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Effect of Scrabble© Expertise on Brain Ageing as Measured with Brain Signal Variability and Event-Related Potentials

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Effect of Scrabble© Expertise on Brain Ageing as Measured with Brain Signal Variability and
Event-Related Potentials

by

Hongye Wang

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Abstract

We examined the effect of Scrabble expertise on brain ageing using brain signal variability as measured with multiscale entropy (MSE) and brain signal mean as measured with event-related potentials (ERP). We collected ERP data while age-matched Scrabble experts and controls (age range: 24 to 83) performed an expertise-related task (lexical decision task; LDT) and a non-expertise-related task (symbol decision task; SDT). During both tasks, fine-scale MSE increased with age for both groups, suggesting that short-range neural communication increases with age. Midscale MSE increased with age for experts but decreased for controls, suggesting that longer-range neural communication is maintained through older age for experts but not for controls. In addition, experts did not show the typical age-related decrease in frontal P300 amplitude. However, all age-related effects, regardless of direction, were associated with worse performance in both groups. This study provides a better understanding of how expertise affects brain ageing.
Acknowledgements

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Table of Contents

Abstract ........................................................................................................................................... ii
Acknowledgements ......................................................................................................................... iii
Table of Contents ............................................................................................................................... iv
List of Tables ..................................................................................................................................... v
List of Figures .................................................................................................................................... vi
List of Abbreviations ......................................................................................................................... vii
Chapter 1: Introduction ...................................................................................................................... 1
Chapter 2: Methods ............................................................................................................................ 11
  2.1 Participants ............................................................................................................................... 11
  2.2 Stimuli ...................................................................................................................................... 11
  2.3 Procedure ............................................................................................................................... 14
  2.4 Behavioural Data .................................................................................................................... 15
  2.5 EEG Acquisition and Preprocessing ..................................................................................... 16
  2.6 Brain Signal Variability Analysis ......................................................................................... 17
  2.7 Partial Least Squares (PLS) Analysis .................................................................................... 18
Chapter 3: Results – the relationship between expertise and age ....................................................... 21
  3.1 Behavioural Results ............................................................................................................... 21
  3.2 MSE Analysis ....................................................................................................................... 28
    3.2.1 The relationship between expertise, age, and MSE in LDT ........................................ 28
    3.2.2 The relationship between expertise, age, and MSE in SDT ........................................ 31
  3.3 ERP Analysis ....................................................................................................................... 34
    3.3.1 The relationship between expertise, age, and ERPs in LDT ........................................ 34
    3.3.2 The relationship between expertise, age, and ERPs in SDT ........................................ 37
Chapter 4: Results - the relationship between expertise, age and performance................................. 40
  4.1 MSE Analysis ....................................................................................................................... 40
    4.1.1 The relationship between expertise, age, behaviour measures, and MSE in LDT ....... 40
    4.1.2 The relationship between expertise, age, behaviour measures, and MSE in SDT ...... 43
  4.2 ERP Analysis ....................................................................................................................... 46
    4.2.1 The relationship between expertise, age, behaviour measures, and ERPs in LDT ...... 46
    4.2.2 The relationship between expertise, age, behaviour measures, and ERPs in SDT ...... 49
Chapter 5: Discussion ......................................................................................................................... 51
  5.1 Summary ............................................................................................................................... 51
  5.2 MSE ...................................................................................................................................... 52
    5.2.1 The relationship between expertise, age and MSE ...................................................... 52
    5.2.2 The association between age-related changes and behaviour measures .................. 55
  5.3 ERP ...................................................................................................................................... 57
    5.3.1 The relationship between expertise, age and ERPs ...................................................... 57
    5.3.2 The association between age-related changes and behaviour measures .................. 58
  5.4 Implications ............................................................................................................................ 60
  5.5 Limitations and future directions .......................................................................................... 61
References ......................................................................................................................................... 63
List of Tables

Table 1. *Mean characteristics and cognitive test scores of participant groups*

Table 2. *Mean characteristics of performance measures*
List of Figures

Figure 1. Examples of test stimuli (Lexical Decision Task).

Figure 2. Examples of test stimuli (Symbol Decision Task).

Figure 3. Two group (Scrabble experts vs. controls) behavioural PLS examining the relationship between MSE and age in LDT.

Figure 4. Two group (Scrabble experts vs. controls) behavioural PLS examining the relationship between MSE and age in SDT.

Figure 5. Two group (Scrabble experts vs. controls) behavioural PLS examining the relationship between ERPs and age in LDT.

Figure 6. Two group (Scrabble experts vs. controls) behavioural PLS examining the relationship between ERPs and age in SDT.

Figure 7. Two group (Scrabble experts vs. controls) behavioural PLS examining the relationship between MSE, age, response time, and anagramming scores in LDT.

Figure 8. Two group (Scrabble experts vs. controls) behavioural PLS examining the relationship between MSE, age, response time, and anagramming scores in SDT.

Figure 9. Two group (Scrabble experts vs. controls) behavioural PLS examining the relationship between ERPs, age, response time, and anagramming scores in LDT.

Figure 10. Two group (Scrabble experts vs. controls) behavioural PLS examining the relationship between ERPs, age, response time, and anagramming scores in SDT.
List of Abbreviations

EEG – Electroencephalography
ERP – Event Related Potential
fMRI – functional Magnetic Resonance Imaging
ICA – Independent Component Analysis
LDT – Lexical Decision Task
LV – Latent Variable
MSE – Multiscale Entropy
PLS – Partial Least Squares
SDT – Symbol Decision Task
Chapter 1: Introduction

Numerous studies suggest that cognitive abilities deteriorate in late adulthood. For instance, older adults often experience difficulty in word production, both phonologically and orthographically as compared to younger adults (Burke & MacKay, 1997). Specifically, the decline in the ability to retrieve the sound or phonology of words is evident as decreased accuracy of word finding during picture naming and discourse (Au et al., 1995; Heller & Dobbs, 1993), and increased difficulty in producing proper names, especially names of non-famous people (Cohen & Faulkner, 1986). Studies also show an age-related deficit in spelling, but not in recognizing correct or incorrect spelling (MacKay & Abrams, 1998; MacKay, Abrams & Pedroza, 1999). This age-related deterioration appears in other cognitive domains as well, including memory, decision making, and executive functions (as examples, see Brown & Ridderinkhof, 2009; Buckner, 2004; Burke & Light, 1981; Grady et al., 1995; Vallesi, McIntosh, & Stuss, 2011).

Expertise and aging

Although scientists agree that there exists age-related decline across many cognitive domains, they also notice but still do not have a good explanation for the fact that in real life, older individuals with cognitively demanding jobs, e.g., scholars of universities or leaders of governments and major companies, continue to maintain a high level performance in the face of general cognitive decline (Horn & Masunaga, 2006). In fact, older individuals who are skilful or considered experts in a particular field, e.g., expert typists (Salthouse, 1984), normally show little age-related performance decline in their area of expertise until very old age (Glisky, 2007).
In laboratory settings, however, the findings on the relationship between expertise and aging are mixed. For example, Charness (1981) found that the quality of a move in chess was only related to a player’s expertise but not age. Another study examining age and aviation expertise demonstrated that when the task was domain-relevant, age-related differences in performance declined (Morrow, Leirer, Altiteri, & Fitzsimmons, 1994). A study with professional pianists (Krampe & Ericsson, 1996) also did not find a negative relationship between age and performance on expertise-related tasks, although both experts and novices showed an age-related decline in performing non-expertise-related tasks. There also exist studies that suggest that expertise does not compensate for age-related declines. For example, Jastrzembski, Charness & Vasyukova (2006) showed that chess expertise did not attenuate the ageing effect on the speed of detecting a game position after testing 29 young players and 30 older players who were classified as novices, intermediates and experts, with around ten players in each skill level. A recent meta-analysis pointed out that even for chess experts, age was negatively related to the performance of selecting the best move in a game (Moxley & Charness, 2013), which contradicted a previous finding (Charness, 1981). Taken together, behavioural findings on the relationship between expertise and aging are not consistent.

Using structural MRI, fMRI and PET, researchers have already studied the brain mechanisms underlying expertise. Compared with novices, experts within a specific domain either showed both higher and lower activation in task-related brain areas (Basso et al., 2013; Hanakawa, Honda, Okada, Fukuyama, & Shibasaki, 2003; Olesen et al., 2004), or recruited additional brain regions when solving domain-specific tasks (Maguire, Valentine, Wilding, & Kapur, 2003; Pesenti et al., 2001; Protzner et al., 2015). However, very few imaging studies examined the relationship between expertise and ageing. One recent electroencephalography
(EEG) study examined the effect of tactile expertise gained from extensive and skilful manual work on brain ageing (Reuter, Voelcker-Rehage, Vieluf, Winneke, & Godde, 2014). Although they did not identify a significant interaction between the effect of age and tactile expertise on behaviour and event-related potentials (ERPs), they showed that expertise did modify the age effect on P300 amplitude at midline electrodes (e.g., Fz, Cz, and Pz ) in that although both older experts and non-experts showed reduced P300 amplitude, only the latter showed a positive correlation between P300 amplitude and task performance. Thus, it is possible that expertise delays age-related performance deterioration in the context of tactile perception. As the neural correlates underlying the relationship between normal aging and different expertise might be varied, more imaging studies are needed to investigate the effect of expertise from different areas on normal aging. This thesis focuses on Scrabble expertise.

Scrabble is a popular board game that requires word recognition experience. What differentiates a competitive Scrabble player from a novice/casual player is that the former invests significant amount of time on memorizing words from the official Scrabble dictionary as well as practicing anagramming (Halpern & Wai, 2007). On average, experts play Scrabble 211 days a year, and their official rankings are positively correlated with years of practice (Halpern & Wai, 2007). Long term practice makes Scrabble experts faster at reading vertically presented words than controls (Hargreaves, Pexman, Zdrazilova, & Sargious, 2012). Moreover, Scrabble experts are less dependent on semantic information to recognize a word than novices when performing lexical decisions (Hargreaves et al., 2012). In addition, one study showed that Scrabble experts had better visuospatial memory for words and letters and their positions on real and modified Scrabble boards than a group of college students who were decades younger (Halpern & Wai, 2007). However, no work has directly investigated the effect of Scrabble expertise on brain aging.
Why are Scrabble experts an ideal group for studying the effects of expertise on brain aging?

Competitive (or tournament) Scrabble is a suitable activity in which to investigate the effects of expertise on brain ageing. Scrabble experts are ideal for this purpose because first, the wide age range of Scrabble experts, ranging from early twenties to eighties, is suitable for an ageing study. Second, compared with simple motor skill acquisition associated with tactile perception (Reuter et al., 2014), Scrabble is a more sophisticated skill to develop in the context of expertise due to the high-level cognitive processes it requires (e.g., language, visuospatial, and logical thinking). Finally, the activities involved in Scrabble practice is more consistent than those of some other expert groups (e.g., musicians), which makes it easy to investigate the effects of a specific form of long-term training.

In addition to focusing on behavioural changes, an alternative approach to examining the effect of expertise on brain ageing is to explore how the brain is modified in this context. In other words, there are two ways to show that expertise benefits brain ageing. First, the effect of expertise can be verified by behavioral improvements, such as faster response time or greater accuracy, or no evident decline of performance with ageing. Second, the effect of expertise also can be demonstrated by showing that expertise-related training makes your brain function like a “younger” brain, via neuroimaging techniques. Thus, this thesis aims to investigate how Scrabble expertise affects normal ageing with both behavioral and neuroimaging measures.

What does normal brain ageing look like?

Not surprisingly, the structure of the brain changes with advancing age. This is evidenced by the reduction in brain weight and volume, the expansion of cerebral ventricles, the shrinkage
of gray matter, and the widespread loss of white matter (for a review, see Raz & Rodrigue, 2006). For example, the negative correlation between age and the volume of the prefrontal cortices is the most significant in the frontal regions (Raz & Rodrigue, 2006). The volume of hippocampus, amygdala, the cerebellum and the neostriatum also negatively correlated with age (Raz & Rodrigue, 2006). Besides gray matter volume, cortical thickness and surface area are additional measures for exploring change in gray matter tissue. Recent research suggested that cortical complexity, indexed by fractal dimensionality, was more sensitive to age-related changes in cortical structure than cortical thickness (Madan & Kensinger, 2016). Although the location of the greatest age-related reduction in gray matter thickness varies with studies (e.g., gyri of the frontal cortex, Salat et al., 2004; temporal lobes, van Velsen et al., 2013), a study examining 216 participants aged from 18 to 87 found widely distributed age-related reduction on cortical thickness, surface area and gray matter volume across the brain, with the most common reduction observed in the prefrontal cortex (Lemaitre et al., 2012). A review on structural brain aging points out that gray matter declines more linearly than white matter. Declines in white matter accelerate with advancing age, similar to the age-related expansion pattern observed in cerebrospinal fluid (Lockhart & DeCarli, 2014).

Historically, age–related structural changes were assumed to underlie age-related decreases in brain activation and behavioral performance during cognitive tasks (Reuter-Lorenz & Lustig, 2005). For example, impairment of memory in older adults was related to under-activation in hippocampus during encoding (Grady et al., 1995). However, several functional neuroimaging studies also revealed increased brain activity in older adults as compared to younger adults in some regions, or activation in extra recruited brain areas (e.g., prefrontal regions) not observed in younger adults (Vallesi et al., 2011; Garrett, Kovacevic, McIntosh, &
Grady, 2011; Rossini, Rossi, Babiloni, & Polich, 2007; Sala-LIonch, Bartres-Faz, & Junque, 2015). Depending on the task demands and choice of behavioral measures, increased activation in older adults can be associated with both improvements and declines in task performance (Grady, 2011). For example, increased brain activity in older adults associated with greater accuracy in a go/no-go task (Vallesi et al., 2011), but associated with slower response time in a perceptual and working memory task (Garrett et al., 2011). In addition, task-fMRI studies revealed that the activity pattern is less lateralized in older adults than in younger adults (Rossini et al., 2007; Sala-LIonch et al., 2015).

Studies on cortical activation using EEG demonstrated a similar age-related bilateral activation pattern during cognitive tasks for older adults, indicating increased coupling interactions among cortical regions bilaterally with aging (Rossini et al., 2007). The amplitudes of event-related potential (ERP) components have been used as neural markers of aging. For example, P300, a positive-going amplitude that peaks around 250 to 500 ms after stimulus onset, demonstrated an age-related amplitude decrease in parietal brain regions and age-related amplitude increase in frontal brain regions. This age-related anterior shift of P300 distribution is widely observed and regarded as evidence that older individuals increase the recruitment of frontal brain regions during cognitive task (O'Connell et al., 2012; Polich, 2007; van Dinteren, Arns, Jongsma, & Kessels, 2014; West, Schwarb, & Johnson, 2010). The P300 is easy to detect due to a relatively larger size as compared to other ERP components, and is widely accepted as reflecting the facets of cognitive information processing (van Dinteren et al., 2014). For example, in an attentional resource-allocation model (Polich, 2007), P300 amplitude is thought to represent the attentional resources assigned to a cognitive task. An increase in P300 amplitude indicates more attentional resources or mental effort involved in the task.
Aging affects functional connectivity and cortical activity during resting state as well. Results from fMRI studies demonstrated weaker functional connectivity among regions within the default mode network (DMN; one of the most studied and easily visualized networks during resting state) in older adults than in younger adults during rest (Andrews-Hanna et al., 2007; Sambataro et al., 2010). Additionally, older adults are less capable of reducing the activity in DMN during cognitive tasks than younger adults (Damoiseaux et al., 2008; Grady et al., 2006). A recent study examined the effect of age on both the DMN and a task-positive network (regions that are activated with the presentation of external stimuli), and found an age-related decrease in the extent of the DMN, as well as an expansion of the task-positive network (Grady et al., 2010). Results from resting EEG study with a large sample size (N = 185, 18-85 years) demonstrated a pronounced age related amplitude decrease in low alpha band (8-10.5Hz) at parietal, occipital, and temporal regions for healthy subjects (for a review, see Rossini et al., 2007).

Most studies examining the age related changes in the brain focus on signal amplitude. However, recent computational modeling studies suggest that brain signal variability (i.e., transient temporal fluctuations in brain signal) conveys important information about network dynamics (e.g., see Deco, Jirsa, & McIntosh, 2011). In a complex non-linear system such as the brain, signal variability facilitates the transition between possible functional network configurations, in the presence or absence of external stimulation (McIntosh et al., 2010). Empirically, brain signal variability has been shown to track maturation and disease, and reflect cognitive capacity (Garrett et al., 2011; McIntosh, Kovacevic, & Itier, 2008; McIntosh et al., 2010; McIntosh et al., 2014; Protzner, Valiante, Kovacevic, McCormick, & McAndrews, 2010; Protzner, Kovacevic, Cohn, & McAndrews, 2013). For example, using signal variability of EEG and MEG data, McIntosh et al. (2014) revealed a robust age effect during a visual perception
task and a multisensory task. For older adults, variability of EEG recordings increased at the fine temporal scales but decreased at the coarse temporal scales across tasks. McIntosh and colleagues interpreted this as an age-related shift from long-range interactions among neural populations (integration) to more local neural processing (specialization) in late adulthood. Our recent work verified the same age effect on signal variability of resting-state EEG data (Wang, McIntosh, Kovacevic, Karachalios, & Protzner, 2016), and further demonstrated that age not only affects the change of resting-state dynamics from pre-to post-task, but also its relationship with performance on the intervening task. Specifically, the change and association decrease with increasing age.

**The way we choose to measure brain aging**

We used both mean and variability of ERP amplitude to measure brain aging. Mean ERP amplitude is a traditional measure to examine the group difference in response to a specific stimulus (O'Connell et al., 2012; Polich, 2007). Variability also is important, as demonstrated by a study showing that spatial pattern based on BOLD signal variability was five times more powerful at predicting age than the spatial pattern based on BOLD mean activation (Garrett, Kovacevic, McIntosh, & Grady, 2010). It was not only robust, but also spatially and statistically different from the mean-based pattern. This study only focused on fixation blocks interspersed among several cognitive task blocks. The authors furthered their study to investigate the relation between BOLD signal variability and cognitive task performance (Garrett et al., 2011). In addition to replicating the previous findings, the new results showed that those participants with higher brain variability were younger, faster, and produced more consistent behaviour across three tasks (perception, attention, and delayed matching tasks). Garrett et al. (2011) argued that
brain signal variability played an important role in brain function. The variability-based brain measures provide information that is different from and complimentary to more traditional measures.

Current study

The main goal of the current study was to investigate the effect of Scrabble expertise on brain aging. We employed the mean and variability analyses to explore the age effect on the ERP recordings during an expertise-related task (lexical decision task; LDT, in which participants identified horizontally- and vertically- presented letter strings as words or nonwords, similar to the requirements in Scrabble) and a non-expertise-related task (symbol decision task; SDT, in which unfamiliar symbol strings replaced letter strings and participants identified strings as with unique symbols or with one symbol presented twice), for both expert and novice groups, with the hypothesis that the expertise may alter brain aging in Scrabble experts. We used expertise-related and non-expertise-related cognitive tasks because we were interested whether the age effects on brain signals are different between the two tasks for Scrabble experts.

For behaviour data, we expected that age would be positively related to response time in both groups, regardless of whether the cognitive task was expertise-related or not. In terms of group differences, we explored if the age-related increase in response time was more evident in control group than in the expert group, and if this potential effect differed when the task was expertise-related and when it was not.

For brain signal variability, we expected that the age effect in the control group would replicate the spatiotemporal pattern of the age effect demonstrated in previous studies (McIntosh et al., 2014; Wang et al., 2016), i.e., increased variability at the fine temporal scales for older
participants. Compared to previous research on relationship between age and multiscale entropy (MSE; McIntosh et al., 2014; Wang et al., 2016), our ERP epoch length was shorter, which resulted in fewer temporal scales calculated for MSE (see methods, p17). Therefore, the coarse temporal scale in our analysis actually corresponds to the middle temporal scales in previous publications (McIntosh et al., 2014; Wang et al., 2016). To be consistent and make easy comparisons between research findings, we named our coarse temporal scale as middle temporal scale. For Scrabble experts, if expertise influences brain ageing, we expected the pattern to be different in some way. As there is no previous research on this topic, we had no specific predictions on how the pattern would be different.

For ERPs, we expected the control group to replicate previously documented age-related ERP effects (O'Connell et al., 2012; Polich, 2007; van Dinteren et al., 2014; West et al., 2010). We chose to focus on P300 amplitude due to the well documented age-related anterior shift of P300 distribution, i.e., amplitude of parietal P300 decreases with age while amplitude of frontal P300 increases with age (O'Connell et al., 2012; Polich, 2007; van Dinteren et al., 2014; West et al., 2010). In addition to showing an age effect, the P300 amplitude is additionally modulated by task difficulty. Specifically, the P300 amplitude is larger for undemanding task, but smaller for tasks that require more attentional resources (Polich, 1987). Research has shown that P300 amplitude decreases when the number of letters increases during an anagramming paradigm (Cansino, Ruiz, & López-Alonso, 1999). These properties of the P300 make it an important ERP component for our study, because we expect that the difficulty level of the expertise-related task (LDT) will be lower for Scrabble experts than controls, especially for words presented vertically due to the vertical fluency shown by Scrabble experts (Hargreaves et al., 2012). Peak latency measures are generally not used for P300 because the peak is diffuse (Luck, 2014).
Chapter 2: Methods

2.1 Participants

Participants were age-matched 19 non-expert controls (9 males) and 19 competitive Scrabble players (10 males). Controls ranged from 24 to 83 years of age. Their total years of education ranged from 12 to 25 years. The Scrabble experts ranged from 24 to 79 years of age. Their total years of education ranged from 11 to 20 years. During the same 1-year period, we recruited control participants through community advertisement in the Calgary area, and Scrabble experts from local and national Scrabble competitions held in the Calgary area.

All participants were right-handed, and underwent comprehensive screening to ensure that they had no neurological disorders, were not experiencing any psychiatric illnesses, were not taking any psychotropic medications, and did not have any vision or hearing deficits that might interfere with task performance. All participants gave written informed consent prior to participation. Ethics approval was obtained from the Conjoint Faculties Research Ethics Board of the University of Calgary. Participants received monetary compensation in exchange for their time.

2.2 Stimuli

The experiment was part of a larger imaging study including both fMRI and EEG techniques (Protzner, et al., 2015; van Hees et al., submitted). My thesis focused on the EEG data because I chose MSE to quantify brain signal variability (see Section 2.6 for a detailed explanation about this analysis technique choice). EEG data with high temporal resolution are more suitable than fMRI data for MSE calculation on multiple temporal scales.
**Lexical Decision Task (LDT)**

Stimuli for LDT were a set of 432 words (216 concrete, 216 abstract) and 288 non-words, similar to those used in a previous study (Hargreaves et al., 2012). The stimuli were divided into three sets, each with 144 words (72 concrete, 72 abstract) and 96 non-words. Two of the three sets were chosen randomly, and presented during EEG testing. (The remaining set was presented during fMRI testing.) Word stimuli matched non-word stimuli for word length and visual characteristics such as orthographic Levenshtein distance (Yarkoni, Balota, & Yap, 2008). Participants decided whether the stimulus was a word/non-word by pressing one of two response buttons as quickly and accurately as possible.

*Figure 1. Examples of test stimuli (Lexical Decision Task).*
Symbol Decision Task (SDT)

Stimuli for SDT were symbol strings made using 26 different non-letter symbols in Microsoft Word. Each string included five symbols, with 216 strings containing two of the same symbol (match e.g. £€汀€) and 144 strings containing all unique symbols (no-match e.g. ɡїΓξ€). The stimuli were divided into three sets. Two of the three sets were chosen randomly, and presented during EEG testing. (The remaining set was presented during fMRI testing.) Participants decided whether the stimulus contained two matching symbols by pressing one of two response buttons as quickly and accurately as possible.

Figure 2. Examples of test stimuli (Symbol Decision Task).
For both LDT and SDT, we presented stimuli on a computer screen one at a time using Presentation software (Neurobehavioral Systems, Inc., Albany, CA, U.S.A.). Half of the stimuli were presented horizontally, and the other half were presented vertically. We counterbalanced the orientation of the stimuli so that each stimulus was presented an equal number of times in each orientation across participants. Each trial began with the presentation of a central fixation cross for a variable time of 250-750 msec (mean 500 msec). The stimulus followed the fixation cross and remained on the screen until the participant made a response, which triggered the beginning of the next trial. For each task, we counterbalanced the order of the two sets of the stimuli across participants. We also counterbalanced the order of the two tasks across participants.

2.3 Procedure

Before EEG acquisition, we tested all participants on a battery of cognitive tests to ensure that group differences were restricted to Scrabble-specific expertise: 1) Category and letter/word fluency were tested by the Controlled Oral Word Association Test (COWAT; Spreen & Strauss, 1998). Participants generated as many words as possible that start with a given letter within one minute. The letters were ‘F’, ‘A’, ‘S’, and ‘UN’. Then participants generated as many words as possible that fit into the category ‘animal’ in one minute. 2) Print exposure was tested by the Revised Author Recognition Test (RART; Acheson, Wells, & MacDonald, 2008). Participants identified real author names from a list of 130 names. 3) Vocabulary was tested by the North American Adult Reading Test (NARRT; Uttl, 2002). Participants pronounced 35 irregularly spelled English words as correctly as possible. 4) Perceptual speed was tested by the WAIS III Digit Symbol test (Wechsler, 1997). Participants matched symbols to a list of numbers based on
nine digit-symbol pairs as fast as possible within two minutes. 5) Anagramming skill was tested when participants verbally solved 51 anagrams presented on a computer screen (Tuffiash, Roring, & Ericsson, 2007). The order of these cognitive tests was fixed for every participant (i.e., COWAT, RART, NARRT, WAIS III, anagramming). The tests requiring verbal responses were not next to each other. Mean scores for age, years of education, measures of cognitive tests and the corresponding t values for group difference are presented in Table 1. These tests confirmed that there were no group differences other than those directly attributable to Scrabble training (e.g., Anagram score).

Table 1.
Mean characteristics and cognitive test scores of participant groups (standard deviations in parentheses).

<table>
<thead>
<tr>
<th></th>
<th>Controls</th>
<th>Scrabble experts</th>
<th>t-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>55.9 (16.3)</td>
<td>57.2 (18.0)</td>
<td>0.2</td>
</tr>
<tr>
<td>Years of Education</td>
<td>17.4 (3.3)</td>
<td>16.6 (2.9)</td>
<td>0.8</td>
</tr>
<tr>
<td>COWAT - F</td>
<td>16.8 (5.3)</td>
<td>22.1 (5.7)</td>
<td>2.9**</td>
</tr>
<tr>
<td>COWAT - A</td>
<td>13.5 (6.1)</td>
<td>20.1 (5.5)</td>
<td>3.5**</td>
</tr>
<tr>
<td>COWAT - S</td>
<td>17.5 (5.7)</td>
<td>22.3 (6.0)</td>
<td>2.5*</td>
</tr>
<tr>
<td>COWAT - UN</td>
<td>9.5 (3.7)</td>
<td>14.0 (5.5)</td>
<td>3.0**</td>
</tr>
<tr>
<td>COWAT - Animals</td>
<td>20.3 (6.2)</td>
<td>24.5 (7.5)</td>
<td>1.9</td>
</tr>
<tr>
<td>RART</td>
<td>27.5 (15.0)</td>
<td>29.3 (11.4)</td>
<td>0.4</td>
</tr>
<tr>
<td>NARRT</td>
<td>23.1 (7.9)</td>
<td>26.5 (6.0)</td>
<td>1.5</td>
</tr>
<tr>
<td>WAIS digital symbol speed</td>
<td>73.0 (16.2)</td>
<td>78.5 (20.0)</td>
<td>0.9</td>
</tr>
<tr>
<td>Anagram score</td>
<td>9.7 (5.0)</td>
<td>27.3 (7.6)</td>
<td>8.4***</td>
</tr>
</tbody>
</table>

*p < .05; **p < .01; ***p < .001.

Note: COWAT = Controlled Oral Word Association Test; RART = Revised Author Recognition Test; NARRT = North American Adult Reading Test; WAIS = Wechsler Adult Intelligence Scale Digit-Symbol Coding Task;

2.4 Behavioural Data

We chose response time as our performance measure because previous research suggests that Scrabble experts’ and controls’ accuracy for LDT and SDT is near ceiling (Protzner, et al.,
Response times have a wider range, making them better suited for regression analyses. We chose anagramming scores as measure of Scrabble expertise because these scores were correlated with official rankings of the Scrabble experts (NASPA ratings). This measure has been used to index Scrabble skill in two previous papers (Protzner et al., 2015; van Hees et al., submitted). We used multilevel regression analysis to explore the combined effects of group (expert vs. control), age, and experimental condition on response time. In the regression model, we used one parametric variable (age), and two categorical variables, group (Scrabble experts and Controls) and conditions (LDT – 2 (horizontal, vertical) x 2 (word, nonword); SDT – 2 (horizontal, vertical) x 2 (match, nomatch)) as predictors.

2.5 EEG Acquisition and Preprocessing

We collected EEG recordings from 64 electrodes with an EasyCap 10/20 positioning system, with Cz as reference, using Brain Vision actiCHamp system (Brain Vision LLC) in a dimly lit, quiet room. The sampling rate and bandwidth of the data were 500 Hz and 99.95 (0.05-100) Hz, respectively.

For pre-processing, we bandpass filtered continuous EEG recordings from 0.1 to 55 Hz and re-referenced to an average reference, rejected data with excessive signal amplitude, then performed artefact removal using independent component analysis (ICA) as implemented in EEGLAB software (Delorme & Makeig, 2004). The removed components from the dataset were those associated with eye blink, saccades, horizontal eye movements, and muscle artefacts. To avoid data overlapping, based on the mean response time of LDT and SDT, we epoched the cleaned continuous EEG data from LDT and SDT into windows including 200 msec pre-stimulus and 1500 msec post-stimulus activity, and baseline corrected to the 200 msec pre-
stimulus interval. We analyzed the event-related potentials of the epoch and signal variability of the 1500 msec post-stimulus activity for both tasks. In addition, we only epoched and analyzed trials with correct responses in LDT and SDT, and combined epochs with the same stimulus from the two blocks of each task for further analysis.

### 2.6 Brain Signal Variability Analysis

Signal variability was calculated using multiscale entropy (MSE; Costa, Goldberger, & Peng, 2002, 2004, 2005; McIntosh et al., 2008; McIntosh et al., 2014). MSE is a better option than the standard deviation technique used by Garrett et al. (2010, 2011) in that it works on multiple temporal scales, which explicitly addresses the inherent multi-scale features of biological signal. More importantly, the estimated signal variability in terms of entropy at multiple scales is a property that cannot be captured by the standard deviation or correlation measures, individually or in combination (Costa et al., 2004). Specifically, MSE algorithm is capable of differentiating the variability in biological signal (e.g., pink noise) and non-biological signal such as white noise. Simulation results showed that MSE characterized the long-range correlated pink noise as more variable than uncorrelated white noise (Costa et al., 2002, 2005).

Full details of MSE are given in previous studies (Costa et al., 2002, 2005). In brief, the MSE method calculates sample entropy as a measure of regularity (predictability) of the signal at different temporal scales. It consists of two procedures: 1) coarse-graining of the time series and 2) calculating sample entropy for each coarse-grained time series. The first step is similar to a smoother version of decimation, where the original time series is scale 1. For scale $\tau$, the coarse-grained time series is constructed by averaging the data points within non-overlapping windows of length $\tau$ from the original time series.
In the second step, sample entropy of each temporal scale measures the regularity of corresponding time series by evaluating the probability of repetitive pattern based on two parameters: the pattern length $m$ and the tolerance level or similarity criterion $r$. For this study, the pattern length was set to $m = 2$, which means two consecutive data points were used for pattern matching. In this case, sample entropy reflected the probability that two sequences that match each other for the first two data points will also match for the next point. Sample entropy was calculated as the natural logarithm of the ratio of the total number of 2-component template matches and the total number of 3-component template matches. The tolerance level was set as $r = 0.5$; that is, for two data points to be considered matching, their absolute amplitude difference should be less or equal to 50% of the original time series standard deviation.

In the current study, for each subject, channel-specific MSE was calculated on single trials and then averaged across all trials within a given condition.

2.7 Partial Least Squares (PLS) Analysis

We used partial least squares analysis (PLS) to analyze ERP and MSE measures. PLS is a multivariate statistical technique that operates on the entire data structure at once, extracting the patterns of maximal covariance between ERP/MSE and groups/conditions simultaneously across all electrodes and temporal scales. A detailed description of PLS’ application to ERP and MSE data can be found in previous studies (McIntosh, Bookstein, Haxby, & Grady, 1996; Lobaugh, West, & McIntosh, 2001; McIntosh & Lobaugh, 2004; Krishanan, Williams, McIntosh, & Abdi, 2011; McIntosh et al., 2008).

In the current study, we used behaviour PLS to examine group- and condition-dependent similarities and differences in correlations between ERP/MSE and age, as well as ERP/MSE, age,
RT, and anagramming scores. We used a non-rotated version of behaviour PLS, which allowed us to specify a priori contrasts to restrict the patterns generated by PLS.

For behaviour PLS, we first calculated the correlations between ERP/MSE and age, as well as behaviour measures (e.g., response time, anagramming score) across the entire sample. We then conducted singular value decomposition (SVD) on the correlation matrix to generate a set of orthogonal latent variables (LVs) that show similarities or difference in spatiotemporal distribution of the ERP/MSE, associated with individual differences in behaviour measures, across groups/conditions. Each LV contains three vectors: design saliences, electrode saliences, and a scalar singular value. Design saliences can be viewed as the contrast between groups and/or conditions depicted in the LV, while electrode saliences identify a particular pattern of electrodes and temporal scales that is most related to the condition/group difference expressed in the LV. The singular value is used to calculate the proportion of the covariance accounted for by the LV, i.e., the strength of the effect expressed by the LV.

Statistical assessment in PLS was performed at two levels. First, the overall significance of each LV was assessed with a permutation test with 500 permutations (Good, 2000). PLS was recalculated for each permuted sample, which was obtained by sampling without replacement to reassign the order of conditions to each participant. An LV was considered significant if the observed singular value exceeded the permuted singular value in more than 95% of the permutations (corresponding to p-value $p < .05$). Second, the stability of the nonzero electrode saliences in each LV was assessed using bootstrap estimation of standard errors for the electrode saliences. PLS was reapplied to each bootstrap sample, which was generated by sampling with replacement while keeping the assignment of experimental conditions fixed for all participants. The bootstrap ratio, which is the ratio of the electrode salience to the bootstrap standard error, is
approximately equivalent to a z score if the bootstrap distribution is Gaussian (Efron & Tibshirani, 1986, 1993). To show simple and clear results, for this thesis, we used a threshold of 3.1 for the bootstrap ratio, which corresponds to a p value of .001. If this threshold was too stringent for a contrast, we lowered the bootstrap ratio to 2.1, which corresponds to a p value of .05. Correction for multiple comparisons is not necessary because the electrode saliences were calculated in a single mathematical step at the level of full spatiotemporal pattern.

Although we used a multivariate analysis technique which could identify expertise, age, and performance (i.e., response time and anagramming skill) related changes in other components in addition to the P300, based on previous research suggesting that the P300 is a key component affected by Scrabble training (van Hees et al., submitted), we decided to focus on this component in our study.
Chapter 3: Results – the relationship between expertise and age

3.1 Behavioural Results

Performance measures (response time and percent correct) are presented in Table 2. As accuracies of LDT and SDT were close to ceiling for both groups, we focused behavioural data analysis on response time only. We performed analyses without considering age first to ensure that we replicated previous Scrabble work (Hargreaves et al., 2012; Protzner, et al., 2015; van Hees et al., submitted).

We examined whether LDT response time differed across group, orientation, and word_type by using a 2 (groups: controls vs. experts) x 2 (orientations: horizontal vs. vertical) x 2 (word_type: word vs. nonword) mixed design ANOVA, with group as between subjects factor and orientation x word_type as 2 x 2 repeated measures factors. We observed a significant main effect of orientation \( F(1,36) = 90.807, p < .001, \eta^2 = .716 \), indicating that both groups responded significantly faster to stimuli displayed horizontally \( (M = 821 \text{ ms}, SD = 33 \text{ ms}) \) than vertically \( (M = 1137 \text{ ms}, SD = 62 \text{ ms}) \); a significant main effect of word_type \( F(1,36) = 74.451, p < .001, \eta^2 = .674 \), indicating that both groups responded significantly faster to words \( (M = 804 \text{ ms}, SD = 30 \text{ ms}) \) than nonwords \( (M = 1154 \text{ ms}, SD = 65 \text{ ms}) \); a significant interaction between orientation and group \( F(1,36) = 9.485, p = .004, \eta^2 = .209 \); a significant interaction between orientation and word_type \( F(1,36) = 52.332, p < .001, \eta^2 = .592 \). The 3-way interaction between group, orientation and word_type was also significant \( F(1,36) = 4.563, p = .04, \eta^2 = .112 \). Therefore, we tested simple interaction effects for controls and Scrabble experts separately. For controls, simple interaction between orientation and word_type was significant \( F(1,18) = 26.941, p < .001, \eta^2 = .599 \). We further tested simple simple main effects. Controls responded to horizontal word...
(M = 713 ms, SD = 31 ms) significantly faster than horizontal nonword (M = 1004 ms, SD = 79 ms) F(1,18) = 26.078, p < .001, $\eta^2 = .592$; Controls also responded to vertical word (M = 1009 ms, SD = 71 ms) significantly faster than vertical nonword (M = 1543 ms, SD = 148 ms) F(1,18) = 36.298, p < .001, $\eta^2 = .668$. For Scrabble experts, simple interaction between orientation and word_type was significant F(1,18) = 35.072, p < .001, $\eta^2 = .661$. We further tested simple main effects. Scrabble experts responded to horizontal word (M = 674 ms, SD = 25 ms) significantly faster than horizontal nonword (M = 895 ms, SD = 53 ms) F(1,18) = 41.05, p < .001, $\eta^2 = .695$; Scrabble experts also responded to vertical word (M = 821 ms, SD = 40 ms) significantly faster than vertical nonword (M = 1175 ms, SD = 84 ms) F(1,18) = 56.525, p < .001, $\eta^2 = .758$.

We examined whether SDT response time differed across group, orientation, and word_type by using a 2 (groups: controls vs. experts) x 2 (orientations: horizontal vs. vertical) x 2 (match_type: match vs. nomatch) mixed design ANOVA, with group as between subjects factor and orientation x match_type as 2 x 2 repeated measures factors. We observed a significant main effect of orientation F(1,36) = 105.835, p < .001, $\eta^2 = .746$, indicating that both groups responded significantly faster to stimuli displayed horizontally (M = 1719 ms, SD = 118 ms) than vertically (M = 1965 ms, SD = 134 ms); a significant main effect of match_type F(1,36) = 69.885, p < .001, $\eta^2 = .66$, indicating that both groups responded significantly faster to match (M = 1378 ms, SD = 73 ms) than nomatch (M = 2307 ms, SD = 180 ms).

Next, we used multilevel regression analysis to investigate the combined effects of Scrabble expertise and age on response time of LDT for Scrabble experts and controls, using repeated measures on 2 (horizontal, vertical) x 2 (word, non-word) conditions. Multilevel regression analysis can partition the total variation of response time into “variation due to
repeated measures” and “variation across participants”. Intra-class correlation (ICC) calculated from a null model without any predictors (model 0 – LDT) was 0.325. A greater than zero ICC indicates clustering in the data. In our case, the repeated measures were nested under individuals. ICC informed us that 32.5% of LDT response time variance happened across participants. To get appropriate statistic test result, we chose multilevel regression analysis to model the hierarchically structured data set.

For response time of LDT, our goal was to examine whether the age-related changes in response time were different between the two groups. As Scrabble experts are known to be faster at recognizing vertically displayed words and non-words than controls, our hypothesis was that group difference in terms of the age-related changes in response time would be more evident in the vertical orientation than in horizontal orientation. Therefore, we were interested in a three way interaction: age by group by orientation. To test the significance of this interaction, we constructed and compared two models (model 1 - LDT and model 2 - LDT) to test the efficacy of the three way interaction as predictor of LDT response time. Model 1 predicted response time using all the main effects (orientation, age, and group) and all the two-way interactions. Model 2 had one more predictor than model 1, which was the three-way interaction in which we were interested. The difference in the deviance statistics between the two models is distributed as a chi-square with one degree of freedom. The likelihood ratio test was not significant, $\chi^2 (1) = 3.117, p = 0.077$, which showed that predicting response time with an additional three-way interaction predictor (model 2) was not a significantly better fit to the data than predicting response time with only main effects and all the two-way interactions (model 1). Therefore, we did not find evidence supporting our hypothesis that Scrabble expertise affects the age-related changes in LDT response time.
A separate, multilevel regression analysis was done for response time of SDT for Scrabble experts and controls, considering repeated measures on four different conditions – 2 (horizontal, vertical) x 2 (match, no-match). Intra-class correlation (ICC) calculated from a null model without any predictor (model 0 – SDT) was 0.499, indicating 49.9% of SDT response time variance happened across participants. Therefore, multilevel regression analysis is appropriate for the hierarchically structured data set.

For response time of SDT, our goal was still to examine whether the age-related changes in response time were different between the two groups. Although response time of controls and Scrabble experts are not significantly different in any condition, we hypothesized that the group difference in terms of the age-related changes in response time might be different across orientations due to the vertical fluency shown by Scrabble experts (Hargreaves et al., 2012). To test the significance of a three-way interaction, age by group by orientation, we constructed and compared two models (model 3 - SDT and model 4 - SDT) to test the efficacy of the three way interaction as predictor of SDT response time. Model 3 predicted response time using all the main effects (orientation, age, and group) and all the two way interactions. Model 4 had one more predictor than model 3, which was the three way interaction in which we were interested. The likelihood ratio test was not significant, $x^2(1) = 0.56$, $p = 0.454$, which showed that, predicting response time with an additional three-way interaction predictor (model 4) was not a significantly better fit to the data than predicting response time with only main effects and all the two-way interactions (model 3). Therefore, we did not find evidence that Scrabble expertise affects the age-related changes in SDT response time.
Table 2
Mean characteristics of performance measures (Standard deviations in parentheses)

<table>
<thead>
<tr>
<th>Task</th>
<th>Controls</th>
<th>Scrabble experts</th>
</tr>
</thead>
<tbody>
<tr>
<td>a. Response time (ms)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Horizontal word</td>
<td>713(135)</td>
<td>674(107)</td>
</tr>
<tr>
<td>Horizontal non-word</td>
<td>1004(345)</td>
<td>895(232)</td>
</tr>
<tr>
<td>Vertical word</td>
<td>1009(311)</td>
<td>821(174)</td>
</tr>
<tr>
<td>Vertical non-word</td>
<td>1543(644)</td>
<td>1175(365)</td>
</tr>
<tr>
<td>Horizontal match</td>
<td>1209(333)</td>
<td>1319(479)</td>
</tr>
<tr>
<td>Horizontal no-match</td>
<td>1984(804)</td>
<td>2365(1268)</td>
</tr>
<tr>
<td>Vertical match</td>
<td>1400(368)</td>
<td>1583(598)</td>
</tr>
<tr>
<td>Vertical no-match</td>
<td>2264(892)</td>
<td>2613(1387)</td>
</tr>
<tr>
<td>b. Percent correct</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Horizontal word</td>
<td>96.6(6.2)</td>
<td>99.0(1.1)</td>
</tr>
<tr>
<td>Horizontal non-word</td>
<td>93.4(5.8)</td>
<td>93.8(4.1)</td>
</tr>
<tr>
<td>Vertical word</td>
<td>93.6(8.8)</td>
<td>98.4(1.3)</td>
</tr>
<tr>
<td>Vertical non-word</td>
<td>91.7(7.3)</td>
<td>92.2(3.9)</td>
</tr>
<tr>
<td>Horizontal match</td>
<td>86.6(1.1)</td>
<td>90.3(7.9)</td>
</tr>
<tr>
<td>Horizontal no-match</td>
<td>96.4(2.4)</td>
<td>96.8(3.1)</td>
</tr>
<tr>
<td>Vertical match</td>
<td>82.7(12.8)</td>
<td>87.7(8.7)</td>
</tr>
<tr>
<td>Vertical no-match</td>
<td>96.3(3.6)</td>
<td>97.0(3.4)</td>
</tr>
</tbody>
</table>
SPSS syntax to estimate the multilevel models is as follows:

Model 0 - LDT

MIXED response_time
   /CRITERIA=CIN(95) MXITER(100) MXSTEP(10) SCORING(1)
   SINGULAR(0.000000000001) HCONVERGE(0,
      ABSOLUTE) LCONVERGE(0, ABSOLUTE) PCONVERGE(0.000001, ABSOLUTE)
   /FIXED=| SSTYPE(3)
   /METHOD=ML
   /PRINT=G  R SOLUTION TESTCOV
   /RANDOM=INTERCEPT | SUBJECT(subjID) COVTYPE(VC)
   /REPEATED=orientation*word_type | SUBJECT(subjID) COVTYPE(ID).

Model 1 - LDT

MIXED response_time BY orientation word_type group WITH age
   /CRITERIA=CIN(95) MXITER(100) MXSTEP(10) SCORING(1)
   SINGULAR(0.000000000001) HCONVERGE(0,
      ABSOLUTE) LCONVERGE(0, ABSOLUTE) PCONVERGE(0.000001, ABSOLUTE)
   /FIXED=orientation word_type age group orientation*group orientation*age group*age | SSTYPE(3)
   /METHOD=ML
   /PRINT=G  R SOLUTION TESTCOV
   /RANDOM=INTERCEPT | SUBJECT(subjID) COVTYPE(VC)
   /REPEATED=orientation*word_type | SUBJECT(subjID) COVTYPE(DIAG).

Model 2 - LDT

MIXED response_time BY orientation word_type group WITH age
   /CRITERIA=CIN(95) MXITER(100) MXSTEP(10) SCORING(1)
   SINGULAR(0.000000000001) HCONVERGE(0,
      ABSOLUTE) LCONVERGE(0, ABSOLUTE) PCONVERGE(0.000001, ABSOLUTE)
   /FIXED=orientation word_type age group orientation*group orientation*age group*age orientation*group*age | SSTYPE(3)
   /METHOD=ML
   /PRINT=G  R SOLUTION TESTCOV
   /RANDOM=INTERCEPT | SUBJECT(subjID) COVTYPE(VC)
   /REPEATED=orientation*word_type | SUBJECT(subjID) COVTYPE(DIAG).
Model 0 - SDT

MIXED response_time
/Criteria=CIN(95) MXITER(100) MXSTEP(10) SCORING(1)
SINGULAR(0.0000000000001) HCONVERGE(0,
   ABSOLUTE) LCONVERGE(0, ABSOLUTE) PCONVERGE(0.00001, ABSOLUTE)
/FIXED=| SSType(3)
/METHOD=ML
/PRINT=G R SOLUTION TESTCOV
/RANDOM=INTERCEPT | SUBJECT(subjID) COVTYPE(VC)
/REPEATED=orientation*match_type | SUBJECT(subjID) COVTYPE(ID).

Model 3 - SDT

MIXED response_time BY orientation match_type group WITH age
/Criteria=CIN(95) MXITER(100) MXSTEP(10) SCORING(1)
SINGULAR(0.0000000000001) HCONVERGE(0,
   ABSOLUTE) LCONVERGE(0, ABSOLUTE) PCONVERGE(0.00001, ABSOLUTE)
/FIXED=orientation match_type age group group*age orientation*age orientation*group |
SSType(3)
/METHOD=ML
/PRINT=G R SOLUTION TESTCOV
/RANDOM=INTERCEPT | SUBJECT(SubjID) COVTYPE(VC)
/REPEATED=orientation*match_type | SUBJECT(SubjID) COVTYPE(AR1).

Model 4 - SDT

MIXED response_time BY orientation match_type group WITH age
/Criteria=CIN(95) MXITER(100) MXSTEP(10) SCORING(1)
SINGULAR(0.0000000000001) HCONVERGE(0,
   ABSOLUTE) LCONVERGE(0, ABSOLUTE) PCONVERGE(0.00001, ABSOLUTE)
/FIXED=orientation match_type age group group*age orientation*age orientation*group | orientation*group*age | SSType(3)
/METHOD=ML
/PRINT=G R SOLUTION TESTCOV
/RANDOM=INTERCEPT | SUBJECT(SubjID) COVTYPE(VC)
/REPEATED=orientation*match_type | SUBJECT(SubjID) COVTYPE(AR1).
3.2 MSE Analysis

3.2.1 The relationship between expertise, age and MSE in LDT

We identified two significant LV’s when examining group- and condition-dependent correlations between MSE values and age. The first LV revealed a positive correlation between fine to middle temporal scale (2-16ms) MSE values and age across all the conditions for both groups ($p < .001$, Figure 3A). The spatiotemporal expression of this correlation is shown in Figure 3B. This pattern was stable at Fp1, Fz, F7, FT9, FC5, C3, TP9, F4, F8, Fp2, AF7, AF3, AFz, F1, FT7, FC3, F2, AF4, and AF8 ($|\text{bootstrap ratio}| > 3.1$). The second LV demonstrated the group differences in the correlation between MSE values and age ($p < .001$, Figure 3C). The spatiotemporal expression of this correlation is shown in Figure 3D. Specifically, at middle temporal scales (14-26ms), MSE values decreased with age for controls but increased with age for experts stably at P3, P8/T6, FT7, C5, P5, P6, P2, and CPz ($|\text{bootstrap ratio}| > 3.1$).
Figure 3. Two group (Scrabble experts vs. controls) behavioural PLS examining the relationship between MSE and age in LDT. A) The bar graph depicts the group similarities in correlations of MSE values and age during LDT. Error bars indicate bootstrap-determined 95% confidence intervals around the correlations. B) The electrodes and timescales at which the positive MSE-age correlation was most stable for both groups (red regions represent electrodes and timescales at which the bootstrap ratio is greater than 3.1, green regions represent electrodes and timepoints where the bootstrap ratio is less than 3.1 and greater than -3.1). C) The bar graph depicts the group differences in correlations of MSE values and age during LDT. D) The electrodes and timescales at which the negative MSE-age correlation for controls, and positive MSE-age correlation for experts were most stable (blue regions represent electrodes and timepoints where the bootstrap ratio is less than -3.1).
3.2.2 The relationship between expertise, age and MSE in SDT

We identified two significant LV’s when examining group- and condition-dependent correlations between MSE values and age during SDT. The first LV revealed a positive correlation between fine to middle temporal scale MSE values and age across all the conditions of SDT for both groups ($p < .001$, Figure 4A). The spatiotemporal expression of this correlation is shown in Figure 4B. Specifically, MSE values increased with age from fine to middle temporal scales (2-18ms) reliably ($|\text{bootstrap ratio}| > 3.1$) at Fz, F3, F7, FT9, FC5, C3, TP9, CP1, P8/T6, CP6, FT10, FC6, F4, F8, Fp2, AF7, FT7, FC3, FCz, C1, PO8, CP4, TP8, FC4, FT8, F6, F2, AF4, and AF8. The second LV demonstrated the group differences in the correlation between MSE values and age during SDT ($p < .001$, Figure 4C). The spatiotemporal expression of this correlation is shown in Figure 4D. Specifically, at middle temporal scales (14-24ms), MSE values decreased with age for controls but increased with age for experts stably ($|\text{bootstrap ratio}| > 3.1$) at FC5 and F5.
Figure 4. Two group (Scrabble experts vs. controls) behavioural PLS examining the relationship between MSE and age in SDT. A) The bar graph depicts the group similarities in correlations of MSE and age during SDT. Error bars indicate bootstrap-determined 95% confidence intervals around the correlations. B) The electrodes and timescales at which the positive MSE-age correlation was most stable for both groups (red regions represent electrodes and timescales at which the bootstrap ratio is greater than 3.1, green regions represent electrodes and timepoints where the bootstrap ratio is less than 3.1 and greater than -3.1). C) The bar graph depicts the group differences in correlations of MSE and age during SDT. D) The electrodes and timescales at which the negative MSE-age correlation for controls, and positive MSE-age correlation for experts were most stable (blue regions represent electrodes and timepoints where the bootstrap ratio is less than -3.1).
3.3 ERP Analysis

3.3.1 The relationship between expertise, age and ERPs in LDT

We identified one significant LV when examining group- and condition-dependent correlations between ERPs and age ($p < .001$, Figure 5A). This LV revealed group similarities in the correlation of ERPs and age. Theses correlations are shown as scatterplots of scalp scores with age in Figure 5B. Electrode saliences, the spatiotemporal expression of the correlations, are shown in Figure 5C. Positive saliences show time points where the ERP-age correlation was positive; negative saliences show time points where the ERP-age correlation was negative. Specifically, the amplitude of parietal P300 (e.g., POz) is negatively correlated with age stably across all the conditions for both groups ($|\text{bootstrap ratio}| > 3.1$). Scatterplots of age with ERP amplitudes for POz at P300 timepoint with the highest bootstrap ratio (312ms) are shown in Figure 5D.

We identified a second significant LV ($p = .024$, Figure 5E). To illustrate results from this LV, we lowered the absolute value of bootstrap ratio to 2.1 because there were no bootstrap values above 3.1 (see Methods p.20 for additional detail about these bootstrap thresholds). This LV revealed group differences in the correlation of ERPs and age. Electrode saliences, the spatiotemporal expression of the correlation, are shown in Figure 5F. Specifically, the amplitude of frontal P300 (e.g., FC4) positively correlated with age for controls, but negatively correlated with age for Scrabble experts, stably across all the conditions ($|\text{bootstrap ratio}| > 2.1$).
Figure 5. A) Two group (Scrabble experts vs. controls) behavioural PLS examining the relationship between ERPs and age in LDT. The bar graph depicts the group similarities in correlations of ERPs and age during LDT. Error bars indicate bootstrap-determined 95% confidence intervals around the correlations. B) Scatterplots of scalp scores and age in each condition. Line of best fit is shown in each plot. C) Electrode saliences for all electrodes, with time (ms) on x axis and salience on y axis. Markers at the top of each plot indicate timepoints with stable saliences. Where saliences are positive, ERPs positively correlated with age; where saliences are negative, ERPs negatively correlated with age. D) ERP-age scatterplots for each condition at the point of maximal saliences for the P300 at POz (312ms) for control (left) and experts (right). Linear fits indicate the similar correlations across conditions. E) The bar graph depicts the group differences in correlations of ERPs and age during LDT. F) Electrode saliences for all electrodes, with time (ms) on x axis and salience on y axis. Markers at the bottom of each plot indicate stable saliences. Where saliences are positive, ERPs positively correlated with age of controls, but negatively correlated with age of experts; where saliences are negative, ERPs negatively correlated with age of controls, but positively correlated with age of experts.
3.3.2 The relationship between expertise, age and ERPs in SDT

We identified one significant LV when examining group- and condition-dependent correlations between ERPs and age \((p < .001, \textit{Figure 6A})\). This LV revealed group similarities in the correlation of ERPs and age. Theses correlations are shown as scatterplots of scalp scores with age in \textit{Figure 6B}. Electrode saliences, the spatiotemporal expression of the correlations, are shown in \textit{Figure 6C}. Positive saliences show time points where the ERP-age correlation was positive; negative saliences show time points where the ERP-age correlation was negative. Specifically, the amplitude of parietal P300 (e.g., POz) negatively correlated with age stably across all the conditions for both groups \(|\text{bootstrap ratio}| > 3.1\). Scatterplots of age with ERP amplitudes for POz at P300 timepoint with the highest bootstrap ratio (362ms) are shown in \textit{Figure 5D}.

We identified a second significant LV \((p = .006, \textit{Figure 6E})\). To illustrate results from this LV, we lowered the threshold of bootstrap ratio to 2.1 because there were no bootstrap values above 3.1 (see Methods p.20 for additional detail about these bootstrap thresholds). This LV revealed group differences in the correlation of ERPs and age. Electrode saliences, the spatiotemporal expression of the correlation, are shown in \textit{Figure 6F}. Specifically, amplitude of frontal P300 (e.g., FC4) positively correlated with age for controls, but negatively correlated with age for Scrabble experts, across all the conditions stably \(|\text{bootstrap ratio}| > 2.1\).
Figure 6. Two group (Scrabble experts vs. controls) behavioural PLS examining the relationship between ERPs and age in SDT. A) The bar graph depicts the group similarities in correlations of ERPs and age during SDT. Error bars indicate bootstrap-determined 95% confidence intervals around the correlations. B) Scatterplots of scalp scores and age in each condition. Line of best fit is shown in each plot. C) Electrode saliences for all electrodes, with time (ms) on x axis and salience on y axis. Markers at the top of each plot indicate stable saliences. Where saliences are positive, ERPs positively correlated with age; where saliences are negative, ERPs negatively correlated with age. D) ERP-age scatterplots for each condition at the point of maximal saliences for the P300 at POz (362ms) for control (left) and experts (right). Linear fits indicate similar correlations across conditions. E) The bar graph depicts the group differences in correlations of ERPs and age during SDT. F) Electrode saliences for all electrodes, with time (ms) on x axis and salience on y axis. Markers at the bottom of each plot indicate stable saliences. Where saliences are positive, ERPs positively correlated with age of controls, but negatively correlated with age of experts; where saliences are negative, ERPs negatively correlated with age of controls, but positively correlated with age of experts.
Chapter 4: Results - the relationship between expertise, age, and performance

4.1 MSE Analysis

4.1.1 The relationship between expertise, age, behaviour measures, and MSE in LDT

We identified two significant LV’s when examining group- and condition-dependent correlations between MSE values and age, as well as behaviour measures (response time and anagramming score). The first LV revealed group similarities, where for both groups, MSE at fine to middle temporal scale (2 – 16 ms) positively correlated with age, and negatively correlated with anagramming score \((p < .001, Figure 7A)\). MSE also positively correlated with response time of controls in vertical non-word condition, and response time of Scrabble experts across all the conditions. The spatiotemporal expression of the correlations is shown in Figure 7B. This pattern is stable at F7, FT9, Fp2, AF7, PO8, F2, and AF8 (\(|\text{bootstrap ratio}| > 3.1\)). The second LV demonstrated the correlation between MSE values and age, response time and anagramming score for Scrabble experts only \((p < .001, Figure 7C)\). The spatiotemporal expression of this correlation is shown in Figure 7D. Specifically, at middle temporal scales (22 – 26 ms), MSE values of Scrabble experts increased with age and longer response time, but decreased with higher anagramming scores across all the conditions in LDT. This pattern was stable at O2 and P8/T6 (\(|\text{bootstrap ratio}| > 3.1\)).
Figure 7. Two group (Scrabble experts vs. controls) behavioural PLS examining the relationship between MSE, age, response time, and anagramming scores in LDT. A) The bar graph depicts the group similarities in correlations of MSE with age, and behaviour measures (response time, anagramming score) during LDT. Error bars indicate bootstrap-determined 95% confidence intervals around the correlations. B) The electrodes and timescales at which the positive MSE-age correlation and negative MSE-anagramming score correlation were most stable for both groups (red regions represent electrodes and timescales at which the bootstrap ratio is greater than 3.1, green regions represent electrodes and timepoints where the bootstrap ratio is less than 3.1 and greater than -3.1). C) The bar graph depicts the correlations MSE with age, and behaviour measures (response time, anagramming score) for Scrabble experts during LDT. D) The electrodes and timescales at which the positive MSE-age and MSE-RT correlation, and negative MSE-anagramming score correlation were most stable for experts (blue regions represent electrodes and timepoints where the bootstrap ratio is less than -3.1).
4.1.2 The relationship between expertise, age, behaviour measures, and MSE in SDT

We identified one significant LV when examining group- and condition-dependent correlations between MSE values and age, as well as behaviour measures (response time and anagramming score) \((p < .001, Figure 8A)\). This LV revealed that, except for the horizontal match condition in controls, MSE values from fine to middle temporal scales \((2 – 24ms)\) positively correlated with age across all the conditions, for both groups. MSE values at the same electrodes and temporal scales negatively correlated with anagramming scores across all the conditions for both groups. In addition, for Scrabble experts only, MSE at the same electrodes and temporal scales also positively correlated with response time across all the conditions. The spatiotemporal expression of the correlations is shown in Figure 8B. This pattern is stable at F7, FC1, C3, and Fp2 \(|\text{bootstrap ratio}| > 3.1\).

We identified a second significant LV \((p < .001, Figure 8C)\). To illustrate results from this LV, we lowered the threshold of bootstrap ratio to 2.1, because there were no bootstrap values above 3.1 (see Methods p. 20 for additional detail about these bootstrap thresholds). This LV revealed group differences in terms of the correlation between MSE values and age, as well as behaviour measures (response time and anagramming score). The spatiotemporal expression of the correlations is shown in Figure 8D. Specifically, for controls, MSE values from fine to middle temporal scales \(2-26ms\) decreased with longer response time across all the conditions. For Scrabble experts, MSE values at the same electrodes and temporal scales increased with age and longer response time, decreased with higher anagramming scores across all the conditions. This pattern was stable at C3, Oz, P4, P8, C5, CP3, PO3, POz, PO4, PO8, P6, and P2 \(|\text{bootstrap ratio}| > 2.1\).
Figure 8. Two group (Scrabble experts vs. controls) behavioural PLS examining the relationship between MSE, age, response time, and anagramming scores in SDT. A) The bar graph depicts the group similarities in correlations of MSE with age, and behaviour measures (response time, anagramming score) during SDT. Error bars indicate bootstrap-determined 95% confidence intervals around the correlations. B) The electrodes and timescales at which the positive MSE-age correlation (except for horizontal match condition in controls) and negative MSE-anagramming correlation were most stable for both groups (red regions represent electrodes and timescales at which the bootstrap ratio is greater than 3.1, green regions represent electrodes and timepoints where the bootstrap ratio is less than 3.1 and greater than -3.1). C) The bar graph depicts the group differences in correlations of MSE with age, and behaviour measures (response time, anagramming score) during SDT. D) The electrodes and timescales at which the negative MSE-RT correlation for controls, positive MSE-age and MSE-RT correlation, and negative MSE-anagramming correlation for experts were stable (blue regions represent electrodes and timepoints where the bootstrap ratio is less than -2.1).
4.2 ERP Analysis

4.2.1 The relationship between expertise, age, behaviour measures, and ERPs in LDT

We identified one significant LV when examining group- and condition-dependent correlations between ERPs and age, as well as behaviour measures (response time and anagramming score) \((p < .001, \text{Figure 9A})\). This LV revealed group similarities in the correlation of ERPs and age, response time and anagramming score. Electrode saliences, the spatiotemporal expression of the correlations, are shown in Figure 9B. Specifically, for both groups, amplitude of parietal P300 (e.g., POz) negatively correlated with age, but positively correlated with anagramming score reliably across all the conditions \((|\text{bootstrap ratio}| > 3.1)\). The amplitude of parietal P300 (e.g., POz; \(|\text{bootstrap ratio}| > 3.1)\) negatively correlated with Response time. However, this pattern was not stable in horizontal word condition for controls, was not stable in horizontal word and horizontal non-word conditions for Scrabble experts.

We identified a second significant LV \((p = .002, \text{Figure 9C})\). To illustrate results from this LV, we lowered the threshold of bootstrap ratio to 2.1 because there were no bootstrap values above 3.1 (see Methods p. 20 for additional detail about these bootstrap thresholds). This LV revealed group differences in the correlation of ERPs and age, as well as behaviour measures (response time and anagramming score). Electrode saliences, the spatiotemporal expression of the correlation, are shown in Figure 9D. Specifically, for controls, the amplitude of frontal P300 (e.g., FC4) positively correlated with age stably \((|\text{bootstrap ratio}| > 2.1)\) across all the conditions except for vertical non-word condition; positively correlated with response time stably \((|\text{bootstrap ratio}| > 2.1)\) across all the conditions except for horizontal word condition; negatively correlated with anagramming score stably \((|\text{bootstrap ratio}| > 2.1)\) across all the conditions. For Scrabble experts, the amplitude of the frontal P300 (e.g., FC4) negatively correlated with age and
response time, but positively correlated with anagramming score stably across all the conditions (|bootstrap ratio| > 2.1).
Figure 9. Two group (Scrabble experts vs. controls) behavioural PLS examining the relationship between ERPs, age, response time, and anagramming scores in LDT. A) The bar graph depicts the group similarities in correlations of ERPs and age, as well as behaviour measures (response time and anagramming score) during LDT. Error bars indicate bootstrap-determined 95% confidence intervals around the correlations. B) Electrode saliences for all electrodes, with time (ms) on x axis and salience on y axis. Markers at the top of each plot indicate stable saliences. C) The bar graph depicts the group differences in correlations of ERPs and age, as well as behaviour measures (response time and anagramming score) during LDT. D) Electrode saliences for all electrodes. Markers at the bottom of each plot indicate stable saliences.
4.2.2 The relationship between expertise, age, behaviour measures, and ERPs in SDT

We identified one significant LV when examining group- and condition-dependent correlations between ERPs and age, as well as behaviour measures (response time and anagramming score) \((p < .001, Figure\ 10A)\). This LV revealed group similarities in the correlation of ERPs, age, response time, and anagramming score. Electrode saliences, the spatiotemporal expression of the correlations, are shown in Figure 10B. Specifically, for both groups, the amplitude of the parietal P300 (e.g., POz) negatively correlated with age, but positively correlated with anagramming score stably across all the conditions (\(|\text{bootstrap ratio}| > 3.1\)). For Scrabble experts only, the amplitude of parietal P300 (e.g., POz) negatively correlated with response time stably across all the conditions (\(|\text{bootstrap ratio}| > 3.1\)).

We identified a second significant LV \((p = .006, Figure\ 10C)\). To illustrate results from this LV, we lowered the threshold of bootstrap ratio to 2.1 because there were no bootstrap values above 3.1 (see Methods p. 20 for additional detail about these bootstrap thresholds). This LV revealed group differences in the correlation of ERPs, age, response time, and anagramming score. Electrode saliences, the spatiotemporal expression of the correlation, are shown in Figure 10D. Specifically, for controls, amplitude of the parietal P300 (e.g., POz) positively correlated with response time stably across all the conditions (\(|\text{bootstrap ratio}| > 2.1\)), except for vertical match condition; negatively correlated with anagramming score stably across all the conditions (\(|\text{bootstrap ratio}| > 2.1\)), except for horizontal no-match condition. For Scrabble experts, amplitude of parietal P300 (e.g., POz) negatively correlated with age and response time, but positively correlated with anagramming score stably across all the conditions (\(|\text{bootstrap ratio}| > 2.1\)).
Figure 10. Two group (Scrabble experts vs. controls) behavioural PLS examining the relationship between ERP, age, response time, and anagramming scores in SDT. A) The bar graph depicts the group similarities in correlations of ERPs, age, response time, and anagramming score during SDT. Error bars indicate bootstrap-determined 95% confidence intervals around the correlations. B) Electrode saliences for all electrodes, with time (ms) on x axis and salience on y axis. Markers at the top of each plot indicate stable saliences. C) The bar graph depicts the group differences in correlations of ERPs, age, response time, and anagramming score during SDT. D) Electrode saliences for all electrodes, with time (ms) on x axis and salience on y axis. Markers at the bottom of each plot indicate stable saliences.
5.1 Summary

In the current study, we examined the effect of Scrabble expertise on brain aging in the context of variability and mean of EEG signal, when control participants and Scrabble experts performed expertise-related (LDT) and non-expertise-related (SDT) cognitive tasks.

We have three main findings. First, the cognitive tests suggested that there were no group differences except for items that were associated with Scrabble practice. Specifically, there were no differences in measures of age, years of education, RART, NARRT, and WAIS. There were differences in verbal tests that are likely related to Scrabble expertise (e.g., COWAT - F, A, S, UN, and anagramming score). The multilevel regression analysis did not find evidence supporting our hypothesis that Scrabble expertise affects the age-related changes in response time, regardless of whether the task was expertise-related or not.

Second, in terms of brain signal variability, we not only replicated previous findings that ageing was associated with increased MSE at fine temporal scales in controls (McIntosh et al., 2014; Sleimen-Malkoun et al., 2015; Wang et al., 2016), but also found a similar correlation pattern between age and MSE in Scrabble experts. However, experts extended this positive correlation between age and MSE into middle temporal scales, which was opposite to the pattern observed in controls. When we related MSE with behaviour measures such as response time and anagramming scores, we found that age-related increased MSE at fine temporal scales was associated with lower behaviour performance characterized by longer response time and lower anagramming scores for both controls and Scrabble experts. Similarly, for experts only, the age-
related increased MSE at middle temporal scales also associated with longer response time and lower anagramming scores.

Lastly, our finding in mean ERP amplitude was consistent with previous findings suggesting that ageing is related to decreased parietal P300 amplitude, but increased frontal P300 amplitude in controls (O'Connell et al., 2012; Polich, 2007; van Dinteren et al., 2014; West et al., 2010). However, we did not observe a similar age-related P300 anterior shift in Scrabble experts. Instead, both posterior and frontal P300 amplitude decreased with age in experts.

5.2 MSE

5.2.1 The relationship between expertise, age, and MSE

We examined group similarities and differences in terms of the age effect on MSE. We performed analyses separately for LDT and SDT because we hypothesized that the age effect on MSE might be different between expertise-related and non-expertise-related cognitive tasks for Scrabble experts. As we used a shorter epoch length than that in previous publications (McIntosh et al., 2014; Wang et al., 2016), we cannot measure coarse temporal scales with our tasks (see methods, p17). We therefore named our coarse temporal scale as “middle temporal scale” for ease of comparison to previous publications.

In terms of the group similarities, for both LDT and SDT, controls and Scrabble experts similarly increased MSE with ageing at fine temporal scales. Although this group similarity of a positive age-MSE correlation was consistent across the two tasks in terms of the temporal scales (2-16ms), the spatial pattern of this correlation was more widely distributed in SDT than in LDT. This makes sense because SDT is non-expertise-related task, which is novel to both groups. Therefore, the group similarities in the age effect on MSE should be larger in SDT than in LDT.
Specifically, the spatial pattern in SDT involved more posterior regions of the brain than the spatial pattern in LDT. This may be caused by the different nature of the two tasks. The posterior part of the parietal lobe has been shown to be involved in symbol recognition (McBean & van Wijck, 2012). For example, previous research found that the posterior parietal cortex was activated for multiple non-alphanumeric character processing (Lobier, Peyrin, Le Bas, & Valdois, 2012). Importantly, the positive correlation between age and MSE at fine temporal scales was in line with previous reports for normal aging (McIntosh et al., 2014; Sleimen-Malkoun et al., 2015; Wang et al., 2016). We further demonstrated that this age effect on MSE at fine temporal scales also existed in Scrabble experts, no matter whether the task was expertise-related or not.

Expertise-related differences were similar across both LDT and SDT. At middle temporal scales, MSE decreased with ageing for controls, but increased with ageing for experts. Although this group difference was consistent across the two tasks in terms of the temporal scales (14-24ms), the spatial pattern of this correlation was more widely distributed in LDT than in SDT. Specifically, the spatial pattern in LDT included several electrodes covering the posterior part of the brain, whereas the spatial pattern in SDT involved only two electrodes located in frontal regions. Interestingly, the regions in which MSE increases with age for Scrabble experts overlap with regions identified in a previous fMRI study, which demonstrated that Scrabble experts had increased activity as compared to controls in parietal regions including inferior and superior parietal lobe (Protzner et al., 2015). In addition, it makes sense that group differences in the age effect on MSE are more widespread in the expertise-related task than they are in the non-expertise related task. Finally, we not only found a negative MSE-age correlation at middle temporal scales with normal aging, but also observed a positive MSE-age correlation at middle temporal scales for Scrabble experts, regardless of whether the task was expertise-related or not.
MSE at fine temporal scales have previously been considered to reflect local neural processing associated with specialization. MSE at coarse temporal scales, by contrast, have been considered to reflect interaction with other neural populations through long-range communication, which is related to integration (McIntosh et al., 2014; Vakorin et al., 2011). In this context, although our finding was on the middle temporal scales, it is still consistent with the idea that normal ageing accompanies a shift from long-range interaction with distal neural populations (represented by lower MSE at middle temporal scales) to more local neural processing (represented by higher MSE at fine temporal scales). For Scrabble experts, it seems that ageing is associated with an increase in both local neural processing (specialization) and more long-range interactions with other neural populations (integration). This may suggest that with ageing, Scrabble experts not only increase independent functional networks similar to controls, but also establish more associations between widespread functional networks than controls. Moreover, this pattern was not dependent on a person’s area of expertise, as it appeared in both expertise-related and non-expertise-related cognitive task.

This finding in Scrabble experts may not seem unreasonable if we consider evidence from behaviour and neuroimaging studies. Behaviourally, Scrabble experts are less influenced by semantic information than controls during LDT; instead, experts rely more on visual information for word recognition (Hargreaves et al., 2012). A recent fMRI study investigating the neural mechanism underlying Scrabble expertise demonstrated that during LDT, Scrabble experts recruited more brain areas associated with working memory and visual perception, but fewer brain areas generally related to word meaning when compared with controls (Protzner et al., 2015). Both behaviour and neuroimaging findings suggest that Scrabble experts develop a unique strategy in LDT which likely is supported by greater integration between language and
working memory networks in the context of visual word recognition. As ageing is related to more independent functional networks (specialization), network integration (captured by MSE at coarser temporal scales) may become more evident in older Scrabble experts because more associated networks may help maintain expertise. This could be the reason we observed age-related increased MSE at middle temporal scales in Scrabble experts. Meanwhile, just like increased brain activity in older adults may not always lead to better task performance (Grady, 2010), we need further examination on the relationship between the age-related increased MSE at middle temporal scales and task performance.

5.2.2 The association between age-related changes and behaviour measures

We examined the group similarities and differences between MSE, age, response time and anagramming skill to see if these age-related changes were associated with better or worse performance. The analyses were separate for LDT and SDT again, for easy comparison to our previous analyses.

In terms of group similarities, our results showed that in LDT, increased MSE at fine temporal scales was associated with increased age and lower anagramming skills for both controls and Scrabble experts; and associated with longer response time for Scrabble experts only. It seems that the age-related increased MSE at fine temporal scales is related to worse behavioural performance and lower anagramming skill. However, we also noted that the spatial pattern of MSE-age-behaviour correlation only partially overlapped with the spatial pattern we observed in the MSE-age correlation. In addition, except for frontal electrodes (Fp2 and AF8), the temporal scales associated with both increasing age and worse behaviour were more fine than those associated only with increasing age. This result suggests that although some increased fine-
scale MSE are negatively associated with performance measures, not all age-related increases in MSE at fine temporal scales have such negative implications (i.e., the age-related increased fine-scale MSE in several electrodes had no behavioural associations). The relationship between MSE and behaviour measures depends on spatiotemporal scales. For Scrabble experts, it makes sense that increased MSE is associated with worse behaviour performance. As we argued before, Scrabble experts rely on a unique strategy in LDT that is supported by greater integration. Therefore, increased local processing (higher MSE at fine temporal scales) may disrupt the integration and result in worse behaviour performance. Similarly in SDT, except for two electrodes (C3 and Fp2), the spatiotemporal scales associated with increasing age were more widely distributed than those associated with both increasing age and worse behaviour. Therefore, our results showed that although MSE at fine temporal scales increased with ageing for both LDT and SDT, only a subset of spatiotemporal scales and electrode locations was related to longer response time and lower anagramming skill.

In terms of group differences, our results showed that in LDT, increased MSE at middle temporal scales was associated with ageing, longer response time and lower anagramming skills for Scrabble experts only. This pattern was observed at O2 and P8/T6, in which P8/T6 was the only electrode that showed up in the spatial pattern for a positive MSE-age correlation at middle temporal scales in LDT. Controls did not show a consistent correlation between MSE and behaviour measures. For SDT, the group difference was not as stable as that in LDT, as the bootstrap values were lower than 3.1. Above all, the spatial pattern did not overlap with the spatial pattern for a positive MSE-age correlation at middle temporal scale in SDT.
Taken together, the relationship between age-related changes in MSE and behaviour measures is dependent on spatiotemporal scale. This is demonstrated in both group similarities and differences, regardless of whether the cognitive task was expertise-related or not.

5.3 ERP

5.3.1 *The relationship between expertise, age, and ERPs*

We examined the group similarities and differences in terms of the age effect on ERP amplitude. Specifically, we focused on amplitude of P300 component due to the prominent age-related anterior shift in P300 distribution. The analyses were performed separately for LDT and SDT, similar to MSE analyses.

In terms of the group similarities, for both LDT and SDT, controls and Scrabble experts had decreased parietal P300 amplitude with increasing age (e.g., POz). This is consistent with previous research findings that normal ageing is related to decline in the parietal P300 amplitude (O'Connell et al., 2012; Polich, 2007; van Dinteren et al., 2014; West et al., 2010). We further demonstrated that this age effect on the parietal P300 amplitude also existed in Scrabble experts, no matter if the task was expertise-related or not.

In terms of the group differences, for both LDT and SDT, frontal P300 amplitude increased with age for controls, but decreased with age for experts (e.g., FC4). For controls, our findings replicated previous reports that normal aging is related to increased frontal P300 amplitude (O'Connell et al., 2012; Polich, 2007; van Dinteren et al., 2014; West et al., 2010). This finding in controls particularly supports the compensatory-related utilization of neural circuits hypothesis (CRUNCH model), which states that older individuals recruited additional neural resources to compensate for potential age-related deterioration in task
performance (Reuter-Lorenz & Mikels, J. A., 2006). However, Scrabble experts did not demonstrate a similar age-related P300 anterior shift. Instead, both posterior and frontal P300 amplitude decreased with ageing in experts. P300 amplitude normally indexes task difficulty or the amount of cognitive resources assigned to a task, where decreased amplitude is associated with increased task difficulty (Polich, 2007). Thus, in our case, age-related reductions on frontal P300 amplitude in Scrabble experts may reflect a real ‘age effect’, i.e., ageing reduces available cognitive resources for older Scrabble experts which makes the task more difficult for them.

Another viewpoint on P300 amplitude relates it with learned skills. Researchers showed that P300 amplitude decreased in participants who learned a decision making task as compared to those who did not learn the task (Sailer, Fischmeister, & Bauer, 2010). Reuter et al. (2014) also reported P300 amplitude decreased for older individuals with expertise on tactile perception. Therefore, our results could also suggest that due to their Scrabble expertise, older Scrabble experts need less cognitive effort than older controls for both LDT and SDT. Obviously, further experiments would have to be performed to disentangle these two possible explanations.

It is worth mentioning that, for both LDT and SDT, the group differences were not as stable as the group similarities, as the bootstrap values were lower than 3.1. By the same reasoning, the group difference for age effect on ERP amplitude analysis was not as stable as the group difference for age effect on MSE analysis. This may suggest that the brain signal variability characterized by MSE is more sensitive than the mean brain signal in determining group difference.

5.3.2 The association between age-related changes and behaviour measures
We examined the group similarities and differences between ERP amplitude, age, response time and anagramming skill to see if these age-related changes were associated with better or worse performance. Again, we focused on the P300 component.

In terms of the group similarities, our results showed that, for both LDT and SDT, decreased parietal P300 amplitude (e.g., POz) was associated with increased age and lower anagramming skill for both experts and controls. The correlation between parietal P300 amplitude and response time were not consistent across tasks and conditions. In LDT, decreased parietal P300 amplitude (e.g., POz) associated with longer response time in vertical word and non-word conditions for Scrabble experts; associated with longer response time in all conditions for controls except for the horizontal word condition. In SDT, decreased parietal P300 amplitude (e.g., POz) associated with longer response time in all the conditions for Scrabble experts only. Overall, it seems that age-related decreased parietal P300 amplitude is related to lower anagramming skill and worse task performance characterized by longer response time, for both controls and experts.

In terms of the group differences, for LDT, decreased frontal P300 amplitude (e.g., FC4) associated with increased age, longer response time, and lower anagramming skill for Scrabble experts; increased frontal P300 amplitude (e.g., FC4) associated with increased age, longer response time, and lower anagramming skill for controls, although the correlations were not consistent across all the conditions for controls. Therefore, it seems that age-related changes in frontal P300 amplitude are associated with lower anagramming skill and longer response time for both controls and experts, no matter whether the age-related change in frontal P300 amplitude increases or decreases. As mentioned above in section 5.3.1, negative correlation between frontal P300 amplitude of Scrabble experts and task performance supports the idea that
the age-related decreased frontal P300 amplitude observed in Scrabble experts was a real age effect, indicating fewer cognitive resources available to older experts. In SDT, for experts, decreased parietal P300 amplitude (e.g., POz) associated with ageing, longer response time and lower anagramming skill; for controls, there was no correlation between age and parietal P300 amplitude.

It is worth mentioning that, for both LDT and SDT, the group difference was not as stable as the group similarity, as the bootstrap values were lower than 3.1. By the same reasoning, the ERP amplitude analysis for the group difference in LDT was not as stable as the MSE analysis for the group difference in LDT. This may suggest that the brain signal variability characterized by MSE is more sensitive than the mean brain signal in determining group differences.

Taken together, for both LDT and SDT, age-related decrease in parietal P300 amplitude for both controls and experts, age-related increase in frontal P300 amplitude for controls, age-related decrease in frontal P300 amplitude for experts, are all associated with lower anagramming skill and worse task performance (i.e., longer response time).

5.4 Implications

This was the first study to investigate the effect of Scrabble expertise on aging in terms of behaviour, mean and variability of brain signal. It demonstrated that there was no effect of expertise on the association between age and performance measures (response time). However, Scrabble expertise modified normal age effects on the mean and variability of ERP, during both expertise-related and non-expertise-related tasks. Further analyses showed that, similar to normal aging, the modified age-related changes of brain signal in Scrabble experts were associated with worse behavioural measurement, i.e., longer response time and lower anagramming skills. This
study provides a better understanding of how Scrabble expertise is related to aging. In addition, based on the bootstrap ratio values, this study suggested that brain signal variability may be more sensitive than mean brain signal in detecting age and expertise-related differences.

5.5 Limitations and future directions

One limitation of this study is that the sample size is not very large. For future directions, we would like to recruit a larger sample across the age range for Scrabble experts and controls so that we could easily disentangle the relationship between expertise, and age-related brain and behavioural changes (admittedly, this would be hard to do, as the expert group is not a large one). With a larger sample, we could examine how mean and variability of brain signal changes for good and bad performers that are similarly aged.

Another limitation of this study is that we associated expertise and age-related changes in MSE and ERP with response time only. Grady (2001) pointed out that age-related increased brain activity can be related to both improvements and declines in task performance in older adults, depending on the choice of behavioural measures. Future studies could examine the relationship between expertise and age-related changes in MSE/ERP and different behavioural measures to complement this study.

Finally, using a cross-sectional study, we have limited capabilities to determine if there were any innate factors that could differentiate the expert and control groups, which may also have an effect on brain ageing. For example, a person with better visuospatial processing skill or greater working memory capacity might find Scrabble play is fascinating, and therefore is likely to engage in career-long competitive playing. A longitudinal study would have a better chance to examine these possible pre-existing variables.
The Scrabble trademark is owned in both Canada and the USA by HASBRO.
References


word recognition in competitive scrabble players as measured during task and resting-state. *Cortex*, DOI:10.1016/j.cortex.2015.03.015


