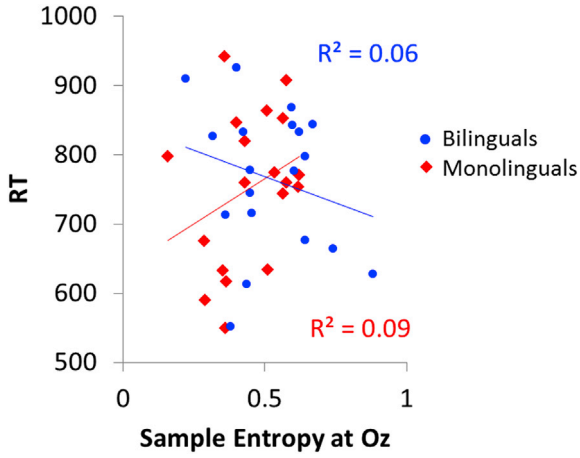

Fig. 5. Mean sample entropy predicting reaction times (RT) at occipital electrode sites.

through the relationship between behavioral outcomes and sample entropy at Oz where the language groups diverged. As shown in Fig. 5, bilinguals had faster RT with increasing entropy whereas monolinguals had slower RT with more entropy. To confirm this pattern, a one-tailed robust linear regression on these data showed an interaction of slopes between groups, $F(1, 34) = 3.24$, $p = 0.04$. Thus, greater entropy in occipital electrode locations was associated with faster performance for bilinguals but was associated with slower performance by monolinguals. The electrode cluster analysis produced similar findings, showing an interaction between the slopes for the groups, $F(1, 35) = 2.86$, $p < 0.05$. There were no significant correlations or interactions between frontal complexity and RT (all $ps > 0.3$). No significant effects with accuracy were revealed (all $ps > 0.3$).

3.4. Fronto-occipital coupling and RT

The relation between greater entropy in occipital regions and poorer performance for monolinguals suggests that monolinguals may be using a different, possibly more top-down approach than bilinguals. Frontal electrode sites are strongly associated with both behavioral and electrophysiological modulations between different trial types during the bivalency effect paradigm (Grundy and Shedden, 2014b; Grundy et al., 2013). Thus, we explored how functional connectivity between occipital and frontal regions was associated with behavior by using the coupling

(correlation) between frontal and occipital sample entropy as the predictor variable for behavioral RT for each trial type.[4] These relationships are shown in Fig. 6. For univalent trials in pure blocks, Fz-Oz coupling was unrelated to RT (Monolinguals: $r = -0.18$, Bilinguals: $r = -0.08$). For univalent trials in conflict blocks, both monolinguals and bilinguals showed a strong negative relationship between RT and Fz-Oz coupling (Monolinguals: $r = -0.66$, Bilinguals: $r = -0.68$). That is, greater coupling of sample entropy between frontal and occipital regions was associated with faster response times for both groups. For the most difficult bivalent trials, there was an interaction of slopes between the groups, $F(1, 34) = 5.11$, $p = 0.01$. Coupling was again associated with faster RTs for monolinguals ($r = -0.43$), but this relationship was reversed for bilinguals: weaker coupling (more independence of regional sample entropy) between frontal and occipital regions was associated with faster RTs ($r = 0.38$).

The frontal-occipital cluster analysis revealed similar findings with an interaction between the slopes: monolinguals performed better with increased coupling between frontal and occipital sites ($r = -0.35$), while bilinguals performed better with increasing independence between frontal and occipital regions ($r = 0.38$), $F(1, 35) = 3.69$, $p = 0.03$. The cluster analysis also again revealed that there was no relationship between RTs to univalent trials in pure blocks and frontal-occipital connectivity ($p > 0.2$). However, diverging from the Fz-Oz coupling analysis, the frontal-occipital cluster analysis showed no relationship between coupling and RTs to univalent trials in conflict blocks for either group ($p > 0.2$). This suggests that the strong correlation between RT to univalent trials in conflict blocks and Fz-Oz coupling is constrained to very localized electrode positions rather than being a distributed effect. Fig. 7 presents a summary of the relationship between bilingualism, behavior and brain signal complexity.

4. Discussion

Multiscale entropy analysis was used to examine brain signal complexity among young adult monolinguals and bilinguals. The results revealed that bilinguals had greater sample entropy (i.e., brain signal complexity) than monolinguals in occipital regions. Furthermore, the relationship between brain signal complexity and behavioral performance differed between the groups: occipital entropy was associated with better performance for bilinguals, but poorer performance for monolinguals. Similarly, functional connectivity between frontal and occipital regions was associated with better performance for both groups on univalent trials in conflict blocks, but this relationship reversed for bilinguals on the more difficult bivalent trials. These findings are consistent with an interpretation of more reliance on automatic visual resources and less reliance on frontal resources for bilinguals than monolinguals.

Bilinguals showed greater sample entropy than monolinguals at occipital electrodes, but monolinguals did not show greater sample entropy than bilinguals in any region. Given that greater brain signal complexity is believed to index the ability to rapidly switch brain states (Deco et al., 2011; Beharelle et al., 2012), these findings suggest a greater ability for bilinguals to switch brain states in occipital (i.e., possibly visual) regions than monolinguals. Recent evidence from our lab suggests that bilinguals are able to disengage attention from visually presented items more rapidly than monolinguals (Grundy et al., 2017b; Grundy and Keyvani-Chahi, 2017), a process that requires more advanced visual processing. In these experiments, the items are visually simple like the stimuli used here. When a stimulus appears on the screen, bilinguals are able to process the item and then rapidly disengage from it before monolinguals are able to do so. This is part of the mechanism involved in switching ability. If bilinguals are more adept at parsing information at an automatic/perceptual level than monolinguals (and hence have greater signal complexity at occipital electrodes), this may help to explain why bilinguals disengage attention more rapidly than monolinguals. This ability is not always expressed as a bilingual advantage to overall behavioral performance because rapidly disengaging is beneficial on trial switches but not trial repetitions (Grundy et al., 2017b).

More complexity in visual regions for bilinguals is in line with a recent model of how second language experience modifies domain-general brain structure and function. The *Bilingual Anterior to Posterior and Subcortical Shift* (BAPSS; Grundy et al., 2017a) posits that lifelong practice with bilingualism leads to more efficient processing of stimuli by relying more on perceptual/motor regions than on frontal regions. The model proposes that when first learning a new language, frontal resources are heavily implicated and much top-down control is required. Over time, recruitment of frontal resources becomes more efficient by enhancing resources and connections to perceptual and motor centers. It is important to note that our use of the term efficiency does not necessarily imply that bilinguals use fewer brain resources overall. Rather, bilinguals shift recruitment from frontal to posterior brain regions to improve performance by relying more on perceptual/automatic processing strategies and less on top-down control strategies. However, there is some evidence that there is more glucose metabolism required for activation in the frontal lobes than in posterior regions (review in Bullmore and Sporns, 2012), a difference that is consistent with an efficiency argument. Continual use of higher-order control centers can enhance early visual processes through feedback loops; uncertainty and conflict can trigger a more in-depth analysis of visual features of stimuli (review in Gilbert and Li, 2013). Thus, the present study provides empirical support for the BAPSS model by showing that bilingualism leads to enhanced visual processing complexity.

Increased complexity at occipital electrodes for bilinguals might help to explain the finding that bilinguals show delayed onset of symptoms of Alzheimer's disease compared to monolinguals (Bialystok et al., 2007; reviews in Bak and Alladi, 2014; Gold, 2015; Guzmán-Vélez and Tranel, 2015). Alzheimer's disease is associated with reduced complexity in occipital regions (Abásolo et al., 2006; Escudero et al., 2006; Park et al., 2007). Bilinguals rely more on posterior regions alone rather than coupling with frontal regions in order to respond faster. A parallel set of findings from the aging literature has revealed that relative to younger adults, older adults robustly rely more on frontal than posterior regions (PASA; Davis et al., 2008). By relying more on posterior regions to accomplish task goals, bilinguals establish (and strengthen) alternate neural pathways leading to similar levels of behavioral performance to that of monolinguals. Thus, bilinguals rely on regions that are largely spared by Alzheimer's disease, whereas the frontal regions (upon which monolinguals draw more heavily) are disproportionately affected. Thus, when AD begins to spread through temporal and frontal regions, bilinguals are well positioned to maintain performance given their alternate strategy.

Abásolo et al. (2006) discuss three possible causes for why a reduction in complexity might be observed for Alzheimer's patients. First, cell death might reduce the complexity of neural signaling in these areas. Second, there may be a general paucity of neurotransmitters. Third, the issue may be a loss of connectivity in the overall networks. Applying these explanations to the young adult population requires considering performance boosts rather than performance deficits. Thus, an account of the group difference is that there is a boost in one or more of these factors in bilingual young adults. Greater complexity in occipital regions for bilinguals might compensate for neural degeneration in frontal lobes over time. It is well known that aging is associated with a posterior to anterior compensatory shift in activation for executive function tasks (Davis et al., 2008; Grady et al., 1994); lifelong practice managing two languages may delay this shift by increasing reliance on posterior regions (Grundy et al., 2017a). We note that our complexity data cannot speak directly to a relationship between bilingualism and the delay in Alzheimer's disease symptoms for bilinguals over monolinguals given that our data were from

[4] The same analyses were performed with accuracy, but no significant findings emerged, so we focus only on RT.

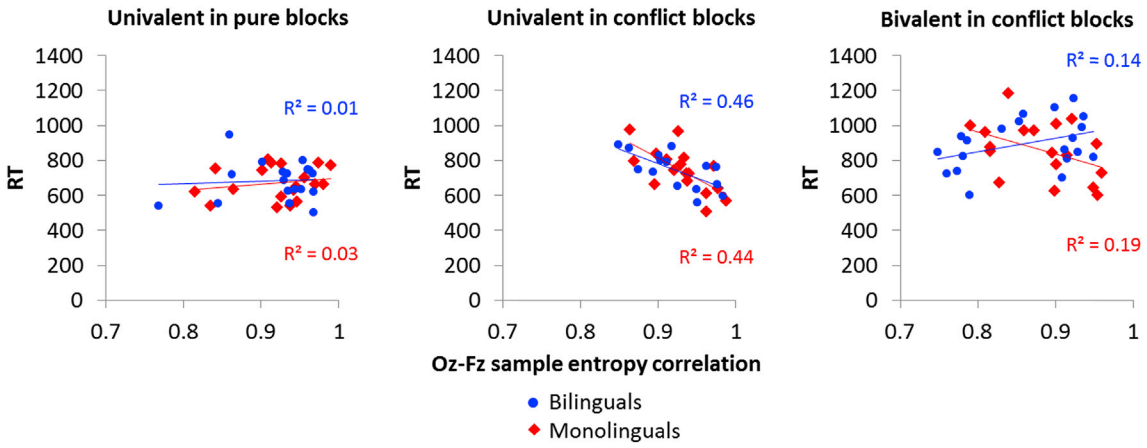

Fig. 6. Functional connectivity between mean occipital (Oz) and mean frontal (Fz) sample entropy predicting reaction times (RT).

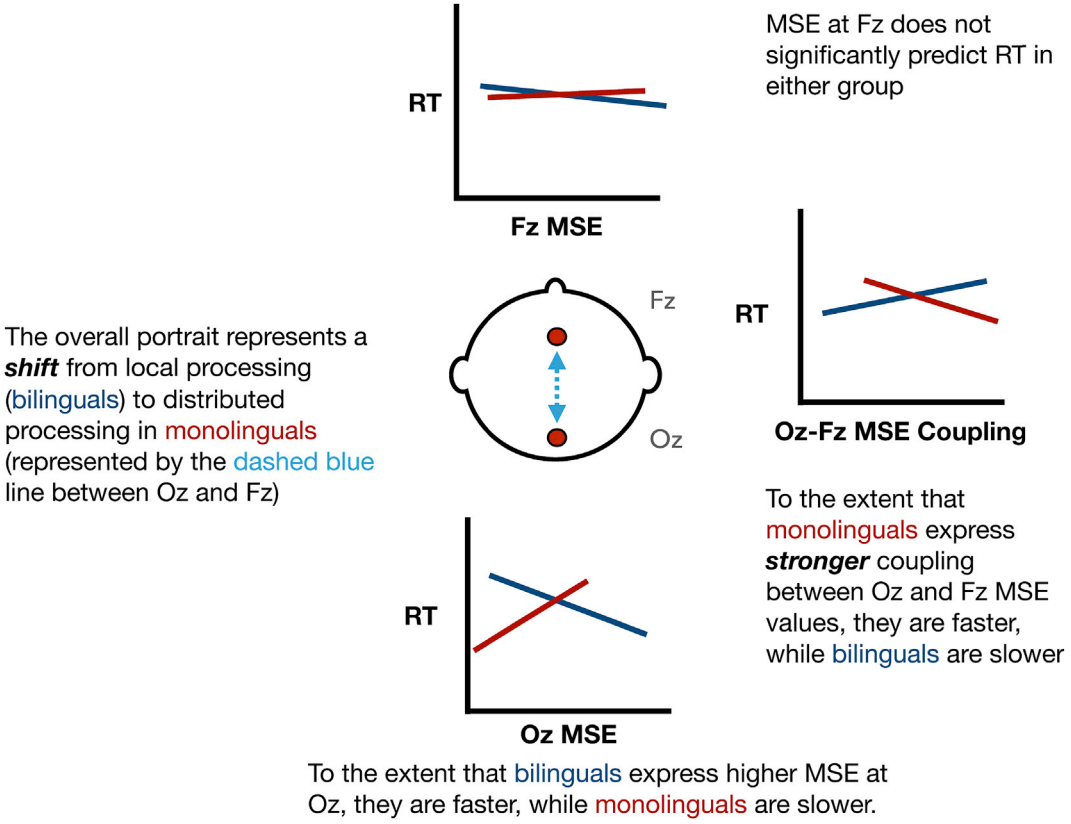

Fig. 7. Summary of the relationship between bilingualism, behavior, and brain signal complexity.

cognitively normal young adults rather than older adults with dementia. Thus, any link between Alzheimer's disease, brain complexity, and bilingualism is hypothetical at this point and future studies are needed to confirm the possibility.

Group differences in brain signal complexity were most evident at coarse, rather than fine, timescales. This might mean that bilinguals have more brain signal complexity in distributed rather than local neural networks within occipital regions; previous work has shown that fine-grained scales are associated with local networks, while coarse-grained scales are associated with distributed networks (Vakorin et al., 2011). However, our data cannot speak to group differences in the distribution of complexity between monolinguals and bilinguals; future studies are needed to investigate this possibility.

Increased brain signal complexity in visual regions was associated with faster RTs for bilinguals but slower RTs for monolinguals, suggesting that there are different approaches being used by these groups. Bilinguals might be more adept at automatically parsing information at lower, perceptual levels than monolinguals. In contrast, brain signal complexity in visual regions appeared to impede monolingual performance; this finding suggests that monolinguals may be using a more top-down approach than bilingual peers.

To test this idea, we computed functional connectivity (coupling) between entropy in frontal and occipital regions. For both language groups, higher coupling predicted faster RTs for univalent trials in conflict blocks, suggesting that this coupling facilitates performance. Coupling between frontal and occipital regions did not predict behavior for either group on univalent trials in pure blocks, suggesting that higher cognitive demand is required before connectivity patterns influence

performance. For bivalent trials, connectivity between frontal and occipital regions affected RT performance in the opposite direction for the two groups. For monolinguals, greater coupling between frontal and occipital brain states (i.e., rate of change was similar in both regions) was associated with faster performance, but for bilinguals, greater *independence* between frontal and occipital regions led to faster responding. Thus, responding to bivalent trials may be more automatic for bilinguals than monolinguals. This is not to suggest that occipital complexity is unimportant for monolinguals; rather, complexity in occipital regions on its own helps performance for bilinguals but does not help monolinguals. Occipital complexity is likely still important for monolinguals, but the importance is revealed in its relationship with frontal complexity (see Fig. 7). In essence, it is more important to behavior for monolinguals that brain states change in tandem between occipital and frontal lobes.

It is important to note that correlation does not indicate causation, so it is possible that greater brain signal complexity leads to better ability to switch between languages and become bilingual. However, most bilinguals are raised in bilingual environments or become so out of life necessity; they do not choose to be bilingual (Bialystok et al., 2009). Therefore, it is unlikely that bilinguals in the present study became bilingual because of greater brain signal complexity, nor is it likely that monolinguals in the present study became so because of less brain signal complexity. Differences in brain signal complexity between bilinguals and monolinguals who are well-matched on background variables like socioeconomic status and intelligence are therefore not likely due to genetic or biological factors, but rather to their linguistic experiences. We propose that second language experience is more likely to increase brain signal complexity in posterior regions than the reverse.

In sum, the present findings demonstrate that second language experience leads to domain-general adaptation that influences brain signal complexity in posterior regions. These complexity changes are associated with more efficient processing of information and may help to explain why bilinguals show later cognitive decline than monolinguals in older age.

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References

Abásolo, D., Hornero, R., Espino, P., Alvarez, D., Poza, J., 2006. Entropy analysis of the EEG background activity in Alzheimer's disease patients. Physiol. Meas. 27, 241–253.
Abutalebi, J., Green, D.W., 2016. Neuroimaging of language control in bilinguals: neural adaptation and reserve. Biling. Lang. Cogn. 19, 689–698.
Anderson, J.A., Mak, L., Keyvani Chahi, A.K., Bialystok, E., 2017. The language and social background questionnaire: assessing degree of bilingualism in a diverse population. Behav. Res. Methods 1–14.
Bak, T.H., Alladi, S., 2014. Can being bilingual affect the onset of dementia? Future Neurol. 9, 101–103.
Beharelle, A.R., Kovačević, N., McIntosh, A.R., Levine, B., 2012. Brain signal variability relates to stability of behavior after recovery from diffuse brain injury. NeuroImage 60, 1528–1537.
Bialystok, E., 2017. The bilingual adaptation: how minds accommodate experience. Psychol. Bull. 143, 233–262.
Bialystok, E., Craik, F.I., Freedman, M., 2007. Bilingualism as a protection against the onset of symptoms of dementia. Neuropsychologia 45, 459–464.
Bialystok, E., Craik, F.I.M., Green, D.W., Gollan, T.H., 2009. Bilingual minds. Psychological science in the public interest, 10, 89-129.Bialystok, E., Craik, F. I., & Luk, G. (2012). Bilingualism: consequences for mind and brain. Trends Cogn. Sci. 16, 240–250.
Bressler, S.L., Kelso, J.A.S., 2001. Cortical coordination dynamics and cognition. Trends Cogn. Sci. 5, 26–36.
Bruin, K.J., Wijers, A.A., Van Staveren, A.S.J., 2001. Response priming in a go/nogo task: do we have to explain the go/nogo N2 effect in terms of response activation instead of inhibition? Clin. Neurophysiol. 112, 1660–1671.
Bullmore, E., Sporns, O., 2012. The economy of brain network organization. Nat. Rev. Neurosci. 13, 336–349.
Costa, M., Goldberger, A.L., Peng, C.K., 2002. Multiscale entropy analysis of complex physiologic time series. Phys. Rev. Lett. 89, 068102.
Costa, M., Goldberger, A.L., Peng, C.K., 2005. Multiscale entropy analysis of biological signals. Phys. Rev. E 71, 021906.
Davis, S.W., Dennis, N.A., Daselaar, S.M., Fleck, M.S., Cabeza, R., 2008. Que PASA? The posterior–anterior shift in aging. Cereb. Cortex 18, 1201–1209.
Deco, G., Jirsa, V.K., McIntosh, A.R., 2011. Emerging concepts for the dynamical organization of resting-state activity in the brain. Nat. Rev. Neurosci. 12, 43–56.
Dimoska, A., Johnstone, S.J., Barry, R.J., 2006. The auditory-evoked N2 and P3 components in the stop-signal task: indices of inhibition, response-conflict or error-detection? Brain Cogn. 62, 98–112.
Escudero, J., Abásolo, D., Hornero, R., Espino, P., López, M., 2006. Analysis of electroencephalograms in Alzheimer's disease patients with multiscale entropy. Physiol. Meas. 27, 1091–1106.
Gajewski, P.D., Stoerig, P., Falkenstein, M., 2008. ERP—correlates of response selection in a response conflict paradigm. Brain Res. 1189, 127–134.
Garrett, D.D., Kovacevic, N., McIntosh, A.R., Grady, C.L., 2010. Blood oxygen level-dependent signal variability is more than just noise. J. Neurosci. 30, 4914–4921.
Garrett, D.D., Samanez-Larkin, G.R., MacDonald, S.W., Lindenberger, U., McIntosh, A.R., Grady, C.L., 2013. Moment-to-moment brain signal variability: a next frontier in human brain mapping? Neurosci. Biobehav. Rev. 37, 610–624.
Ghosh, A., Rho, Y., McIntosh, A.R., Kötter, R., Jirsa, V.K., 2008. Noise during rest enables the exploration of the brain's dynamic repertoire. PLoS Comput. Biol. 4, e1000196.
Gilbert, C.D., Li, W., 2013. Top-down influences on visual processing. Nat. Rev. Neurosci. 14, 350–363.
Gold, B.T., 2015. Lifelong bilingualism and neural reserve against Alzheimer's disease: a review of findings and potential mechanisms. Behav. Brain Res. 281, 9–15.
Grady, C.L., Maisog, J.M., Horwitz, B., Ungerleider, L.G., Mentis, M.J., Salerno, J.A., Haxby, J.V., 1994. Age-related changes in cortical blood flow activation during visual processing of faces and location. J. Neurosci. 14, 1450–1462.
Grant, A., Dennis, N.A., Li, P., 2014. Cognitive control, cognitive reserve, and memory in the aging bilingual brain. Front. Psychol. 5, 1401.
Grundy, J.G., Anderson, J.A., Bialystok, E., 2017a. Neural correlates of cognitive processing in monolinguals and bilinguals. Ann. N. Y. Acad. Sci. 1396, 183–201. http://dx.doi.org/10.1111/nyas.13333.
Grundy, J.G., Benarroch, M.F.F., Woodward, T.S., Metzak, P.D., Whitman, J.C., Shedden, J.M., 2013. The Bivalency effect in task switching: event-related potentials. Hum. Brain Mapp. 34, 999–1012. http://dx.doi.org/10.1002/hbm.21488.
Grundy, J.G., Chung-Fat-Yim, A., Friesen, D.C., Mak, L., Bialystok, E., 2017b. Sequential congruency effects reveal differences in disengagement of attention for monolingual and bilingual young adults. Cognition 163, 42–55.
Grundy, J.G., Keyvani Chahi, A., 2017. Post-conflict slowing effects in monolingual and bilingual children. Dev. Sci. 20, e12488. http://dx.doi.org/10.1111/desc.12488.
Grundy, J.G., Shedden, J.M., 2014a. A role for recency of response conflict in producing the bivalency effect. Psychol. Res. 78, 679–691. http://dx.doi.org/10.1007/s00426-013-0520-x.
Grundy, J.G., Shedden, J.M., 2014b. Support for a history-dependent predictive model of dACC activity in producing the bivalency effect: an event-related potential study. Neuropsychologia 57, 166–178. http://dx.doi.org/10.1016/j.neuropsychologia.2014.03.008.
Gunter, T.C., Jackson, J.L., Mulder, G., 1995. Language, memory, and aging: an electrophysiological exploration of the N400 during reading of memory-demanding sentences. Psychophysiology 32, 215–229.
Guzmán-Vélez, E., Tranel, D., 2015. Does bilingualism contribute to cognitive reserve? Cognitive and neural perspectives. Neuropsychology 29, 139–150.
Heisz, J.J., McIntosh, A.R., 2013. Applications of EEG neuroimaging data: event-related potentials, spectral power, and multiscale entropy. J. Vis. Exp. 76, 50131.
Heisz, J.J., Shedden, J.M., McIntosh, A.R., 2012. Relating brain signal variability to knowledge representation. NeuroImage 63, 1384–1392.
Hsieh, S., Cheng, P., 2006. Task reconfiguration and carryover in task switching: an event-related potential study. Brain Res. 1084, 132–145.
Hsieh, S., Liu, H., 2008. Electrophysiological correlates of task conflicts in task-switching. Brain Res. 1203, 116–125.
Kroll, J.F., Dussias, P.E., Bogulski, C.A., Valdes Kroff, J.R., 2012. Juggling two languages in one mind: what bilinguals tell us about language processing and its consequences for cognition. In: Ross, B. (Ed.), The Psychology of Learning and Motivation, vol. 56. Academic Press, San Diego, CA, pp. 229–262.
Lake, D.E., Richman, J.S., Griffin, M.P., Moorman, J.R., 2002. Sample entropy analysis of neonatal heart rate variability. Am. J. Physiol. Regul., Integr. Comp. Physiol. 283, R789–R797.
Lenartowicz, A., Escobedo-Quiroz, R., Cohen, J.D., 2010. Updating of context in working memory: an event-related potential study. Cogn., Affect. Behav. Neurosci. 10, 298–315.
Lorist, M.M., Klein, M., Nieuwenhuis, S., De Jong, R., Mulder, G., Meijman, T.F., 2000. Mental fatigue and task control: planning and preparation. Psychophysiology 37, 614–625.
Lippé, S., Kovacevic, N., McIntosh, A.R., 2009. Differential maturation of brain signal complexity in the human auditory and visual system. Front. Hum. Neurosci. 3, 1–9.
Makeig, S., Bell, A.J., Jung, T.P., Sejnowski, T.J., 1996. Independent component analysis of electroencephalographic data. In: Touretzky, D., Mozer, M., Hasselmo, M. (Eds.), Advances in Neural Information Processing Systems, pp. 145–151.
Meier, B., Woodward, T.S., Rey-Mermet, A., Graf, P., 2009. The bivalency effect in task switching: general and enduring. Can. J. Exp. Psychol. 63, 201–210. http://dx.doi.org/10.1037/a0014311.
McIntosh, A.R., Kovacevic, N., Itier, R.J., 2008. Increased brain signal variability accompanies lower behavioral variability in development. PLoS Comput. Biol. 4, e1000106.

Mišić, B., Mills, T., Taylor, M.J., McIntosh, A.R., 2010. Brain noise is task dependent and region specific. J. Neurophysiol. 104, 2667–2676.
Neuhaus, A.H., Koehler, S., Opgen-Rhein, C., Urbanek, C., Hahn, E., Dettling, M., 2007. Selective anterior cingulate cortex deficit during conflict solution in schizophrenia: an event-related potential study. J. Psychiatr. Res. 41, 635–644.
Nicholson, R., Karayanidis, F., Poboka, D., Heathcote, A., Michie, P.T., 2005. Electrophysiological correlates of anticipatory task-switching processes. Psychophysiology 42, 540–554.
Niznikiewicz, M.A., Voglmaier, M., Shenton, M.E., Seidman, L.J., Dickey, C.C., Rhoads, R., McCarley, R.W., 1999. Electrophysiological correlates of language processing in schizotypal personality disorder. Am. J. Psychiatry 156, 1052–1058.
Paap, K.R., Greenberg, Z.I., 2013. There is no coherent evidence for a bilingual advantage in executive processing. Cogn. Psychol. 66, 232–258.
Park, J.H., Kim, S., Kim, C.H., Cichocki, A., Kim, K., 2007. Multiscale entropy analysis of EEG from patients under different pathological conditions. Fractals 15, 399–404.
Pérez, A., Dowens, M.G., Molinaro, N., Iturria-Medina, Y., Barraza, P., García-Pentón, L., Carreiras, M., 2015. Complex brain network properties in late L2 learners and native speakers. Neuropsychologia 68, 209–217.
Pincus, S.M., Gladstone, I.M., Ehrenkranz, R.A., 1991. A regularity statistic for medical data analysis. J. Clin. Monit. Comput. 7 (4), 335–345.
Pinneo, L.R., 1966. On noise in the nervous system. Psychol. Rev. 73 (3), 242–247.
Pliatsikas, C., Luk, G., 2016. Executive control in bilinguals: a concise review on fMRI studies. Biling. Lang. Cogn. 19, 699–705.
Prior, A., Macwhinney, B., 2010. A bilingual advantage in task switching. Bilingualism. Lang. Cogn. 13, 253. http://dx.doi.org/10.1017/s1366728909990526.
Richman, J.S., Moorman, J.R., 2000. Physiological time-series analysis using approximate entropy and sample entropy. Am. J. Physiol. Heart Circ. Physiol. 278, H2039–H2049.
Shipley, W.C., Gruber, C.P., Martin, T.A., Klein, A.M., 2009. Shipley-2. Western Psychological Services, Los Angeles, CA.
Vakorin, V.A., Lippé, S., McIntosh, A.R., 2011. Variability of brain signals processed locally transforms into higher connectivity with brain development. J. Neurosci. 31, 6405–6413.
Verhoef, K.M., Roelofs, A., Chwilla, D.J., 2010. Electrophysiological evidence for endogenous control of attention in switching between languages in overt picture naming. J. Cogn. Neurosci. 22, 1832–1843.
Wiseheart, M., Viswanathan, M., Bialystok, E., 2016. Flexibility in task switching by monolinguals and bilinguals. Biling. Lang. Cogn. 19, 141–146. http://dx.doi.org/10.1017/S1366728914000273.
Woodward, T.S., Meier, B., Tipper, C., Graf, P., 2003. Bivalency is costly: bivalent stimuli elicit cautious responding. Exp. Psychol. 50, 233–238.