HOW DOES THE CEREBELLUM CONTRIBUTE TO LANGUAGE LEARNING? A LINGUISTIC EXTENSION OF THE INTERNAL MODEL

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How does the cerebellum contribute to language learning? A linguistic extension of the internal model

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CERTIFICATE OF ORIGINALITY

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Zhuoya Liu

ABSTRACT

The cerebellum, traditionally associated with motor functions, has been increasingly recognised for its role in cognitive processes, such as language learning. The internal model of the cognitive control hypothesis suggests that the cerebellum may contribute to cognitive processing via reinforcement-based and error-based processes, which involve comparing the prediction of outcomes with sensory inputs to generate signals that guide automatic learning.

To explore how the cerebellum contributes to language learning through the framework of the internal model, we examined cerebellar patterns in conjunction with the cerebrum and investigated the effects of individual differences. Specifically, three aspects were examined: (A) The cerebro-subcortical-cerebellar network; (B) Automatic processing versus controlled processing, which investigated the associativity and grammaticality; and (C) Correct- versus error-related processing, which addressed the execution and updating of the internal model. These examinations sought to identify the specific mechanisms underlying artificial language learning.

Thirty-eight young Cantonese-speaking participants were recruited for an artificial language learning experiment, which included longitudinal behavioural and fMRI sessions. The fMRI sessions involved an associative judgment task, in which participants judged the associativity between artificial words and their Chinese meanings, and a grammar judgment task, in which participants judged the grammaticality of artificial sentences.

Our findings suggest that the cerebellum contributes to associative learning and grammar learning in cooperation with the cerebral and subcortical regions, although with functional heterogeneity. No universal mechanism fully explains its role or interactions with the cerebrum, and these patterns are significantly shaped by cognitive and language individual differences, which supports the idea that the cerebellar circuit has multiple computational functions. Therefore, we propose that although the internal model is a domain-general hypothesis, investigating cerebellar function within specific mechanisms will clarify its computational diversity. A common principle may only be evident through an abstract description of neuronal network population dynamics.

LIST OF PUBLICATIONS

In Preparation

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Conference Abstract

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I have long understood that a PhD is not an end, but rather the beginning of a lifelong journey in scholarship. The past few years have been a tapestry woven with joy, uncertainty, and tears, each thread shaping the person I am today. Now, as I stand at this milestone, I look ahead, knowing the road beyond will be long and challenging. Yet, I also know that I am braver, stronger, and more ready than ever to face what lies ahead, carrying with me the resilience and passion born from this journey.

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CHAPTER 1

INTRODUCTION

In the evolution of higher primates, specifically anthropoid apes and humans, there has been a dramatic enlargement of the lateral parts of the cerebellum (Barton & Venditti, 2014; Schoenemann, 2009). This enlargement is believed to be associated with the development of more advanced cognitive abilities. The cerebellum has also increased in cell number at a rate equal to or greater than the expansion of the prefrontal cortex. In humans, it contains 80% neurons in the brain and has almost 80% of the surface area of the cerebral cortex (Sereno et al., 2020), suggesting that it may also be important for the emergence of higher-level cognition. Moreover, the cerebellum ages slowly according to the epigenetic clock (Horvath et al., 2015). Taking the evidence together, the latest advances in neuroscience have further deepened our understanding of the cerebellum, traditionally considered primarily involved in motor functions, by providing compelling support for its involvement in cognitive functions such as language (Diedrichsen et al., 2019; Fiez, 2016; Leiner, 2010). Interestingly, a recent study revealed that a cerebellar artificial neural network model, integrating the newly identified cerebello-cerebellar recurrent pathway, develops the capacity for next-word prediction and grammatical processing. (Ohmae & Ohmae, 2024).

For the motor functions of the cerebellum, the internal model hypothesis provides a robust conceptual framework for how the cerebellum supports the flexible abilities of prediction. The internal model can mimic the input-output relationship of motor commands and sensory consequences based on prior experience and feedback, allowing the cerebellum to perform motor functions automatically (Kawato, 1999; Schmahmann, 2019; Wolpert

& Kawato, 1998). Specifically, the inputs are efferent signals, such as instructions to move a limb, and the outputs are afferent feedback, including the tactile sensations resulting from the movement. Two important characteristics of the cerebellum, including its uniform anatomical structure (Ramnani, 2006) and its extensive connectivity to nearly all major brain regions (G. P. Argyropoulos & Muggleton, 2013), suggest that its internal model may extend beyond motor function. In this regard, based on Craiks mental model (Craik, 1967) and Piagets theory of cognitive development (Piaget & Inhelder, 1969), the internal model of the cognitive control hypothesis was proposed by Ito (2008), suggesting that the cerebellum can implicitly regulate the speed, capacity, consistency, and appropriateness of cognitive processes, similar to how it regulates the rate, force, rhythm, and movement of motor processes. Unfortunately, in contrast to a motor function that has already been computationally represented in an internal model, it is unclear how a mental model with an abstract conceptual nature is represented within a neuronal circuit of the cerebrum and subsequently copied by a circuit in the cerebellum.

The internal model is formed and updated through repeated performance of the same action and fine-tuned via reinforcement-based and error-based learning. This process involves comparing the prediction of the outcome of a movement or mental activity with sensory inputs to generate error signals that guide habitual learning (Doya, 1999; Ebner, 2013). Language learning is similar to other forms of learning behaviour that become habitual. From speech sounds to grammar processing, the acquisition and refinement of language typically require many years of repetition and adjustment, including correcting pronunciation errors and revising ungrammatical sentences. Therefore, it is suggested that the cerebellum contains internal models of linguistic properties, which help predict and generate language elements, and adapt to environmental contexts, thus facilitating language learning and proficiency (G. P. D. Argyropoulos, 2016; Mariën & Borgatti, 2018). Exploring these underlying mechanisms can provide valuable insights into the process of language acquisition.

The cerebellar internal model supports diverse functions beyond language learning, including memory, emotion, and social processing. Considering its uniform structure, this functional diversity may stem from varied inputs to the cerebellar cortex (Diedrichsen et al., 2019). Neuroimaging studies have confirmed robust cerebro-cerebellar connectivity during cognitive processing, such as the connection between cerebellar lobule VII and prefrontal and parietal association areas (Buckner et al., 2011; Ji et al., 2019; Marek et al., 2018). Therefore, to understand cerebellar function comprehensively, we should examine cerebellar activity in conjunction with cerebrum patterns, because isolated studies only provide limited insights. Comparing cerebellar and cortical representations is crucial for obtaining more comprehensive and integrated findings.

Furthermore, since the formation and updating of the internal language model can be affected by various individual differences, there should be some variability in language learning mechanisms among individuals. For example, individuals with higher cognitive competencies, such as working memory, may be better equipped to process and integrate linguistic information, resulting in more effective internal models. Better language competencies, such as language analytical ability, can also enable learners to form more accurate predictions about vocabulary and grammar. Understanding how individual differences affect this process can contribute to the identification and development of educational and learning approaches.

In this thesis, we aim to bridge the knowledge gap that prevents us from unraveling the enigma of the cerebellums role in language learning through the lens of the internal model account. Specifically, we investigated its role in artificial language learning using longitudinal functional Magnetic Resonance Imaging (fMRI) experiments. This exploration can provide a deeper understanding of cerebellar function beyond its role in movement. However, it is important to clarify that we do not claim the cerebellum is the sole driver of language. Instead, it works in conjunction with the cerebrum, with its unique circuitry offering a distinct and complementary contribution to language processing, unlike other brain regions. Moreover, we explored whether a universal transform or a set of multiple functions would provide a more useful description of cerebellar processing (Diedrichsen et al., 2019). The novelty of this research lies in its focus on the cerebro-subcortical-cerebellar network and individual differences. These insights may have far-reaching implications, not only for language education but also for the clinical assessment of neurological disorders commonly linked to cerebellar dysfunction, such as dyslexia, dysarthria, and autism.

1.1 RESEARCH QUESTIONS

In this project, we asked three main research questions (RQ): (1) What is the role of the cerebellum in the internal model of language learning? (2) How does the cerebellar internal model contribute to language learning differently from cortical and subcortical areas? (3) What are the individual differences that influence the internal model of language learning?

For RQ1, since the internal model hypothesis predicts the cooperation between the cerebellum and cerebrum regions during the performance of mental tasks (Ito, 2008), we investigated the co-activations and functional connectivity between cerebral, subcortical, and cerebellar areas. Furthermore, previous studies have explored the internal model hypo-

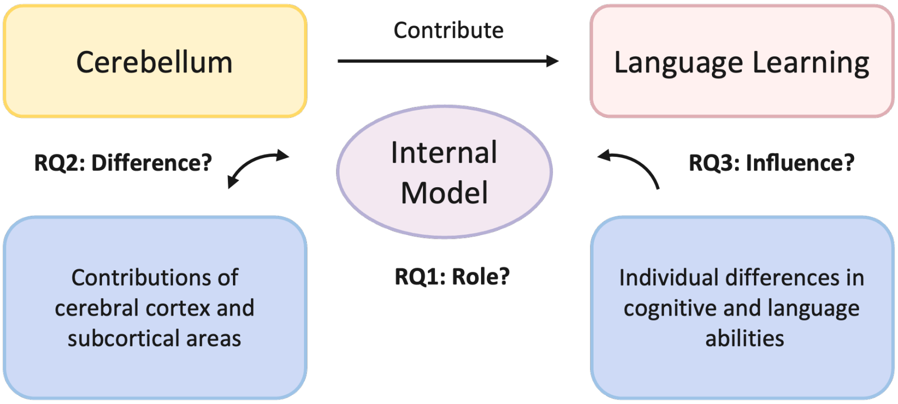


Figure 1.1: Framework of the thesis. For RQ1, we examined the role of the cerebellum in the internal model by (a) investigating the cerebro-subcortical-cerebellar cooperative network, (b) differentiating the cerebellums contribution to automatic versus controlled processing, and (c) differentiating the cerebellums contribution to correct-related and error-related processing. RQ2 and RQ3 were examined by differentiating between automatic and controlled processing, as well as correct-related and error-related processing.

thesis by examining the cerebellums involvement in both automatic processing and controlled processing (Ramnani, 2014; Koziol et al., 2014), but these studies are relatively independent and have reported inconsistent findings. Therefore, we aimed to investigate the differences between the two processes. Finally, the cerebellar internal model matures progressively through long-term training, allowing for both accurate and erroneous execution of the model. Additionally, the internal model undergoes continuous updates through positive feedback enhancement and negative feedback refinement. In this context, we investigated correct-related and error-related processes during both the execution and updating of the internal model.

For RQ2 and RQ3, we investigated the same two aspects to examine the functional differences in the internal model between the cerebellum and other brain regions, as well as the impact of individual differences on cerebellar dynamics: (1) varying roles in automatic and controlled processing, and (2) distinct contributions to correct and error-related processing. These aspects reflect the different mechanisms of the internal model, through which we sought to pinpoint the specific processes the cerebellum employs to facilitate language learning.

1.2 STRUCTURE OF THE THESIS

This dissertation is divided into six chapters.

Chapter 2 provides the background and reviews relevant literature on the theoretical and empirical basis of this thesis. We first introduced the structure of the cerebellum and its related functions. Moreover, we outlined the motivations for investigating three RQs grounded in the internal model hypothesis. Finally, we reviewed relevant studies addressing the specific aspects associated with RQs.

Chapter 3 describes the methodology employed in this thesis. Cantonese-speaking young adults were recruited to participate in the artificial language learning experiment. This experiment included associative learning and grammar learning tasks. In the chapter, we provided details on the materials, experimental paradigms, and data analysis.

Chapter 4 presents a detailed account of the experimental results. We reported behavioural results to demonstrate proficiency in artificial language learning and identify individual difference factors for neural analysis. Moreover, we reported neural findings, organised according to RQs and aspects. In the summary of each section, we provided a short discussion of the results.

Chapter 5 summarises the findings and offers a comprehensive discussion that integrates the results of this research. We proposed potential explanations for the findings and, more importantly, revisited the internal model, connecting it to a broader neurobiological framework of language.

Chapter 6 discusses the significance and limitations of the dissertation and points out possible directions for future study.

CHAPTER 2

LITERATURE REVIEW

This chapter provides background for the three research questions from the account of the internal model. It explores the multifaceted role of the cerebellum in language learning through theoretical frameworks and empirical studies. Moreover, it discusses the distinct contributions of cortical, subcortical, and cerebellar regions to language learning, as well as the effects of individual differences on the internal model of language learning.

This chapter begins by outlining the cerebellum's anatomical structure and fundamental functions (Sections 2.1.1 and 2.1.2). It then explores the internal model hypothesis to explain potential mechanisms of cerebellar involvement in cognitive processes, from which the RQs and key aspects of this study were derived (Section 2.1.3). Subsequently, specific dimensions of RQs are addressed, including the cerebro-subcortical-cerebellar network, automatic and controlled processing, and correct-related and error-related processing (Sections 2.2-2.4). Furthermore, we discussed the distinct contributions of cortical, subcortical, and cerebellar regions (Section 2.5). Finally, we investigated individual difference effects on cerebellar patterns(Section 2.6).

The literature review aims to consolidate the current understanding and establish a foundation for research into the intricate relationship between the cerebellum, language learning, and individual differences.

2.1 CEREBELLUM AND THEORETICAL FRAMEWORK

2.1.1 Cerebellum Anatomy

The cerebellum is located below and behind the cerebrum hemispheres and above the medulla oblongata. Figure 2.1 shows the cerebellum anatomy. Similar to the cerebrum, it is divided into two lateral hemispheres, which are connected by a central structure known as the vermis. Additionally, the cerebellum is subdivided into three distinct lobes: the anterior, posterior, and flocculonodular lobes. These lobes are separated by two transverse fissures. The V-shaped primary fissure divides the anterior and posterior lobes, while the posterolateral fissure separates the posterior lobe from the flocculonodular lobe. Within the posterior lobe, a deep horizontal fissure further divides the superior and inferior surfaces of the cerebellum (Klein et al., 2016).

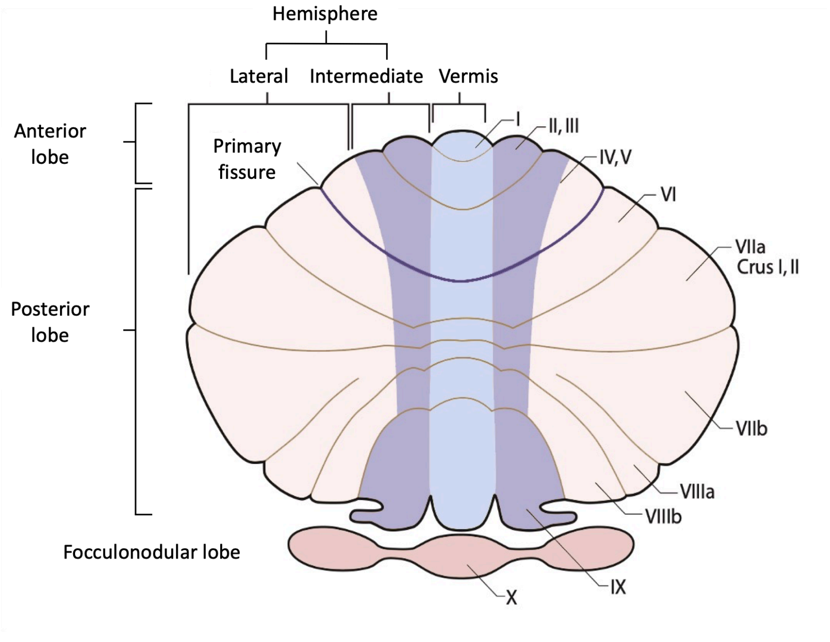


Figure 2.1: Cerebellar anatomy. The cerebellum is divided mediolaterally into a central vermis and two lateral hemispheres, and rostrocaudally into three lobes: anterior (lobule I-lobule V), posterior (lobule VI-lobule IX), and flocculonodular (lobule X).

The fundamental functional unit within the cerebellum is called the cerebellar microcomplex. It consists of a well-defined circuit that integrates sensory and motor information, processes it, and contributes to fine-tuning movements. Information enters the cerebellum via two pathways: mossy fibres, which convey sensorimotor signals, and climbing fibres, which carry error-related information about discrepancies between intended and actual movements. Within this circuit, granule cells process mossy fibre input and transmit it to Purkinje cells via parallel fibres. Purkinje cells, the key computational units, integrate these signals with the potent error signals from climbing fibres. This convergence at Purkinje cell synapses facilitates long-term synaptic modifications (i.e., long-term potentiation, LTP, and depression, LTD), enabling the cerebellum to adjust motor or cognitive output based on experience. Through these mechanisms, the cerebellum continuously refines movement, supporting error correction, adaptation, and the smooth execution of complex tasks (Passot et al., 2012).

Moreover, the cerebellum is interconnected with the contralateral cerebrum primarily through two polysynaptic circuits. In the descending cortico-ponto-cerebellum (CPC) pathways, the inputs from the cerebral cortex project to the ipsilateral pons, before crossing to the contralateral cerebellar cortex. In the ascending cerebello-thalamo-cortical (CTC) pathways, the Purkinje cells inhibitory outputs are projected to the dentate nucleus, before crossing to the contralateral thalamus and cerebral cortex. These pathways play a vital role in coordinating various motor and cognitive functions (Buckner, 2013).

2.1.2 Cerebellum Functions

The idea of cerebellar cognition comes from the discovery of areas in the cerebellums posterior lobe that are involved in mental processing and are connected to parts of the cerebrum responsible for higher-order functions. These areas differ from the cerebellum's motor areas, which are connected to the spinal cord and brain regions that control movement.

The anterior lobe is mainly involved in sensorimotor processing. Damage to the anterior lobe can lead to dysmetria of movement, a condition where movements become uncoordinated, which is known as cerebellar motor syndrome. The posterior lobe is involved in more complex functions beyond motor control, particularly cognitive and emotional processing. Damage to the posterior lobe can cause uncoordinated thinking and emotional responses, referred to as cerebellar cognitive affective syndrome.

Moreover, the medial part, including the vermis and the intermediate zone, is primarily involved in basic motor functions and the coordination of axial muscles. Lesions in this region can lead to problems with balance, posture, gait, and coordinated limb movements. The lateral part, which includes the cerebellar hemispheres, is more involved in complex motor tasks and planning higher-order cognition. Lesions in this area can lead to impaired fine motor control, difficulty with planning movements, and cognitive impairments.

In terms of the cerebellar contribution to language, neuroimaging studies consistently demonstrate cerebellar activation patterns are task-dependent, particularly in posterior regions such as lobule VI, lobule VII (i.e., Crus I, Crus II, and lobule VIIb), lobule VIII, and lobule IX (KerenHappuch et al., 2014; Stoodley et al., 2010). These studies have also revealed a significant right-lateralisation of cerebellar activation during language tasks, as the cerebellum is contralaterally connected with the cerebral cortex. Furthermore, numerous clinical studies have reinforced the association between the cerebellum and language (Bolduc & Limperopoulos, 2009; Mariën & Manto, 2015; Mariën & Borgatti, 2018).

However, functional boundaries in the cerebellum do not always align with macro-anatomical labels such as lobules, which are commonly used for anatomical and functional localisation. Quantitative analysis reveals that lobular divisions have limited predictive value for functional specialisation, as seen in lobule VII, where functional changes occur multiple times within the hemisphere (Nettekoven et al., 2024). Using lobules as modular units for analysis might mix signals from distinct functional regions.

2.1.3 Internal Model Hypothesis

In neuroscience, the internal model refers to a neural representation that simulates the input-output dynamics of a specific process, enabling precise and rapid predictions of environmental events and outcomes. It can be categorised as either forward or inverse. A forward internal model generates sensory predictions based on a current command, while an inverse internal model predicts the necessary command to achieve a desired movement. The cerebellar forward model is suggested to be the mechanism for thought processes such as language learning (Figure 2.2), which is supported by the cerebellums connections to the cerebral cortex through the subcortical areas (Bulut & Hagoort, 2024; Petrosini et al., 2024; Strick et al., 2009).

The semantic and syntactic tasks engage complex cognitive processes that require the integration of learned meanings and sequences. During this process, the cerebellum is believed to facilitate the prediction of linguistic information through an internal model. For example, in terms of semantic processing, the cerebellum can contribute towards information integration by predicting semantic context based on prior language input (D'Mello et al., 2020). Furthermore, during syntactic processing, when the malfunctioned cerebellum cannot correctly predict sentence structures or detect error signals, patients with damage to the right cerebellar hemisphere often exhibit agrammatic speech (Mariën et al., 2014). Therefore, in the current research, we explored the cerebellar contribution to semantic and syntactic processing.

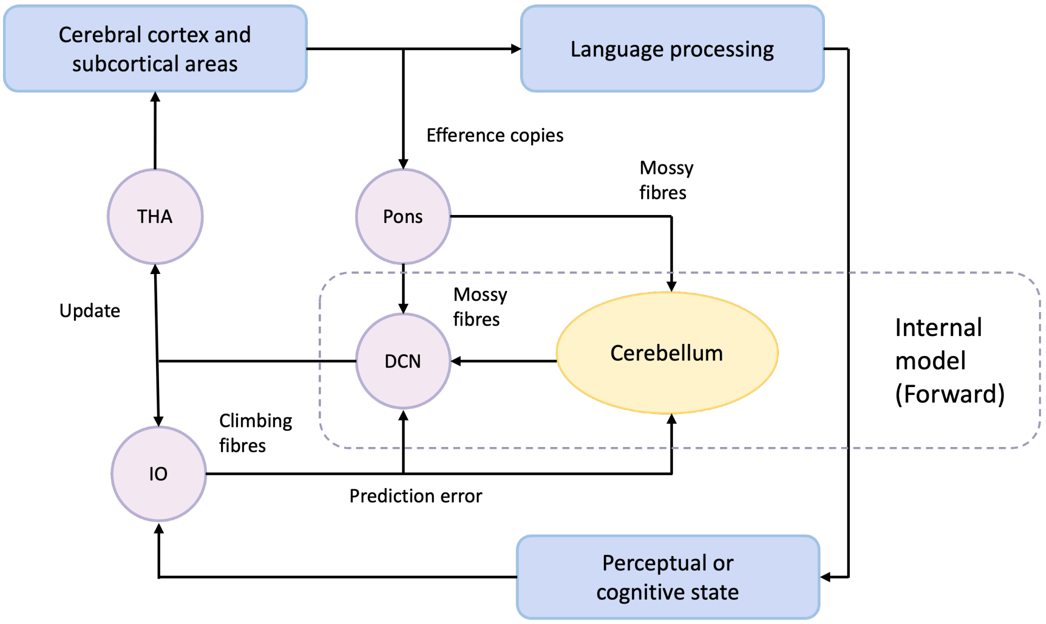


Figure 2.2: The cerebellar forward internal model in language processing. The cerebellum models interoceptive and cognitive prediction errors through its connections with the cerebral cortex via the thalamus (THA). Output from the cerebral cortex is relayed to the cerebellum via the pontine nuclei (Pons). Predictions from the cerebellum are sent back to the neocortex through Purkinje cells and deep cerebellar nuclei (DCN). Mismatches between predicted and actual outcomes are compared in the inferior olive (IO), with error signals sent to the cerebellar cortex, triggering long-term depression at parallel fibre-Purkinje cell synapses to update the internal model.

2.1.3.1 Investigation aspects

This project examined three key aspects of the internal model: (1) the cerebro-subcortical-cerebellar network; (2) the cerebellums distinct roles in automatic processing versus controlled processing; and (3) the cerebellums distinct roles in correct-related versus error-related processing. The first aspect examines the various components, including the controller, instructor, and controlled object, within the proposed internal model control system. The second distinguishes between implicit and explicit cognitive processes. The third focuses on the accurate and erroneous execution or updating of the internal model. The proposed aspects are based on the mechanisms of the internal model, which are described below.

Firstly, the internal model hypothesis of mental control assumes that the thought process involves interactions between regions in the cerebrum and the cerebellum (Ito, 2008). It involves a process where an instructor in the anterior cingulate gyrus (generating signals), is controlled by the prefrontal cortex (taking instruction), is expressed in the temporoparietal cortex (expressing or implementing the mental model), and is then used to create forward or inverse models in the cerebellum (automating activity). These regions constitute the components of neural systems for thought, together with the sensory/perception system and the attentional system. For language processing, the internal hypothesis posits that the cerebellar internal model, which replicates the language-related processing in the cerebrum, co-activates and connects with the prefrontal and temporoparietal cortex.

Secondly, the cerebellar internal model facilitates a shift from explicit to implicit thought. When learning a new task, explicit thinking dominates, involving conscious effort, attention to rules, and feedback processing. The cerebellum forms initial internal models by integrating sensory feedback with cognitive commands. These models are coarse and require frequent updates. The prediction error occurs when the internal model predicts one sensory outcome, but the actual feedback differs from this prediction; this discrepancy serves as a signal to update and refine the model. With practice, the task becomes automatic, shifting to an implicit level of thinking. The cerebellar internal models become highly refined, requiring less conscious oversight. This shift reduces dependence on the prefrontal cortex, allowing the cerebellum to handle the task more efficiently. The result is fluent, unconscious performance. Furthermore, for the cerebellar support of cognitive learning, Ramnani (2014) introduced a dual account of information processing: (1) automatic processing, which implements well learned, habitual operations; and (2) controlled processing, which engages deliberate, effortful adjustments.

Finally, the cerebellums internal model is dynamically shaped through an intricate interplay of execution and updating processes. During execution, the internal model generates predictions based on the learned knowledge. An accurate internal model yields precise predictions, which are more correct-related, while an inaccurate internal model results in erroneous predictions, which are more error-related. During updating, the cerebellum integrates sensory and cognitive inputs from the cerebrum, receiving either reinforcing signals that strengthen accurate representations, which are more correct-related, or error signals that drive refinement, which are more error-related. These inputs trigger synaptic plasticity, adjusting neural connections to enhance predictive accuracy. This continuous cycle of updating and executing ensures the cerebellums ability to adapt and optimise cognitive processing.

2.1.3.2 Automatic versus controlled and correct-related versus error-related processing

To elucidate the distinction between the second and third aspects, we aim to explore the precise definitions of "error" processing in cognitive tasks. The reason is that we are still unclear about the nature of error signals in cognitive processing (Moberget & Ivry, 2016). For example, in language processing, although an internal model detects violations of linguistic expectations, it remains unclear how these errors refine the internal model, particularly in a manner comparable to how error signals adapt internal models in sensorimotor control.

Therefore, we investigated error signals in two ways. Specifically, error processing can be defined: (1) as an instance where the sensory input misaligns with the predicted outcome, reflecting predictive violation, or (2) as an instance where the task is performed inaccurately, indicating unsuccessful task completion. In real-world tasks, such as grammaticality judgments, these two definitions often converge, making their dissociation complicated. For example, in language judgment tasks, errors may arise from misaligned predictions or incorrect task execution, necessitating a nuanced understanding of how these processes interact with each other. To address this issue, we examined two contrasts. The contrast between automatic and controlled processing investigates the predictive mechanisms, focusing on how aligned versus misaligned predictions of language shape neural responses. Furthermore, the contrast between correct-related and error-related processing reveals the execution and update of the internal model, based on the prediction of the consequences of the judgment.

In addition to the difference mentioned above, we also consider the effect of cognitive load. Cognitive load can modulate neural activity (Zhang et al., 2018), which has been identified as a confounding factor in many cerebellar internal model investigations (Lesage et al., 2017; Nakatani et al., 2022). When examining the effects of automatisation, studies often contrast simple and complex tasks (Tao et al., 2024). However, it remains unclear whether the observed results stem from automatisation itself or differences in cognitive load. Therefore, we analysed two contrasts. Automatic and controlled processing, defined by whether the input aligns with or violates predictions based on language knowledge, is not influenced by cognitive load. In contrast, the distinction between correct- and error-related processing may reflect differences in cognitive load.

2.1.4 Summary

The internal model hypothesis offers a theoretical framework for examining the cerebellum's role in language learning. Although it addresses the neural changes in learning over time, there remains a lack of empirical evidence regarding cerebellar cognitive function. The formation and updating of internal models are a dynamic process that requires longitudinal studies to capture these temporal shifts. Without such an approach, our understanding of how the internal model in the cerebellum evolves during language learning remains incomplete. Therefore, based on the RQs and aspects, we sought to identify the specific mechanisms underlying artificial language learning.

Moreover, the scope of the internal model hypothesis has been largely confined to the cerebral cortex and the cerebellum, with insufficient attention given to the distinct functions of the subcortical area. Recent research, such as the super learning hypothesis (Caligiore et al., 2019), increasingly emphasises the role of subcortical areas in supporting connections between the cerebral cortex and the cerebellum. We need more evidence to clarify the involvement of these subcortical regions in language-related internal models and to discern how the learning mechanisms of the cerebral cortex, subcortical structures, and cerebellum differ from each other.

Lastly, there is a lack of discussion addressing individual differences in language learning. The process of language acquisition may vary significantly across individuals, and understanding these variations is crucial, particularly for educational purposes. Investigating individual differences will not only enhance theoretical models but also yield practical implications for personalised approaches to language learning.

Therefore, in this thesis, we explored the cerebellar contribution to language learning through the lens of the internal model hypothesis using the longitudinal experiment, addressing the three aspects of the internal model.

2.2 CEREBRO-SUBCORTICAL-CEREBELLAR LANGUAGE NETWORK

Regarding the question of how the cognitive internal model is represented in the cerebellum, as mentioned earlier, the exploration of co-activation and functional connectivity between the cerebrum and cerebellum is a standard approach (for a review, see Ito (2008)). This addresses the cooperation between the cerebrum (e.g., the cerebral cortex and subcortical areas) and the cerebellum (e.g., the posterior lobe) during cognitive processing, such as language.

The broad body of literature on the neurobiology of language learning suggests that its neural representation extends beyond the classical language regions. As with most other cognitive functions, the idea of a one-to-one mapping between areas and functions is almost certainly incorrect for language learning. It is more likely that any given cortical region acts as a node involved in multiple functional networks (Petersson et al., 2012). However, the cerebellum is often overlooked in this type of research.

The idea of the cerebellums contribution to language learning or processing arose from identifying primary neural linkages between the cerebellum and the cerebral and subcortical regions (Starowicz-Filip et al., 2017). Prior research has discovered numerous specific facets of the linguistic cerebellum, including tasks such as the auditory description (Olulade et al., 2020), generation of letters (de Zubicaray et al., 1998) and verbs (Fiez et al., 1996), verbal fluency (Schlösser et al., 1998), phonological processing (Lesage et al., 2017), word processing (Perani et al., 1999), and sentence semantics and syntax processing (Nakatani et al., 2022).

However, it should be recognised that the language system cannot be reduced to the sum of some individual linguistic functions, as it is highly complex. To fully comprehend the neural mechanisms supporting language learning or processing, research should consider the interconnected nature by using tasks that address not only simple letter or word levels but also advanced structures. Therefore, the current research longitudinally explored cerebro-subcortical-cerebellar language network through the combination of semantic (i.e., associative learning) and syntactic (i.e., grammar learning) tasks.

2.2.1 Associative and Grammar Learning

Language learning is underpinned by two distinct memory networks (Figure 2.3). According to the Declarative/Procedural Model, declarative memory governs the explicit acquisition of facts, such as vocabulary, and procedural memory controls the implicit and automatic aspects, like grammar processing (Ullman, 2001, 2004). Compared to declarative memory, procedural memory is more involved in the later stages of language learning. Evidence suggests that specific areas of the cerebellum are involved in tasks related to declarative memory, including the retrieval of memories. Additionally, while the procedural system primarily involves the frontal lobe and basal ganglia, a later version of the model extended this network by assigning a role to the cerebellum (Ullman, 2016).

Associative learning and grammar learning are the applications of declarative and procedural networks. Associative learning is the explicit process of connecting or associating stimuli, concepts, or behaviours together to foster understanding. For language learning,

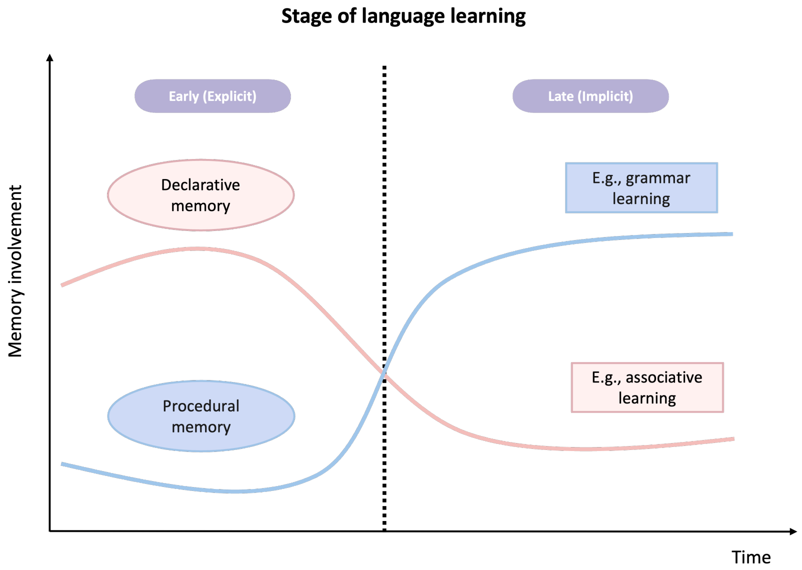


Figure 2.3: Declarative/Procedural Model of language learning. The Declarative/Procedural Model suggests that declarative memory handles explicit fact acquisition like associative learning, while procedural memory manages implicit, automatic processes like grammar, becoming more prominent in later language learning stages.

this may involve combining linguistic units, including word formation and meaning, which is supported by declarative memory. Meanwhile, grammar learning involves understanding the rules that govern the structure of a language and internalising the knowledge implicitly, which is associated with procedural memory.

It is important to note that within Ito (2008)'s hypothesis, the mechanism of explicit learning should not be conflated with that of explicit processing in the Declarative/Procedural Model, as the former is based on the stage of learning rather than task form.

2.2.1.1 Associative learning

It is well-documented that cerebellum internal models contribute to different forms of associative learning, including high-order cognitive learning, which is supported by parts of the posterolateral cerebellar hemispheres (for a review, see Timmann et al. (2010)). For example, the search and retrieval of memory for idioms or irregular past tense lexicons was found to be related to grey matter volume in the cerebellum (Pliatsikas et al., 2014). Clinically, patients with either cerebellar lesions or atrophy demonstrated impairments in verbal paired associates learning (Bracke-Tolkmitt et al., 1989) and the acquisition of word-colour associations (Canavan et al., 1994; Drepper et al., 1999; Thoma et al., 2008). Furthermore, Transcranial Magnetic Stimulation (TMS) of a lateral cerebellar site associated with verb generation was found to selectively enhance semantic associative priming (G. P. Argyropoulos & Muggleton, 2013). The right cerebellum was also found to be more involved in semantic judgment compared with letter-matching tasks (Jackson et al., 2015).

Vocabulary learning is based on explicit instruction in the associations between word forms and meanings. In the cerebrum, the acquisition of new words is initially represented in the hippocampus, whereas left posterior middle temporal cortex activation increases with lexicalisation Takashima et al. (2019). Unfortunately, how the word acquisition is represented in the cerebellum remains to be elucidated.

2.2.1.2 Grammar learning

Early proposed theoretical accounts of rule learning demonstrated that the acquisition of grammatical rules is developed via a feedback-dependent, trial-and-error learning process (Ashby & O'Brien, 2005; Opitz et al., 2011), suggesting that the cerebellum is involved in the acquisition of novel grammar. Research into the neural architecture behind grammar acquisition often employs highly controllable paradigms modelling an isolated aspect of grammar. The artificial grammar learning (AGL) paradigms, for instance, provide a way to explore language acquisition neural prints without the interference of prior exposure.

Friederici et al. (2002) designed an artificial language system called BROCANTO to investigate the critical period hypothesis of language learning. This system was adapted in the present research as its miniature grammar meets the universal requirements of natural language. In a whole-brain functional connectivity study using the BROCANTO system, the cerebellar network of the acquisition of artificial grammar was identified, in which the cerebellum was found to connect with the right inferior frontal gyrus (IFG), thalamus, and basal ganglia (BG) (Kepinska et al., 2017b). A longitudinal study using the modified version of BROCANTO also revealed the cerebellum involvement in AGL (Feng et al., 2021).

However, a meta-analysis of learning lexical and grammatical knowledge did not observe any activation in the cerebellum (Tagarelli et al., 2019). However, this may be due to the insufficient included studies examining the cerebellum to show converging activation in this region. Therefore, further research is needed to investigate the role of the cerebellum in AGL.

Most traditional AGL studies employed an implicit learning approach, which involves the passive acquisition of knowledge about environmental regularities, often without conscious awareness. However, recent studies have begun exploring the use of explicit learning methods to ensure real language processing. The primary reason for this change is that explicit, but not implicit, learning mode was found to lead to rule knowledge acquisition in the AGL context. Opitz and Hofmann (2015) used BROCANTO language to investigate the effect of learning mode. They found that the impact of rule knowledge was only significant for participants who were informed about the existence of a rule system underlying the sentences before the experiment and had to learn this rule. In contrast, participants who were instructed to complete only a working memory test did not exhibit any rule knowledge effect, and their acquisition of artificial language was minimal. Moreover, Chen et al. (2019) found that individuals who were explicitly taught artificial grammar rules before undergoing fMRI demonstrated a tendency to employ rule-based processing strategies. Conversely, those who learned without rule instructions did not exhibit the same degree of rule-based processing, suggesting a guessing strategy based on the target chunks/combinations. Steinhauer and Drury (2012) and Dikker and Pylkkänen (2013) also suggested that the effects under implicit conditions may be based on visual form-based expectation rather than semantic or syntax processing.

The choice of learning mode is a trade-off between unconscious acquisition and conscious mastery. Given the limited duration of experiments and the automatic processing nature of the cerebellum, we believe this research should prioritise ensuring that participants genuinely learn the artificial language in an explicit mode.

2.2.2 Coactivations and Connectivity

The internal model hypothesis describes a dynamic interplay among key regions in the cerebrum, including the prefrontal cortex, temporoparietal cortex, and cerebellum. Validating the hypothesis involves demonstrating that artificial language learning tasks evoke activation in both the cerebrum and the cerebellum, as well as showing task-related functional connectivity between these regions.

Structurally, the cerebellum has various connections not just with the supratentorial motor areas, but also with the paralimbic and association cortices. This interaction enables the cerebellum to participate in higher-level cognitive tasks, including language learning. A recent and comprehensive meta-analysis study confirmed the involvement of the right posterior lateral cerebellar hemisphere in language via crossed anatomic connections with the language-dominant left frontal, parietal, and temporal association areas (KerenHappuch et al., 2014). In this regard, several studies demonstrated co-activation and functional connectivity patterns between the cerebrum and cerebellum regions, providing regions of interest (ROIs) for exploration.

Co-activation and resting-state connectivity. Nakatani et al. (2022) used task-based and resting-state fMRI to investigate the roles of cerebellar Crus I and II in syntactic and semantic sentence comprehension. They found that syntactic processing depends on the right Crus I and Broca's area. Additionally, semantic processing involved the right Crus II and several left hemisphere regions–including IFG, middle frontal gyrus (MFG), anterior temporal lobe (ATL), angular gyrus (AG), fusiform gyrus (FG), and hippocampus. Although the left middle temporal gyrus (MTG), the ROI of this study, did not yield significant findings, it was considered important for semantic processing based on other research highlighting its role in connecting speech perception and conceptual-semantic systems (Matchin & Hickok, 2020). The right Crus I and II also showed significant activity under high cognitive load, possibly reflecting working memory demands rather than solely supporting the internal model hypothesis. Moreover, significant intrinsic functional connectivity was observed between cerebellar regions and key cerebral language-processing areas. Specifically, between Brocas area and right Crus I in syntactic processing, and between the left ATL and AG and right Crus II in semantic processing.

Functional connectivity. Kepinska et al. (2017b) conducted a whole-brain functional connectivity analysis using fMRI data from a grammar-learning task, decomposing the data into maps representing separate cognitive processes, including cerebellar networks. They found that the cerebellar activations were coupled with the right IFG and BG(pallidum and putamen), which are components of the procedural learning system (Ullman, 2004). The cerebellum was also found to interact with the thalamus, right temporal pole, and left temporal fusiform gyrus. The thalamus is the node connecting the cerebellum to the cortex. Structural connectivity suggests that the temporal pole acts as a convergence centre important for language and multimodal semantic processing. Moreover, the involvement of the left temporal fusiform gyrus, associated with recognising written words, and its connectivity with the temporal pole, suggests that semantic features are assigned to letter strings used in the task, which are then holistically processed by the procedural learning system as grammar.

Effective connectivity. Yuan et al. (2022) used fMRI to investigate the cerebellums role in bilingual language control, suggesting that the bilateral posterolateral cerebellum (lobule VI and lobule VIII) contributes to language control by forming functional connections with various cerebrum areas, including prefrontal, parietal, and subcortical regions. More importantly, they built an effective connectivity brain network between the cerebrum and cerebellum, selecting cerebellar nodes based on activation analyses (i.e., left lobule VI, left lobule VIII, right lobule VI, and right lobule VIII) and cerebral nodes (i.e., left MFG, right IFG, dorsal anterior cingulate cortex and presupplementary motor area, left inferior parietal lobe, left caudate nucleus, left thalamus, and right thalamus) based on Abutalebi and Green (2016) network model. This study provided a framework for the cerebro-subcortical-cerebellar connection of bilingual language control, which includes networks supporting conflict monitoring, interference suppression, and speech production in the target language.

2.2.3 Specific Contributions to Language

The BROCANTO paradigm was initially employed to explore the primary mechanism of grammatical acquisition: abstract rule-learning versus item-specific similarity learning (Opitz & Friederici, 2004). The researchers designed three violation types–agreement, word-category repetition, and phrase structure–to dissociate the two learning mechanisms. Participants were trained by agreement violation, which was a controlled condition. Subsequently, participants were divided into two groups: one was tested on word-category violations (associated with similarity-learning) and the other on phrase-structure violations (associated with rule-learning). The findings suggested the critical role of rule-based abstraction in later learning stages. Although the observed neural patterns implicate the cerebellum, the original authors did not directly address this region. Therefore, the current research seeks to explicitly investigate and validate the cerebellum's contribution to the learning process.

Evidence also points to the cerebellum's role in processing parts of speech (POS), demonstrated by differential left and right cerebellar activation during the production of nouns and verbs (Shapiro et al., 2005). This observed noun-verb dissociation has led some researchers to propose that the distinction is not purely grammatical, but is instead rooted in fundamental semantic differencesspecifically, the neural representation of objects versus actions. Therefore, the current research will explore whether the cerebellum shows dissociated patterns to different POS.

The processing of grammatical violations is more complex than POS processing. Although early studies assigned the cerebellum a low-level linguistic function, recent work contradicts this, showing its engagement in high-level cognition. Crucially, one study found that cerebellar responses to language are predominantly driven by high-level (e.g., semantics) but not low-level linguistic features (e.g., POS) (LeBel et al., 2021). Therefore, the present research aims to compare the cerebellum's involvement across two language tasks to delineate its specific contribution to higher-level grammatical analysis.

2.2.4 Summary

Associative learning and grammar learning involve distinct learning mechanisms, yet this distinction has not been thoroughly addressed in artificial language research. Although

Nakatani et al. (2022) revealed that the right Crus I is involved in syntactic processing and the right Crus II is in semantic processing, there is a lack of subsequent empirical evidence to fully support and validate this differentiation.

Moreover, although previous studies have identified multiple regions that are activated during language processing, most have often presented experimental results in isolation, without thoroughly analysing the specific functions associated with each activated region. In the internal model hypothesis, the instructor, controller, controlled object, and other components serve distinct roles, necessitating an in-depth analysis to explore the specific implications represented by the activated regions.

However, it is important to note that not all activated regions are directly connected to the internal model framework. For example, participants engaged in language learning tasks might read texts that can trigger orthographic processing or reading mechanisms (Kepinska et al., 2017b). Additionally, participants might experience an increase in cognitive load due to the bilingual setting or the increasing difficulty of the tasks, as in Nakatani et al. (2022) and Yuan et al. (2022). These factors necessitate a more thorough examination to determine the exact functions of activated regions.

Lastly, although the internal model hypothesis did not mention the critical role of subcortical regions in linguistic processing, an increasing number of studies have begun to uncover its importance recently (Fong, 2023). For instance, early research suggested that the subcortical regions, such as BG, contribute to the orderly operation of the prefrontal cortex as a controller by exerting the stabilisation-by-selection mechanism against numerous simultaneous, competing, and even conflicting inputs received from the entire neocortex (Hikosaka et al., 2000). Within this regard, the cerebellum is responsible for control augmentation, and BG is responsible for stabilisation augmentation (Ito, 2012). However, there is a notable lack of research focusing on the cerebro-subcortical-cerebellar view, which represents a significant research gap.

2.3 AUTOMATIC AND CONTROLLED PROCESSING

The second aspect of the internal model account concerns the cerebellums involvement in automatic processing and controlled processing. As the locus of implicit learning within the internal model framework, the cerebellum has been implicated in automatic processing (Koziol et al., 2014) and has also been suggested to play a critical role in error-based learning (Doya, 2000; Wolpert & Kawato, 1998). Accordingly, several hypotheses–some mutually exclusive and others overlapping–have been proposed regarding the mechanisms by which the cerebellum supports cognition. For example, the former perspective motivates an automatisation mechanism, whereas the latter supports a supervised errortuning mechanism.

Marr (1982) proposed that information processing systems can be understood at three separate levels: (a) Computational level: The task goal and the abstract problem to be solved; (b) Algorithmic/representational level: The representations and processes that carry out the computation; and (c) Implementation level: The neural hardware that realizes the algorithm. Given the cerebellums relatively uniform anatomic and cytoarchitectural structure, researchers have proposed several general accounts to explain how a single computation could apply across motor control, attention, working memory, language, and social cognition. Schmahmann (1996) and Guell et al. (2018) created the term universal cerebellar transform to capture the idea of a unitary cerebellar computation. For instance, the cerebellum is argued to contribute to language, analogously to its role in motor control, by modulating cortical activity through precise timing and sequencing (Mariën & Borgatti, 2018). The internal model hypothesis is likewise domain-general, positing a mechanism that supports both motor and cognitive functions, aligning with evidence that implicates the cerebellum in prediction, timing, sequencing, and error-driven adjustment.

In contrast to the universaltransform view, multiplefunctionality models posit that different tasks rely on varying contributions from several computations, each requiring a distinct algorithmic description (Diedrichsen et al., 2019). Growing evidence for functional diversity among structurally similar cerebellar modules suggests both that any putative universal computation may have a broader scope than previously recognised and that additional functional processes remain to be delineated (Sokolov et al., 2017).

In this study, we examined whether the cerebellum implements a uniform algorithm or multiple distinct algorithms to support its diverse functions. If a uniform algorithm such as automatisation is operative, we would expect cerebellar regions to show greater engagement in automatic processing across both associative learning and grammar learning tasks, particularly when accounting for proficiency. Moreover, the engagement pattern should remain consistent across early and late learning stages. By contrast, under a multiple algorithm account, we would expect taskspecific and regionally distinct neural patterns across learning tasks and stages.

2.3.1 Dual Processing

Kahneman (2011) described two distinct modes of cognitive processing–system 1 and system 2 to classify intuitive and effortful thinking. Based on this view, Ramnani (2014) proposed that two interacting systems can account for some properties of automatic and controlled violation processing. As learning progresses, performance typically shifts from an explicit controlled violation processing stage, where actions are effortful and slow, to a more implicit automatic state (Evans, 2008). The achievement of the automatic state requires cumulative experience derived through practice. In the later stage, performance becomes rapid and effortless. Multiple features of automatic processing resemble those of implicit forward models proposed by the internal model hypothesis, suggesting that this difference may be instantiated within the interaction between the cerebrum and cerebellum circuits.

Indeed, the evaluation of the domain-general internal model hypothesis requires a distinct functional description of modules. To investigate automatic and controlled processing, we examined the contrast in associativity (i.e., matched versus mismatched) and grammaticality (i.e., grammatical versus ungrammatical) and correlated functional activation and connectivity differences with the proficiency of participants. Moreover, we explored change, which addresses the differences between early and late stages of language learning.

2.3.2 Automatic Processing

There is substantial evidence indicating that the cerebellum plays a crucial role in facilitating automatic processing. For example, in the probabilistic classification task (i.e., predicting sun or rain based on combinations of playing cards), Lam et al. (2013) found that the higher the predictive value of a card combination, the more activation was found in the lateral cerebellum. If cerebellar activity represented violation errors, stronger activation would be expected for low-value trials, where subjects made more errors. However, cerebellar activity increases in tasks with less cognitive demand. They suggested that this greater cerebellar involvement in automatic processing reflects the formation of an internal model.

Additionally, Petríková et al. (2023) used transcranial direct current stimulation (tDCS) to assess and compare the contribution of the cerebellar processing to automatic (i.e., free-associative) and controlled (i.e., inhibition, switching) semantic retrieval in healthy adults. Automatic retrieval refers to the bottom-up activation of semantic representations triggered by environmental cues or spontaneous thoughts. In contrast, executive control of retrieval involves the top-down regulation of semantic processing, which is employed when the outputs of automatic retrieval are inappropriate for the task at hand. This study revealed that anodal cerebellar tDCS facilitated the retrieval of sequentially related concepts within free-associative word chains but had no influence on retrieval conditions that require semantic control, such as the delivery of unrelated words and flexible alternating between retrieval rules. These findings indicate that the cerebellum is engaged in automatic rather than controlled retrieval from semantic memory.

2.3.3 Controlled Processing

However, it is also suggested that the cerebellum contributes to cognitive functions based on error learning, as the violation of the prediction would elicit enhanced cerebellar activation compared with automatic processing. For example, Moberget et al. (2014) found focal cerebellar activation when the sentence context made the final word predictable, whereas more widespread activation corresponded to prediction violations (e.g., two plus two is apple*). The broader activation in bilateral Crus I/II, left lobule IV, and right lobule VI reflects the cerebellums engagement in recalibrating the internal model to incorporate unexpected linguistic inputs. This study provides evidence that the cerebellum not only maintains internal models of language but also continually updates these models in response to feedback, resulting in increased efficiency and proficiency in language processing over time.

Additionally, Lesage et al. (2017) found activity in the right Crus II correlated with the predictability of the upcoming target word, and this region also responded to prediction error during the outcome of the trial. Importantly, the sentence for prediction was created independently from a context sentence through which predictability was manipulated and from the final word of the sentence. This design enables the researchers to capture the effects of prediction in the absence of outcome evaluation or prediction error. This study supports the idea that cerebellar internal models facilitate language comprehension by predicting upcoming stimuli, and the update of the internal model is based on addressing violations of these predictions.

However, these studies focus primarily on word-level prediction. It remains uncertain how the brain processes sentences that violate standard sequencing rules. Our research will therefore investigate both word-level and sentence-level processing.

2.3.4 Associativity and Grammaticality

Prior studies have typically examined narrow conditions while advancing broad claims about cerebellar mechanisms. Yet few functional neuroimaging studies have directly contrasted these mechanisms. We therefore ask: What is the cerebellums role in the formation and refinement of internal models, and how does this role change over the course of learning?

A central challenge is to distinguish between automatic and controlled processing. When language knowledge is acquired, the internal model generates predictions of the upcoming stimuli based on the context and experience. Moreover, actual outcomes, conveyed by prefrontal signals derived from external feedback, are compared with predictions for developing the internal model. When incoming linguistic information violates predictions (e.g., semantic violation or ungrammatical sentence), the cerebellum engages controlled processing to refine the model, whereas when inputs conform to predictions (e.g., semantic congruency or grammatical sentence), the processing is more automatic, requiring minimal error correction.

Processing grammatical versus ungrammatical sentences differentially engages cerebral and cerebellar networks. Relative to a sensorimotordecision baseline, grammaticality classification activates bilateral inferior frontal cortex (Brodmann areas 44/45) and the right cerebellum (Petersson et al., 2012; Forkstam et al., 2006). Moreover, the left cerebellumtogether with the left postcentral gyrus and right intraparietal sulcusshows greater activation for ungrammatical than grammatical sentences (Ungrammatical > Grammatical), reflecting sensitivity to grammaticality rather than complexity Friederici et al. (2006). The left inferior frontal cortex is likewise selectively responsive to syntactic violations (Ungrammatical > Grammatical). By contrast, the caudate nucleus and posterior cingulate cortex exhibit stronger responses to correct syntactic structure later in learning but not at the outset (Grammatical > Ungrammatical) (Forkstam et al., 2006). Additional increases for grammatical items are observed in right frontal and cingulate cortices, left occipital cortex, premotor areas, and the right cuneus (Grammatical > Ungrammatical) (Petersson et al., 2012).

2.3.5 Summary

The prediction of upcoming words was found to depend upon the cerebellar internal model (D'Mello et al., 2020; Lesage et al., 2017; Miall et al., 2016; Moberget et al., 2014). Therefore, although violations of semantic meaning have been studied less extensively, we investigated the automatic processing and controlled processing in both associative learning and grammar learning tasks, focusing on engagement (i.e., condition difference) and change (i.e., stage difference).

We first explored how the cerebellum contributes to automatic and controlled processing, while accounting for task proficiency (i.e., d-prime and reaction time). If the cerebellum primarily supports automatic processing, we would expect greater cerebellar activation in participants with higher proficiency during automatic processing conditions. Conversely, if the cerebellum is more involved in processing syntactic violations, we would observe the opposite pattern, with stronger activation during violation conditions.

Subsequently, we examined cerebellum-cerebrum functional connectivity in relation to task proficiency factors as individual difference variables. If the cerebellum primarily supports automatic processing, we would anticipate stronger cerebellum-cerebrum connectivity in highly proficient participants under automatic processing conditions. In contrast, if the cerebellum is more engaged in controlled processing, we would expect enhanced connectivity in conditions involving associative or grammatical violations.

Lastly, we examined changes in activation and functional connectivity between the early and late stages of language acquisition. We also investigated whether individuals with greater proficiency changes exhibited larger differences in activation or functional connectivity contrasts.

2.4 CORRECT-RELATED AND ERROR-RELATED PROCESSING

The third aspect of the internal model account concerns correctrelated and errorrelated processing. Language learning is a dynamic process that results in changing neural patterns over time. In acquiring and developing internal models, supervised and error-based learning guide the cerebellum to execute and update the internal model (Sokolov et al., 2017). Although climbing fibre input has traditionally been viewed as an error signal, recent evidence indicates it may function as a broader teaching signal, potentially linked to reward as well as error (Heffley et al., 2018).

Guided by the universal transform and multiple functionality hypotheses Diedrichsen et al. (2019), we further investigated whether the cerebellum supports language learning via correctrelated mechanisms, errorrelated mechanisms, or their combination, and whether the operative mechanism remains stable over time.

For this aspect, we investigated two phases: execution (i.e., judgment) and updating (i.e., feedback) of the internal model. In the execution phase, the cerebellums internal model uses previously learned knowledge to generate predictions about sensory or cognitive events. Accurate knowledge leads to precise predictions, which are associated with correct-related processing. Inaccurate knowledge produces incorrect predictions, resulting in error-related processing. During the updating phase, the cerebellum receives feedback from the cerebrum, including sensory information (e.g., touch and vision) and cognitive information (e.g., thought and memory). Correct feedback strengthens accurate neural representations, promoting learning. Error feedback highlights inaccuracies, prompting adjustments to improve predictions. The interplay between execution and updating allows the cerebellum to adapt dynamically. This cycle optimises cognitive processing, enabling better anticipation and response to the environment.

Similar to the investigation of automatic versus controlled processing, we not only analysed the differences between correct-related and error-related conditions but also explored change over time by comparing differences between the early and late stages.

2.4.1 Correct and Incorrect Processing

The distinction between correct-related and error-related activities during the execution of the internal model highlights two complementary processes in associative or grammar judgment tasks: correct judgments strengthen and stabilise existing knowledge, whereas incorrect judgments trigger activities to identify and address gaps or misunderstandings. Even when participants are unaware of their incorrect judgment, the brain can still detect subtle differences between correct and incorrect execution of the language model. This pattern relates to prediction error mechanisms, such as the error-monitoring network, which involves prefrontal regions. For instance, the Error-Related Negativity (ERN) signal can occur without conscious awareness of an error (L. Wang et al., 2020).

The cerebellum facilitates motor automation through plasticity in circuits that interact with the motor cortex (Penhune & Doyon, 2005; Ramnani et al., 2000). For example, in a study investigating how people learn a computer mouse with a novel rotational transformation, results revealed two types of activity (Imamizu et al., 2000; Imamizu & Kawato, 2009). One was widespread throughout areas of the cerebellum and was precisely proportional to the error signal that guides the acquisition of internal models during learning (i.e., error-related activity). The other was confined to the area near the posterior superior fissure and persisted even when errors were controlled, suggesting that these areas were involved in acquiring a new tool rather than just responding to errors (i.e., correct-related activity). Compared with the correct-related activity, the error-related activity showed a more drastic decrease.

Although the cerebellums role in sensorimotor control is well established, far less is known about how it differentially supports correctrelated and errorrelated processes in cognition. To our knowledge, only one study has examined changes in correct-related activity over time. Balsters and Ramnani (2011) reported that, as rule acquisition progressed toward automatisation, activity in Crus I decreased on correct trials, reflecting the cerebellar plasticity during cognitive processing. This reduction was larger for rule sets that automatised rapidly than for those that automatised more slowly. These findings have been interpreted as evidence for the acquisition of internal models of prefrontalcerebellar information processing that enable the automatic execution of cognitive operations (Balsters & Ramnani, 2008). However, changes in errorrelated activity were not assessed.

In contrast, it is reported that lateral and inferior cerebellar regions showed greater activation to errors as compared to correct responses in a change-signal task (Becerril & Barch, 2013). Additionally, cerebellar activity was observed to increase during tasks with higher cognitive demands. For instance, Turker, Kuhnke, Schmid, et al. (2023) found that compared to processing simple stimuli, which are more automatic, processing complex stimuli resulted in enhanced cerebellar activation. ? (?) also reported that the task presented at a fast speed elicited greater cerebellar activation compared to those presented at a slow speed. Furthermore, the cerebellum exhibited a preference for high-level conceptual processing, such as context-level semantic processing, over lower-level language processing, such as word class (LeBel et al., 2021). These findings suggest that the cerebellum exhibits stronger activity during error-related processing, as participants had limited proficiency in the linguistic knowledge required by complex tasks.

2.4.2 Positive and Negative Feedback

Updating the internal model is a finetuning process. In many situations where the correct response is uncertain, errors cannot be detected at response onset or from internal signals alone, making external feedback necessary. Here we focus on the information content of feedback rather than its valence. The reason is that, during associative learning, the right cerebellar lobule VI is sensitive to informative feedback irrespective of valence Bischoff-Grethe et al. (2009), suggesting that information content, not valence, may drive cerebellar activity.

In associative and grammar learning, external feedback is essential for acquiring meanings and grammatical rules, and accumulating evidence indicates cerebellar involvement in feedback processing (for a review, see Berlijn et al. (2024)). Typically, feedback engages bilateral Crus I/II. Prior studies have demonstrated the effects of feedback on bilateral Crus I/II in both explicit and implicit learning, highlighting the importance of feedback timing during grammar learning (Opitz et al., 2011; Schiff et al., 2017).

The cerebellum also differentiates positive and negative feedback: positive feedback reinforces successful outcomes (correctrelated activity), whereas negative feedback conveys error signals (errorrelated activity). Greater activation for negative relative to positive feedback has been observed when feedback is tied to goal attainment. For instance, in a symbolreward associative task, increased activity for negative versus positive feedback was reported in lobule VI and Crus I, and this activity predicted strategy changes Peterburs et al. (2018). By contrast, Bischoff-Grethe et al. (2009) found increased bilateral lobule VI activation following positive feedback and right lobule VI activation following negative feedback compared with uninformative feedback, implying broader cerebellar engagement for positive feedback. These inconsistencies motivate further investigation of feedback valence effects.

Regarding temporal dynamics, Peterburs et al. (2018) also showed that the final negative feedback preceding a strategy switch elicited greater activity than negative feedback not followed by a switch, with effects in Crus I/II and lobule VI. Moreover, in these regions, responses to the second through sixth feedback events were weaker than the response to the first positive feedback.

2.4.3 Summary

To investigate correct-related and error-related processing, we examined cerebellar engagement (i.e., condition difference) and change (i.e., stage difference).

For engagement, we assessed whether cerebellar activation differed between correct and incorrect judgments, as well as positive and negative feedback. If the cerebellum plays a greater role in correct-related processing, we would observe stronger activations during correct judgment and positive feedback. If the cerebellum is more involved in error-related processing, we would observe an opposite pattern. Furthermore, we used proficiency parameters (i.e., d-prime and reaction time) to correlate the activation differences to explore the effect of proficiency. Additionally, we examined the differences in correct-related and error-related processing, as well as those in functional connectivity, taking into account proficiency.

For change, we investigated whether correct-related and error-related processing exhibited distinct changes from the early to late stages of language learning. Furthermore, we examined whether individuals with greater changes in proficiency demonstrated larger differences in activation or functional connectivity.

To maximise participants proficiency in the artificial language, we did not strictly balance positive and negative feedback in this study. However, the investigation of correct- and error-related activity remains valuable as we explored how proficiency influenced the activation difference and examined changes in the two types of activities. Unfortunately, since participants reached a ceiling effect even during the early stage of the associative learning task, we focused solely on examining this aspect in grammar learning.

2.5 DIFFERENT CONTRIBUTIONS OF CORTICAL, SUBCORTICAL, AND CEREBELLAR REGIONS TO LANGUAGE LEARNING

While this research primarily examines the cerebellum's role in language learning, we do not claim that the cerebellum is the sole driver of language. Rather, it plays a supportive, modulatory role in collaboration with other brain regions, including cortical and subcortical regions (Mariën et al., 2014; Mariën & Borgatti, 2018). In a meta-analysis of language processing including 403 experiments, researchers found cerebellar contributions across all subdomains and modalities. Specifically, the right cerebellum was engaged in speech production, visual, and phonological tasks. However, cortical, subcortical, and cerebellar regions showed varying degrees of specialisation across specific language domains, such as semantics and syntax (Turker, Kuhnke, Eickhoff, et al., 2023). Furthermore, the super-learning hypothesis also suggests that they play distinct roles in unsupervised learning, reinforcement learning, and supervised learning (Caligiore et al., 2019).

To achieve a comprehensive understanding of cerebellar function, it is essential to examine cerebellar activity in conjunction with cerebral patterns. In the previous sections, we reviewed the involvement of the cerebellum in automatic and controlled processing, as well as learning-related and error-related processing, alongside findings related to the cerebrum in these studies. In this section, we mainly focused on the differences among cortical, subcortical, and cerebellar regions.

2.5.1 Automatic and Controlled Processing

During the progression of automaticity, the prefrontal region is believed to transmit efference copies to cerebellar forward models, which simulate processing within prefrontal targets. While the prefrontal region handles controlled, conscious processing, the cerebellum is more involved in automatic, unconscious processing (Koziol et al., 2014; Ramnani, 2006; Tao et al., 2024). An important prerequisite for these ideas is that cerebellar circuitry should have access to higher-order error feedback, which signals the success or failure of cognitive processing via the inferior olive and the dopamine system. However, the role of the subcortical regions is less clear.

Except for the univariate analysis, we used the representational similarity analysis (RSA) method in multivariate pattern analysis (MVPA) to examine how cortical, subcortical, and cerebellar regions process automatic and controlled conditions differently during associative and grammar learning. RSA focuses on comparing the representational geometry of neural data, which is particularly useful for understanding how information is encoded in the brain. It revolves around constructing a representational dissimilarity matrix (RDM), which quantifies the dissimilarity between neural response patterns for different conditions (Kriegeskorte et al., 2008). Using this method, studies have found different neural processing of musical pitch (Sankaran et al., 2018), semantics (Carota et al., 2017; Devereux et al., 2013), and syntax (Tyler et al., 2013).

Furthermore, the internal model implies that there is a continuous exchange of neural signals between the cerebrum and the cerebellum. Previous research has provided evidence of closed-loop connectivity, reflecting bidirectional connectivity between the same areas of the cerebellum and the cerebrum. The core idea is that novel information from the cerebrum is fed downwards to the cerebellum to identify sequences, and is then fed back upwards to the same cerebral area to signal confirmation or violation of the sequence (Pu et al., 2022). Therefore, we investigated how automatic and controlled processing change the strength of coupling among regions.

We performed dynamic causal modelling (DCM) analysis to investigate the effective connectivity among cortical, subcortical, and cerebellar regions. Specifically, we aimed to determine which processing model better aligns with the actual information flow. DCM enables causal interpretations of neural loops and distinguishes between fixed connectivity and modulatory connectivity influenced by experimental conditions (K. J. Friston et al., 2003). Previous research suggests that cerebrum-cerebellum effective connectivity plays a critical role in understanding social sequences and violations (Pu et al., 2022; Van Overwalle et al., 2020), bilingual language control (Yuan et al., 2022), and word reading (H. Li et al., 2022). For instance, during the automatic or controlled processing of social sequences (i.e., social routine and social violation), all fixed connections from the posterior cerebellum were found to be negative, whereas the connections to the posterior cerebellum were positive (Van Overwalle et al., 2020). However, this study did not dissociate the modulatory effects of the two conditions of social sequence. We therefore addressed this gap in the context of language learning by examining how automatic and controlled processing modulate cerebello-thalamo-cortical connections, which are the primary routes for cerebellar-cortical communication (Murdoch, 2010; Palesi et al., 2015; Stoodley et al., 2010, 2012). Notably, the selected ROIs (i.e., left IFG, left thalamus, and right Crus I/II) showed greater activations during automatic or controlled processing of semantic prediction compared with baseline unpredictable condition (Moberget et al., 2014).

The right Crus I and II, located in the lateral posterior cerebellum, are consistently implicated in language processing (Schmahmann, 2019). These regions interact with cortical language networks, particularly the IFG, via cerebello-thalamo-cortical pathways, facilitating automatic processing, error detection, and integration of linguistic information. Given the cerebellums contralateral connections to the cerebrum, our DCM analysis focuses on the right Crus I/II, left thalamus, and left IFG. Right Crus I/II show co-activation and intrinsic resting-state functional connectivity with the left IFG during semantic and syntactic comprehension tasks (Nakatani et al., 2022), aligning with IFGs role in the semantic and syntactic network (Binder et al., 2009; Petersson et al., 2012). The left thalamus serves as a relay hub, mediating communication between cortical and cerebellar regions, with its role in language processing confirmed by a meta-analysis (Bulut & Hagoort, 2024).

Based on the perspectives of automatic and controlled processing, we created two DCM models with the four ROIs. On the one hand, from the perspective of automatic processing, in automatic conditions (i.e., matched and grammatical), the processing is relatively streamlined, as it aligns with expected semantic or syntactic rules. The right Crus I/II would generate accurate predictions, which are then confirmed by the unification of the left IFG. The left thalamus maintains a stable relay, supporting working memory and attention without significant error signals. In contrast, the controlled conditions (i.e., mismatched and ungrammatical) trigger violation errors. The IFG engages in more complex processing to resolve violations, showing top-down control. On the other hand, from the perspective of controlled processing, the automatic conditions would enhance forward processing from the left IFG to the right Crus I/II. On the contrary, in controlled conditions, the right Crus I/II would be dominant in dealing with the prediction violations, sending error signals to the IFG via the thalamus.

2.5.2 Correct-Related and Error-Related Processing

In terms of correct-related processing, correct judgments of grammar likely involve efficient processing within language-specific regions. Incorrect judgments, on the other hand, appear to engage additional regions related to error monitoring and conflict resolution.

For the cortical regions, a study on AGL found that left angular gyrus activity was coupled with high performance, and engagement of the right parietal regions is crucial for efficient grammar learning, indicating their roles in successful syntactic processing (Kepinska et al., 2017b). Moreover, Weber et al. (2016) revealed different effects of the repetition of known and unfamiliar artificial grammar knowledge. In the left IFG and posterior temporal cortex, the repetition of novel syntactic structures led to repetition enhancement, whereas repetition of known structures resulted in repetition suppression. These findings suggest that the effect of repetition enhancement reflects learning processes that strengthen the new representation being built, which would change to repetition suppression once a stable memory representation has been established.

For the subcortical regions, it seems likely that as language skills mature, activity in subcortical regions would decrease, with cortical areas taking on more complex language processing (Youssofzadeh et al., 2018). Although the findings mentioned above did not directly investigate the differences between correct-related and error-related processes, the task designs addressed a key distinction between them: whether participants successfully acquired the knowledge required for the task.

For the cerebellum, although the difference was examined in terms of motor tasks (Imamizu et al., 2000; Imamizu & Kawato, 2009), much less is known about cognitive tasks. Interestingly, Balsters and Ramnani (2011) suggested that the decreased activity in cerebellar Crus I during rule automation is due to its connectivity with the prefrontal cortex.

Moreover, neural responses to feedback in associative learning also vary across cortical, subcortical, and cerebellar regions. The bilateral nucleus accumbens, caudate nucleus, anterior insula, left putamen, and right cerebellar lobule VI showed activation in response to informative feedback regardless of its valence. Furthermore, cortical and subcortical regions, including the insula, amygdala, putamen, and supplementary motor area, exhibited stronger activation for positive feedback compared to negative feedback, with no regions showing greater sensitivity to negative feedback (Bischoff-Grethe et al., 2009). However, less is known about their differences in feedback processing during grammar learning.

2.5.3 Summary

To explore the different contributions of cortical, subcortical, and cerebellar regions to language learning, we compared their activations in automatic and controlled processing, as well as correct-related and error-related processing. Similar to the cerebellum investigation, we not only compared the activation differences between the conditions, but also analysed stage differences. Moreover, we also used task proficiency to correlate with the neural difference. In these analyses, we were interested in which regions exhibited patterns similar to those of the cerebellums language-related regions and which regions showed distinct patterns. Due to a ceiling effect observed early in the associative learning task, where participants rapidly achieved optimal performance, we only focused on investigating correct- and error-related processing in grammar learning.

We base our investigation on the premise that the functional heterogeneity of the cerebellum arises from its distinct cerebro-cerebellar circuits (Diedrichsen et al., 2019). We therefore hypothesize that the strength of structural connectivity predicts the similarity of neural activity patterns between the cerebellum and cerebral regions. This is supported by prior work linking Crus I/II to areas such as the IFG, thalamus, and temporal pole. To comprehensively test this hypothesis, our study will extend this analysis to a wider array of cerebral cortical and subcortical regions, examining how connectivity profiles correlate with functional co-activation patterns.

Lastly, to investigate the difference between automatic and controlled processing, we examined directional information flow within the cerebro-subcortical-cerebellar network, considering d-prime effects (i.e., the proficiency of the measurement task). We created two DCM models to represent automatic processing and controlled processing. If the cerebellum predominantly supports automatic processing, we would expect that in participants with higher proficiency, automatic conditions would enhance the bottom-up pathways and intrinsic right Crus I/II connections. Conversely, controlled conditions would likely reinforce the top-down pathways and intrinsic left IFG connections. The opposite effective connectivity pattern would be observed if the cerebellum primarily facilitates controlled processing.

2.6 THE INFLUENCE OF INDIVIDUAL DIFFERENCES

Individual differences are pervasive throughout the linguistic system (Kidd et al., 2018). During language acquisition, individuals exhibit varying learning efficiencies, a disparity that persists into adulthood (Rosselli et al., 2014). To investigate these differences, recent studies have employed neuroimaging approaches to uncover the neurocognitive characteristics of highly effective learners (Feng et al., 2021; Kepinska et al., 2017a; P. C. Wong et al., 2007; Yang et al., 2015). This line of work illuminates how individuals adapt their neural systems to optimize behaviour in response to environmental demands. Understanding how individual differences shape neural patterns is also essential for designing personalized educational strategies and interventions.

Whether cerebellar support for language is domain-general or domain-specific is a topic of ongoing research. The domain-general view posits that the cerebellum contributes to language as part of its broader role in cognitive processing, rather than being uniquely tailored to language. Its canonical function is often described as prediction and error-driven updating of internal models through long-term synaptic modifications, operating within a largely uniform microcircuitry (Kawato et al., 2021; Marr, 1982). This architecture supports a wide range of cognitive domains. For example, cerebellar activation was found to overlap between language and general cognitive tasks (KerenHappuch et al., 2014). The domain-specific view argues that certain cerebellar computations are uniquely involved in linguistic processing, distinct from their role in other cognitive domains. For example, while not exclusively language-dedicated like Broca's area, certain cerebellar subregions (e.g., Crus I/II) showed preferential activation for linguistic processes (Mariën & Manto, 2015), suggesting languagespecific adaptations.

These opposing views motivate our examination of both domain-general and language-specific individual difference effects on the cerebellum. Our analysis encompasses a broad range of individual differences, including general cognitive abilities (e.g., cognitive flexibility) and specific language abilities (e.g., language experience), to evaluate their influences across the learning process.

2.6.1 Cognitive Abilities

When investigating individual differences in cognitive functions and brain functioning, the neural efficiency hypothesis is frequently employed to understand the mechanisms behind high cognitive abilities. It posits that neural efficiency entails utilising fewer mental resources in a focused and purposeful manner when confronted with the cognitive demands of a task. To illustrate, Prat et al. (2007) revealed that individuals with higher reading capacities demonstrated greater neural efficiency during sentence comprehension in comparison to those with lower reading capacities. However, when the cognitive load increases in more complex tasks, more mental resources are required to handle the task demands. This increased cognitive load can lead to a decrease in neural efficiency (Neubauer & Fink, 2009).

Studies have shown that individuals with lower cognitive abilities or increased cognitive load often exhibit greater cerebellar activation during task performance compared to those with higher cognitive abilities or lower cognitive load (Bernard, 2022; Sisakhti et al., 2021). This increased cerebellar activation is thought to reflect compensatory mechanisms, as the cerebellum assists in regulating and optimising neural processes to support task performance under challenging conditions.

Specifically, during language learning, as the processing of words or sentences becomes more complex, individuals may experience an increased cognitive load, which researchers have found to be associated with increased activity in the cerebellum. For instance, the right Crus I and Crus II showed significant activity only when the cognitive load was high in semantic and syntactic tasks (Nakatani et al., 2022). Furthermore, the high-load test, but not the low-load one, was found to increase fMRI activity in some areas of the bilateral cerebellar lobule VIIA and VI, the right lobule VIIB, and portions of the posterior vermis (lobule VI and superior VIIA) in the verbal working memory task (Desmond & Fiez, 1998).

When doing the language learning tasks, individual cognitive load may vary due to differences in participants cognitive abilities, such as interference control, working memory, intelligence, and cognitive flexibility. However, there remains a significant gap in our understanding of how our cognitive abilities affect the formation and updating of internal models.

2.6.1.1 Interference control

Interference control plays a significant role in language learning because it helps individuals filter out irrelevant information and focus on processing and producing new language structures (Green, 1998). Strong interference control supports faster and more effective language acquisition by reducing cognitive load and allowing for more efficient use of working memory. For example, when learning a new language, interference control is crucial for suppressing the grammatical rules of one's native language while applying the correct rules of the new language. This prevents cross-linguistic interference and ensures correct grammatical processing in the target language.

The Stroop test (Golden, 1978; Stroop, 1935) is a widely used neuropsychological assessment that evaluates the ability to inhibit cognitive interference. Its effect demonstrates how automatic processes (i.e., reading) can interfere with less automatic processes (i.e., colour naming). As language skills develop, the cognitive load associated with managing multiple languages changes, which can be observed through interference control assessment. Moreover, a neuroimaging study related to the Stroop task has shown that specific brain areas, such as the anterior cingulate cortex (ACC) and dorsolateral prefrontal cortex (DLPFC), are involved in managing the cognitive demands of language tasks (Roelofs & Hagoort, 2002). These areas are crucial for executive control and become engaged when bilinguals selectively activate one language while suppressing the other. For the cerebellum involvement, the Stroop effect was observed involving a cross-hemispheric, excitatory-inhibitory loop functionally connecting the lateral prefrontal cortex and cerebellum (Okayasu et al., 2023).

2.6.1.2 Working memory

Language learning involves retaining new vocabulary, rules, and structures. A person with a greater working memory capacity can handle this information more efficiently (Huang et al., 2022; Linck et al., 2014). For instance, individuals vary in (1) their capacity to retain newly encountered information during reading, (2) their skill in making inferences about the information they read, (3) their ability to retrieve knowledge from long-term memory, and (4) their ability to combine new information with existing knowledge from long-term memory (Daneman & Hannon, 2007). More importantly, Ito (2008) posits that working plays an integral role within the thought system.

Working memory assessments are commonly divided into two types: tasks that evaluate an individuals capacity to store and rehearse information, known as simple span tasks, and tasks that assess the ability to retain information while simultaneously handling additional processing demands, referred to as complex span tasks. The forward digit span (Wechsler, 1955) is a simple span task, which consistently accounts for significant variance in L1 and L2 vocabulary development (Linck et al., 2014). The reading span task (Just & Carpenter, 1980) is more complex because it involves both the storage and reading components of working memory. Furthermore, as for the relationship between the cerebellum and the working memory, a positive linear relationship between verbal working memory load and activity was observed in the right lobule VI, extending into Crus I bilaterally (Ashida et al., 2019).

2.6.1.3 Intelligence

Intelligence, especially fluid intelligence, is also important for novel language learning as it involves deciphering and applying new grammar rules and vocabulary. Since the early stages of intelligence research, the ability to learn has been closely associated with most definitions of intelligence (Sternberg, 1997). In Cattells investment theory, fluid intelligence is believed to be largely biologically determined and closely linked to the ability to learn in new situations (Cattell, 1987). Accordingly, he proposed a strong relationship between fluid intelligence and the rate of acquiring academic skills. However, apart from research related to working memory, there is limited evidence concerning intelligence. Among the few available studies, Pishghadam and Khajavy (2013) investigated young adult foreign language learners and found that fluid intelligence was a significant predictor of performance on a comprehensive foreign language acquisition test.

Ravens Standard Progressive Matrices (Ravens SPM) (Raven, 2000) is a non-verbal test typically used to measure general human intelligence and abstract reasoning and is regarded as a non-verbal estimate of fluid intelligence. An fMRI study addressing the effects of Ravens SPM task revealed broad cerebellar activations, including bilateral lobule IX, right Crus I, and right lobule VII (Anat et al., 2024).

2.6.1.4 Cognitive flexibility

Feedback-error learning is the basis of the cerebellums capacity to form and update internal models (Kawato & Gomi, 1992). This cerebellar feedback loop helps to smooth out and improve the learning process in the cerebral cortex, enhancing both motor and cognitive functions (Boven et al., 2023). Therefore, individuals with better cognitive flexibility are expected to exhibit heightened sensitivity to error feedback, enabling them to use such feedback effectively to refine their internal decision-making models.

The Wisconsin Card Sorting Test (WCST) is a neuropsychological test widely used to assess executive functions, specifically cognitive flexibility and set-shifting abilities (Grant & Berg, 1948). The individual must notice the change in the sorting rule, inhibit the previous strategy, and shift to a new strategy to achieve successful sorting. The WCST has been instrumental in researching the functional aspects of the prefrontal cortex and the cerebellum (Nagahama et al., 1996). During the experiment, participants were given cards that could be sorted by colour, shape, or name, and their mental task was to deduce the correct sorting criterion. After several correct responses, the correct sorting criterion was changed without notice. Positron Emission Tomography (PET) imaging revealed that the test co-activated the left (or bilateral) dorsolateral prefrontal cortex, bilateral inferior parietal cortex, left superior occipital gyrus, and left neocerebellum. These findings suggest a coordinated neural network involving these areas during task execution. Further emphasising the importance of the cerebellum in executive functions, a clinical study examined patients who had cerebellar tumours removed (Karatekin et al., 2000). These patients exhibited difficulties in generating and testing hypotheses, highlighting the cerebellums role in hypothesis testing and adaptive problem-solving.

Although most of these studies have focused on psychiatric patient groups and healthy controls, healthy subjects exhibit more consistent behavioural performance, which holds significant relevance for understanding brain function (Nyhus & Barceló, 2009). Given these backgrounds, the WCST was used to measure cognitive flexibility.

2.6.2 Language Abilities

Language proficiency, experience, and analytical ability are interconnected factors that influence language learning. Proficiency reflects the efficiency of neural processing in language areas, honed through experience and practice. Language experience shapes the neural substrates through neuroplasticity, strengthening connections within language networks. Language analytical ability (LAA) engages executive functions and working memory, facilitating the processing of complex linguistic structures. Together, these factors contribute to the dynamic neural processes underlying language learning.

2.6.2.1 Language proficiency

Language proficiency refers to the ability to use language effectively and accurately across various contexts. Proficient language users often exhibit reduced neural effort when processing familiar linguistic structures, indicating automaticity in language processing (Perani & Abutalebi, 2005). In bilinguals, language proficiency has been suggested to influence the involvement of domain-general control networks in language selection (Mouthon et al., 2020). Several fMRI studies have demonstrated the relationship between language proficiency and cerebellar activity (Cullum et al., 2019; Yuan et al., 2022). In this research, we used the Hong Kong Diploma of Secondary Education Examination (HKDSE) grades in Chinese and English to measure language proficiency.

2.6.2.2 Language experience

Language experience encompasses the exposure to and practice with language over time. It plays a crucial role in shaping the neural architecture of language processing. From the perspective of neuroplasticity, extensive exposure to languages strengthens neural connections within language networks. Moreover, the Adaptive Control Hypothesis posits that managing multiple languages requires constant monitoring and selection processes, engaging executive control networks in the brainespecially the prefrontal cortex, anterior cingulate cortex, and basal ganglia (Green & Abutalebi, 2013). This enhanced executive control translates to improved cognitive flexibility, attentional control, and working memory, all of which are crucial for language learning.

In addition, multilingual individuals tend to develop a heightened awareness of language as a system, known as metalinguistic awareness. This allows them to analyse and manipulate linguistic structures more effectively, facilitating learning new languages (Prat & Just, 2011). In terms of the cerebellum, Umejima et al. (2021) found multilinguals exhibited sustained cerebellum activation across new language learning phases, reflecting a more efficient and cumulative learning process. In contrast, bilinguals showed cyclic cerebellum activation, indicating that their cerebellum required re-engagement when exposed to new grammatical rules.

In this research, we used the Language History Questionnaire (LHQ) (P. Li et al., 2020) to assess the linguistic background of participants. This tool has now become widely used by scholars in bilingualism and multilingualism research. While the LHQ can evaluate language proficiency, we opted for Hong Kong Diploma of Secondary Education Examination (HKDSE) grades to represent Chinese and English proficiency, as they provide a more objective measure.

2.6.2.3 Language analytical ability

Language aptitude is often considered a set of abilities crucial for new language learning (Skehan, 2014). Within this framework, LAA stands out as a crucial facet, especially pertinent to vocabulary and grammar learning. LAA involves analysing and processing new linguistic input. People with high degrees of LAA tend to have faster word retrieval, be more sensitive to the grammatical structure of new languages, and can make linguistic generalisations easily. Although a previous AGL study found that cerebellar involvement was not driven by LAA (Kepinska et al., 2017a), this result may be limited by the participants' limited exposure to the new language, which prevented automatic processing from being reached. To address this limitation, this research set learning and training sessions before the fMRI experiment, ensuring participants had sufficient and sustained exposure to artificial language. However, it is important to note that the current research used an explicit learning mode, which differs from the approach taken by Kepinska et al. (2017a). This difference may lead to varying impacts of individual differences (Kalra et al., 2019). Moreover, Kepinska et al. (2017a) found that only the contrast testing for differential BOLD-response in ungrammaticality (ungrammatica > grammatical) yielded significant differences between high and low LAA participants.

To measure LAA, we used the Language Aptitude for Modern Language Aptitude (LLAMA) test (Rogers et al., 2023). The LLAMA test is a standardised tool designed to evaluate various dimensions of language aptitude, including phonetic coding ability, grammatical sensitivity, associative memory, and inductive language learning aptitude. For the purposes of this research, which centres on associative and grammar learning, we selectively chose two specific subtests: vocabulary and grammar tasks.

2.6.3 Summary

Individual differences in cognitive abilities, such as interference control, working memory, intelligence, and cognitive flexibility, can significantly influence neural efficiency and the cognitive load experienced during language learning tasks. These variations have been associated with increased cerebellar activity or cerebro-cerebellar connectivity (Ashida et al., 2019; Mariën & Borgatti, 2018; Nakatani et al., 2022). However, the existing studies have examined these abilities in isolation, without comparing their effects on language learning. Furthermore, although the effects of language proficiency, language experience, and language analytical ability on cerebral regions have been extensively studied, there is a lack of research examining how these language abilities are associated with cerebellar function.

Regarding individual differences, we investigated which cognitive or language abilities significantly modulate automatic and controlled processing, as well as correct-related and error-related processing. Specifically, the measures of individual differences were used to correlate activation and functional connectivity. Before conducting the neural imaging analysis, we performed correlation and regression analyses to examine their effects on the d-prime results, identifying individual difference measures for subsequent analysis.

CHAPTER 3

METHODOLOGY

This chapter outlines the methods used in the thesis. Our investigation has three main objectives: first, to explore the cerebellums role in artificial language learning, particularly from the internal model account. Second, to investigate how the internal cerebellar linguistic model contributes to language learning differently from the cortical and subcortical areas. Third, to examine how individual differences affect the internal model. To address these objectives, we collected both behavioural and imaging data from two cohorts. All the stimuli and experimental paradigms were calibrated using a pilot experiment involving 43 participants for the behavioural test and 6 participants for the fMRI test.

This project has obtained the Hong Kong Polytechnic University (PolyU) Faculty of Humanities Faculty Reserve for Research, Scholarly and Other Endeavors approval. Moreover, this project has received research safety approval (Reference number: ARSA-23205-OTH-CBS) from the PolyU Research Safety Committee, human ethical approval from the PolyU Institutional Review Board (IRB) (Reference number: HSEARS20230518004), and MRI approval from the PolyU University Research Facility in Behavioral and Systems Neuroscience (UBSN).

3.1 PARTICIPANTS

Thirty-eight young Hong Kong Cantonese speakers were recruited. The exclusion criteria include left dominance, a history of disease of the central nervous system, a history of mental illness, a history of neurodevelopmental disorders such as dyslexia, a history of cancer, and the identification of severe physical illnesses. Additionally, participants were screened using the PolyU UBSN MRI safety form to ensure there were no contraindications, such as dental brace and claustrophobia. All participants were native Cantonese speakers and reported having normal or corrected-to-normal vision. They provided written informed consent before participating and were compensated financially for their involvement.

Participants were divided into two cohorts. Cohort 1 consisted of 20 individuals who underwent one fMRI scan at the end of the experiment. Cohort 2 consisted of 18 participants who underwent two fMRI scans, one before the training sessions and one at the end. There were no significant differences between the two cohorts in terms of gender, age, education, or DSE grades. Table 3.1 summarizes the demographic information.

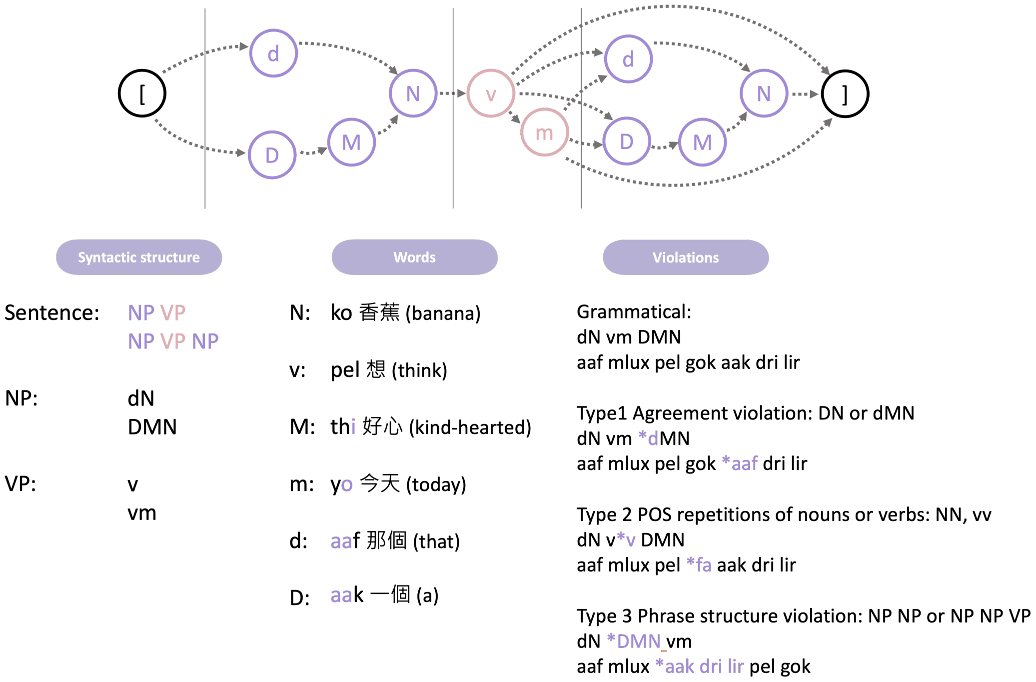
	Cohort 1 (n = 20)	**Cohort 2 (n = 18)**
Age	21.7 (19-27)	21.1 (19-25)
Education	15.25 (13-17)	15.27 (13-18)
Gender	11 females/9 males	9 females/9 males
Chinese DSE grade	3-5*	2-5*
English DSE grade	2-5	2-5*

Table 3.1: Demographics of the participants. DSE = Hong Kong Diploma of Secondary Education. Level 5 is the highest grade, and it is further divided into 5, 5* (five-star), and 5** (five-double-star). The 5* represents the top 30% of students who achieved Level 5. Level 1 is the lowest passing grade.

3.2 MATERIALS

The stimuli used in this project are based on the BROCANTO language, and the experimental design was adapted from Friederici et al. (2002), Opitz and Friederici (2003), Kepinska et al. (2017a), and Kepinska et al. (2017b). Figure 3.1 shows the schematic representation of the artificial language system in this research.

Thirty artificial words were created using BROCANTO as a reference, yet they were modified to suit the needs of the present research. There are eight nouns, eight verbs, six adverbs, six adjectives, and two determiners. These artificial words feature a distinct vowel



Syntactic structure

Sentence: NP VP
NP VP NP

NP: dN
DMN

VP: v
vm

Words

N: ko 香蕉 (banana)

v: pel 想 (think)

M: thi 好心 (kind-hearted)

m: yo 今天 (today)

d: aaf 那個 (that)

D: aak 一個 (a)

Violations

Grammatical:
dN vm DMN
aaf mlux pel gok aak dri lir

Type1 Agreement violation: DN or dMN
dN vm *dMN
aaf mlux pel gok *aaf dri lir

Type 2 POS repetitions of nouns or verbs: NN, vv
dN v*v DMN
aaf mlux pel *fa aak dri lir

Type 3 Phrase structure violation: NP NP or NP NP VP
dN *DMN vm
aaf mlux *aak dri lir pel gok

Figure 3.1: Representation of the artificial language system based on the BROCANTO structure. The top panel outlines the grammatical rules used to form sentences, with nodes indicating POS, including N for noun (e.g., ko, "banana"), v for verb (pel, "think"), M for adjective (thi, "kind-hearted"), m for adverb (yo, "today"), d for noun determiner (aaf, "that"), and D for adjective determiner (aak, "a"). Noun phrases (NP) are indicated in purple and verb phrases (VP) in pink. The lower panel provides a list of the syntactic structures, words, and ungrammatical violation types. The vowel hints for POS and grammatical errors within the sentences are highlighted in purple colour. For more details on the stimuli design, see Appendix A.

system that signals POS, except for nouns and verbs: o denotes adverbs, i denotes adjectives, and a denotes determiners. Nouns and verbs may contain any vowel–"a", "e", "i", "o", or "u". This vowel system allows for the clear differentiation of each POS while avoiding participants from focusing solely on vowel cues rather than engaging with word meaning and sentence structure. Then, each artificial word was assigned a Chinese meaning according to the POS. The mismatched word pairs were created by randomising the artificial words and their meanings.

Grammatical sentences ranging from 3 to 8 artificial words in length were constructed based on the subject-verb[-object] structure. The ungrammatical sentences were constructed based on the grammatical sentences according to the determiner-noun-agreement violation (Type 1), POS repetitions of nouns or verbs (Type 2), and phrase structure violation rules (Type 3). For fMRI sessions, only sentences ranging from 5 to 6 artificial words were used to control the covariates.

To make the artificial language more closely mimic authentic language use, all grammatical and ungrammatical sentences were designed to be semantically plausible. However, it is worth noting that some ungrammatical sentences, particularly those that fall under the Type 2 violation (e.g., noun phrase repetitions like "the banana the apple"), may inherently lack semantic plausibility due to the syntactic structure. For all learning, training, and fMRI sessions, the word occurrence, sentence length, and violation type were controlled. Artificial sentences in all sessions, tasks, and blocks were distinct.

3.3 EXPERIMENTAL PARADIGMS

Participants in Cohort 1 attended six visits, including one fMRI session after the training (Post-fMRI). Participants in Cohort 2 also attended six visits, with an additional fMRI session before the training (Pre-fMRI) and one fewer training session to ensure both cohorts achieved the same level of artificial language proficiency. To minimize fatigue and transient practice effects and to allow overnight consolidation, the Pre-fMRI and Post-fMRI sessions took place the day after the learning session and the last training session, respectively. All participants completed the artificial language experiment in four weeks.

3.3.1 Cohort 1

3.3.1.1 Screening

Before visiting the laboratory, participants were requested to complete a questionnaire for screening purposes. They were required to provide information about their age, gender, educational background, their dominant hand according to the Edinburgh Handedness Inventory (Oldfield, 1971), and results of an MRI safety screening.

3.3.1.2 Visit 1 (first week): behavioural test session

In the first visit, participants completed a cognitive battery using E-Prime 3.0 software programs[1]. The cognitive battery included: (1) Stroop test (Golden, 1978; Stroop, 1935), (2) Digit Span (forward) (Wechsler, 1955), (3) Reading Span (Just & Carpenter, 1980), (4) Raven's SPM (Raven, 2000), and (5) WCST (Grant & Berg, 1948).

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[1] https://pstnet.com/products/e-prime/

Furthermore, we measured specific language abilities, which are more specialised, focusing on skills tied to language use. Participants were asked to provide their DSE grades in both Chinese and English to measure their language proficiency. Furthermore, to test LAA, participants completed two subtests of Language Aptitude for Modern Language Aptitude (LLAMA) (Rogers et al., 2023), including LLAMA B (vocabulary) and LLAMA F (grammar). The online version of the LLAMA test [2] was developed based on the standardised Modern Language Aptitude Test (MLAT) (Carroll & Sapon, 1959). Participants also completed the online version of the Language History Questionnaire (LHQ3) (P. Li et al., 2020) [3] to measure their language experience. The detailed descriptions of these assessments and the questionnaire are provided below.

Stroop (~5 minutes). To assess the interference control, participants were asked to complete three tasks. In the first Word task (W), participants read a list of Chinese colour words (e.g., red and blue) in white ink displayed on a black background. In the following Colour task (C), participants named the colour of coloured blocks without any conflicting text. In the final Colour Word task (CW), participants saw colour Chinese characters printed in a colour that did not match the word itself (e.g., the word yellow in red), and they were asked to read the colour of the ink aloud. The participants were given 45 seconds for each task to name the word or the colour as quickly and accurately as possible. The score for each task was calculated by subtracting the number of incorrect responses from the total number of words read. Following the method used by Fong et al. (2021), the interference control score was calculated using Equation 3.1.

$$Interferencecontrol = CW^2/((W+C)/2) \tag{3.1}$$

Digit span forward (~10 minutes). This tests the working memory. Participants were asked to repeat the digits in the same order in which they were heard. Digits were presented in series spans that gradually increased in number from 4 to 14. Each span consisted of three trials, and the participant would proceed to the next span only when they answered two out of three trials correctly. The digit span was defined as the longest series that the participant could repeat. If participants correctly answered only one trial of the last span, 0.5 points were added to their digit span, but the test was discontinued.

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[2] https://www.llamatests.org

[3] https://lhq-blclab.org

Reading span (~20 minutes). This task measures working memory related to language processing. Participants were asked to read sentences aloud and remember the last phrase (i.e., two Chinese characters) of each sentence. The task consisted of five blocks, each containing three sections, with the number of sentences per section increasing from block to block (from two to six sentences). At the end of each section, they should recall all phrases in the correct order. The participants earned one point for each correctly recalled phrase but lost one point if the order was incorrect. The participants completed all the sections and blocks.

Ravens SPM (~22.5 minutes). This test assesses non-verbal abstract reasoning, particularly fluid intelligence. We used a modified version of Ravens SPM adapted from Hui et al. (2020). Participants were given 22.5 minutes to complete the test, which consisted of 30 questions. This adaptation maintained the tests challenge while fitting into a shorter time frame, allowing for assessment within half the duration of the full test. Each question featured an image with a missing piece located in the lower right corner. Participants had to select the correct piece from a set of 6 to 8 options to complete the image accurately.

WCST (~10 minutes). This task assesses executive functions, particularly cognitive flexibility. Participants were asked to sort cards according to different criteria (i.e., colour, shape, or number) as quickly as possible. They received feedback immediately after pressing the button. The sorting rules changed every 10 trials, and the participants were unaware of the sorting and changing rules, requiring them to adjust their strategies based on the feedback. There were four practices and 60 critical trials in total. Task parameters include the mean accuracy, the number of perseverative errors (e.g., when a participant continues to sort cards according to a previously correct rule), the number of non-perseverative errors (e.g., when a participant makes an incorrect sort that does not follow the previously correct rule), and the mean reaction time.

LLAMA vocabulary task (~7 minutes). This task assesses participants language memory and declarative learning ability. The participants were presented with a set of 20 unfamiliar objects and were asked to memorise their names within 2 minutes. The program then asked the participants to click the object according to the given name, but there was no time limit for this part. This task can typically be completed in 5 minutes, with a maximum possible score of 20.

LLAMA grammar task (~14 minutes). This task assesses participants ability to learn the grammatical rules of a novel language (procedural learning ability). This task consists of two parts. In the learning part, participants were required to learn grammar rules by extracting the associations between 20 figures and 20 artificial phrases within a four-minute time frame, during which they were permitted to take notes. In the untimed assessment

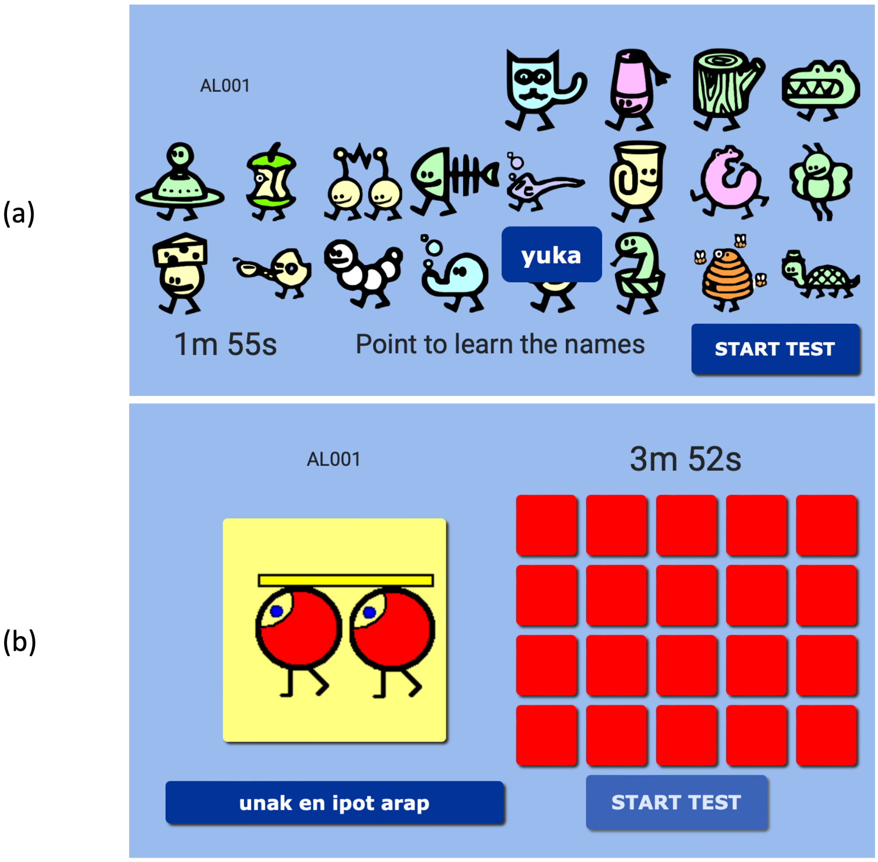

Figure 3.2: Examples of the learning part of LLAMA test. (a) LLAMA vocabulary task. Participants learned the names of 20 unfamiliar objects in two minutes. (b) LLAMA grammar task. Participants learned the grammar rules based on the 20 figures and artificial phrases in four minutes.

part, they were required to use artificial phrases to describe new figures, and they were allowed to refer to the notes. This part could usually be finished in 10 minutes. The task has a total possible score of 20. Figure 3.2 shows examples of the learning part of LLAMA vocabulary and grammar tasks.

LHQ (~10 minutes). The modular version of LHQ was used to assess proficiency, dominance, and usage. The parameters included L1 proficiency score, L2 proficiency score, L1 immersion score, L2 immersion score, L1 dominance score, L2 dominance score, L1 to L1 dominance ratio, L2 to L1 dominance ratio, and multilingual language diversity score.

3.3.1.3 Visit 2 (second week): learning session

In the second visit, participants completed the learning session on artificial language using the Gorilla platform[4]. Before the session, participants were taught association and grammar rules explicitly by watching a five-minute video. Then, they completed four tasks: Associative Learning (AL), Associative Judgment (AJ), Grammar Learning (GL), and Grammar Judgment (GJ). The description of the learning session is provided below.

AL task (~10 minutes). In the AL task, participants learned the association between 30 pairs of artificial words and Chinese meanings. Each pair was presented for 5 seconds after a fixation (1 second). Moreover, to enhance memorisation, an icon representing the Chinese meaning was supplied alongside each word pair during AL. There were three blocks, each containing 30 matched pairs.

AJ task (~5 minutes). Each AL block was followed by an AJ block. In the AJ task, participants were instructed to judge whether the association between the artificial word and its Chinese meaning was correct within 3 seconds by pressing a button, followed by instant feedback on whether the response was correct or not (1 second). A green tick symbol was used to indicate that the response provided by the participants was correct, whereas a red cross symbol was used to indicate an incorrect response. If participants failed to respond in 3 seconds, no feedback was provided. Each AJ block consisted of 20 trials, equally divided into 10 matched and 10 mismatched pairs.

GL task (~15 minutes). In the GL task, participants were instructed to infer the artificial grammatical rules of the language. Following a fixation (1 second), grammatically correct sentences containing 3-8 artificial words were presented for 10 s. There were three blocks, and each GL block comprised 20 grammatical sentences.

GJ task (~10 minutes). Each GL block was followed by a GJ block, and there was an extra GJ block at the end. In the GJ task, participants judged whether a sentence was grammatical or not within 6 seconds, and instant feedback was provided after they pressed the button. Each GJ block contained 24 trials, with 12 grammatical and 12 ungrammatical sentences. To facilitate a gradual learning curve for participants, the complexity of the GL and GJ tasks was incrementally increased across the first three blocks. In the first GL and GJ block, participants learned and judged shorter sentences consisting of 3-5 artificial words, easing them into the task. The difficulty was increased in the second block with sentences of 5-6 words. In the third block, participants were challenged with sentences comprising the longest words, ranging from 7 to 8 words. To assess the performance improvement dur-

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[4] https://gorilla.sc

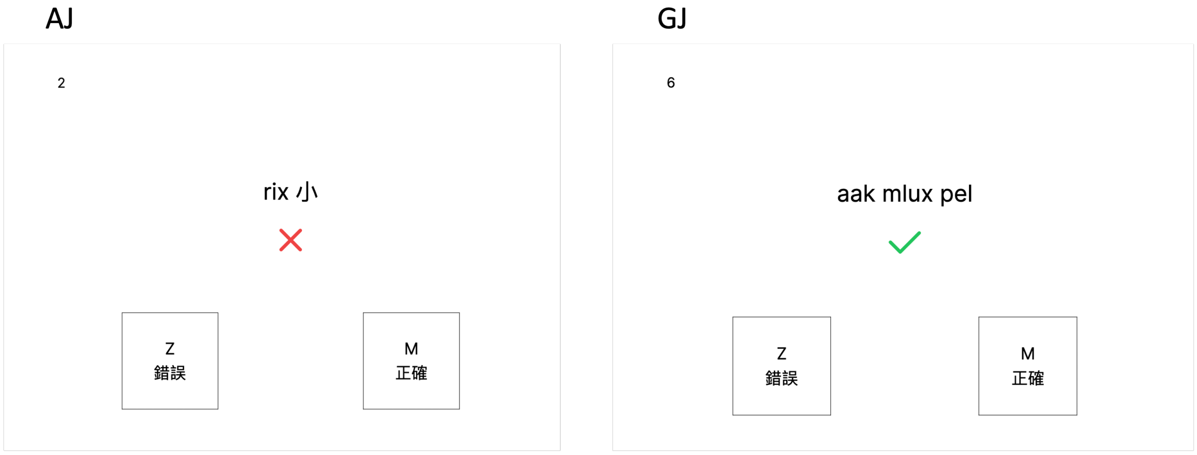

Figure 3.3: Examples of Associative Judgment and Grammar Judgment tasks in learning and training sessions. Participants made judgments by pressing Z or M on the keyboard. The green tick feedback represents that the participant made a correct judgment, whereas a red cross indicates an incorrect judgment. The countdown is shown in the upper left corner. AJ = associative judgment; GJ = grammar judgment.

ing the learning session, the fourth block was designed for comparison with the first block, which included sentences of 3-5 words. Figure 3.3 shows the examples of AJ and GJ tasks.

After the learning session, participants were provided with printed materials containing all the artificial words and their Chinese meanings, along with the grammar rules. This material served as a reference for participants to reinforce their understanding of artificial language and aid them in further training and fMRI sessions. Participants were allowed to retain the printed materials throughout the experiment.

3.3.1.4 Visit 3-5 (third and fourth week): exercises and training sessions

During the training sessions (three sessions), participants first completed a written exercise, during which they were allowed to refer to the printed materials. This exercise was for familiarisation, so the results were not used for further analyses. Instructions were provided by the experimenter if participants were unable to complete the exercise successfully. Then, they were asked to complete the Gorilla training session. The participants were required to achieve at least 75% accuracy for both AJ and GJ tasks during the second training session. If they failed to meet this criterion, they were required to complete an additional training session before proceeding to the final training session. Only one participant underwent a total of four training sessions. The next paragraphs describe the implementation of the tasks.

Exercises (~10 minutes). This exercise includes matching, translation, and correction tasks. In the matching exercise, participants associated the eight artificial words with their corresponding Chinese meanings. In the translation exercise, participants were required to translate six Chinese sentences or artificial sentences, not word by word but according to the correct grammar rules. In the correction exercise, participants were tasked with correcting six ungrammatical sentences.

Training sessions (~30 minutes). In each training session, participants had four minutes to learn the rules and then completed one AL block, three AJ blocks, two GL blocks, and two GJ blocks (each GL block was followed by a GJ block). They were unable to use the printed material during the training sessions. The presentation of stimuli and the number of trials in each block remained consistent with the learning session. However, sentence lengths were randomised across blocks. The last training session was completed the day before the MRI session.

3.3.1.5 Visit 6 (fourth week): fMRI session

Before the scanning session, participants did a mock test for familiarisation using the E-Prime program. The mock test comprised 10 AJ trials and 14 GJ trials. During the fMRI session, participants completed AJ and GJ tasks, followed by T1 and T2-weighted Sampling Perfection with Application-optimized Contrasts (T2w_SPC) scans. The fMRI tasks for AJ and GJ were also implemented using E-Prime. Details are provided below.

AJ fMRI task (10 min). Each trial began with a fixation cross for 0.8 seconds, followed by an artificial word for 0.8 seconds and its Chinese meaning for 2.4 seconds. Participants had 2.4 seconds to judge whether the pair was associated via button press. Feedback then appeared for 1.6 seconds, indicating the correctness of the word pair (not the participants response): a red checkmark signaled a correct pair, and a red cross signaled an incorrect pair. Feedback congruent with the participants response was defined as positive; incongruent feedback as negative. A blank interstimulus interval (ISI) of 0.8, 1.6, or 2.4 seconds followed. The task consisted of six blocks, each containing 10 trials (five matched and five mismatched pairs); the first two trials in each block served as fillers. A rest block of 24 seconds followed each AJ block. During rest, participants were instructed to keep their eyes open and refrain from rehearsing the artificial language.

GJ fMRI task (22 min). Each trial began with a fixation cross, after which a sentence of 56 artificial words was presented for 3.2 seconds. Participants judged its grammaticality within the 3.2 seconds during which the sentence was displayed, after which feedback and the ISI were shown. The task consisted of 16 blocks, each containing seven trials, with the

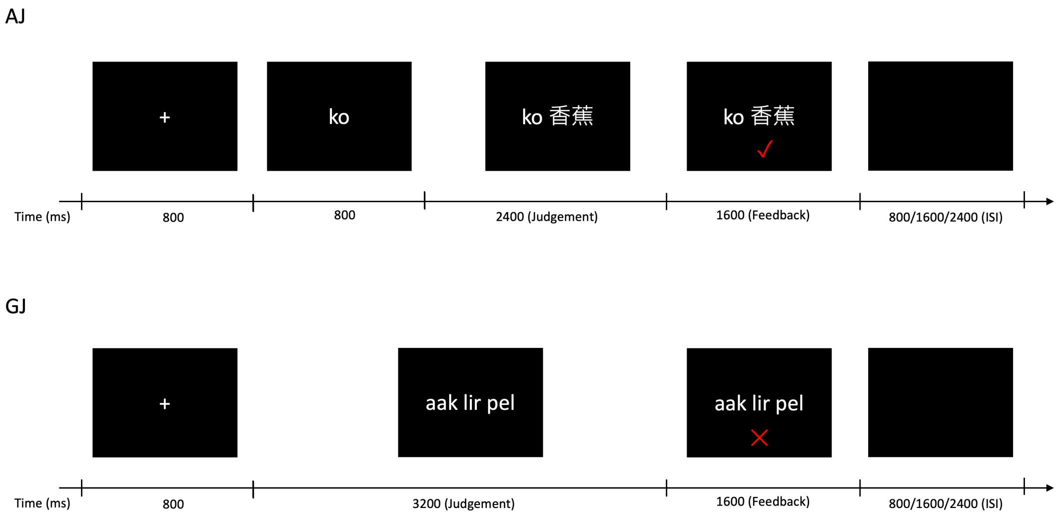

Figure 3.4: Examples of AJ and GJ tasks in fMRI sessions. Red tick feedback indicates a matched word pair or grammatical sentence, while a red cross indicates a mismatched or ungrammatical one. Feedback was provided regardless of whether the participant made a response. AJ = associative judgment; GJ = grammar judgment.

first trial in each block serving as a filler. Each block contained three grammatical sentences and three ungrammatical sentences (one per violation type). A rest block of 24 seconds followed each GJ block. Word occurrences were controlled across the AJ and GJ tasks. Figure 3.4 shows example trials for the AJ and GJ fMRI tasks.

The stimuli were carefully designed. For each grammatical structure, three corresponding ungrammatical structures were created. The ungrammatical sentences contained no more than two different artificial words compared to the grammatical sentences. In cases of phrase structure violations (Type 3), the artificial words were the same, but the structure differed. Additionally, half of the ungrammatical sentences were presented prior to their grammatical counterparts, and half were presented subsequently. Notably, the ungrammatical sentences were not within the same block as the grammatical sentences. Table 3.2 shows the selected grammar structures for the GJ fMRI task.

3.3.2 Cohort 2

For Cohort 2, the procedures and stimuli remained largely consistent with Cohort 1 (see Figure 3.5 for experimental design). After completing the questionnaire, participants proceeded to engage in one behavioural test session, one learning session, one Pre-fMRI session, two training sessions, and one Post-fMRI session.

Grammatical	Type 1	Type 2	Type 3
dNvdN	DNvdN	dNvvm	dNdNv
DMNvdN	dMNvdN	dNNvdN	DMNdNv
dNvDMN	DNvDMN	dNvdNN	dNDMNv
dNvmdN	DNvmdN	dNvvdN	dNdNvm

Table 3.2: Artificial grammar structures in the GJ task. Type 1: determiner-noun-agreement violation, Type 2: POS repetitions of nouns or verbs, Type 3: phrase structure violation. N: noun, v: verb, M: adjective, m: adverb, d: noun determiner, D: adjective determiner. Magenta words are the words that are different from the grammatical sentence. GJ = grammar judgment.

The first visit (behavioural test session) was in the first week. The second visit (language test and learning session) and the third visit (Pre-fMRI) were in the second week. The Pre-fMRI session took place the day after the learning session. The fourth visit (Training 1) was in the third week. The fifth visit (Training 2) and the sixth visit (Post-fMRI) were in the fourth week. The Post-fMRI session took place the day after the last training session. During both fMRI sessions, participants performed AJ and GJ tasks, followed by T1 and T2w_SPC scans. The Post-fMRI used the same stimuli as those for the Cohort 1 Post-fMRI session, but the Pre-fMRI and Post-fMRI used different stimuli. In all learning, training, and fMRI sessions, word frequency, sentence length, and violation type were carefully regulated. The artificial sentences used across sessions, tasks, and blocks were unique.

3.4 DATA ACQUISITION AND ANALYSIS

3.4.1 Imaging Protocol

A Siemens MAGNETOM 3.0T XR MRI (Siemens Medical System, Erlangen, Germany) was utilised with a 32-channel head coil. Functional images were collected using a multi-slice EPI sequence (FOV = 208 mm, TE = 37 ms, TR = 800 ms, flip angle = 52°, voxel size = $2 \times 2 \times 2\,\text{mm}^3$, slice thickness = 2.0 mm, and SMS acceleration factor = 8).

High-resolution T1-weighted structural images were acquired using a 3D sequence (FOV = 256 mm, TR = 2500 ms, TE = 2.22 ms, flip angle = 8°, voxel size = $0.8 \times 0.8 \times 0.8\,\text{mm}^3$, slice thickness = 0.8 mm, and GRAPPA acceleration factor = 2). The T2-weighted scan was conducted using a 3D SPC sequence (FOV = 256 mm, TR = 3200 ms, TE = 563 ms, flip angle

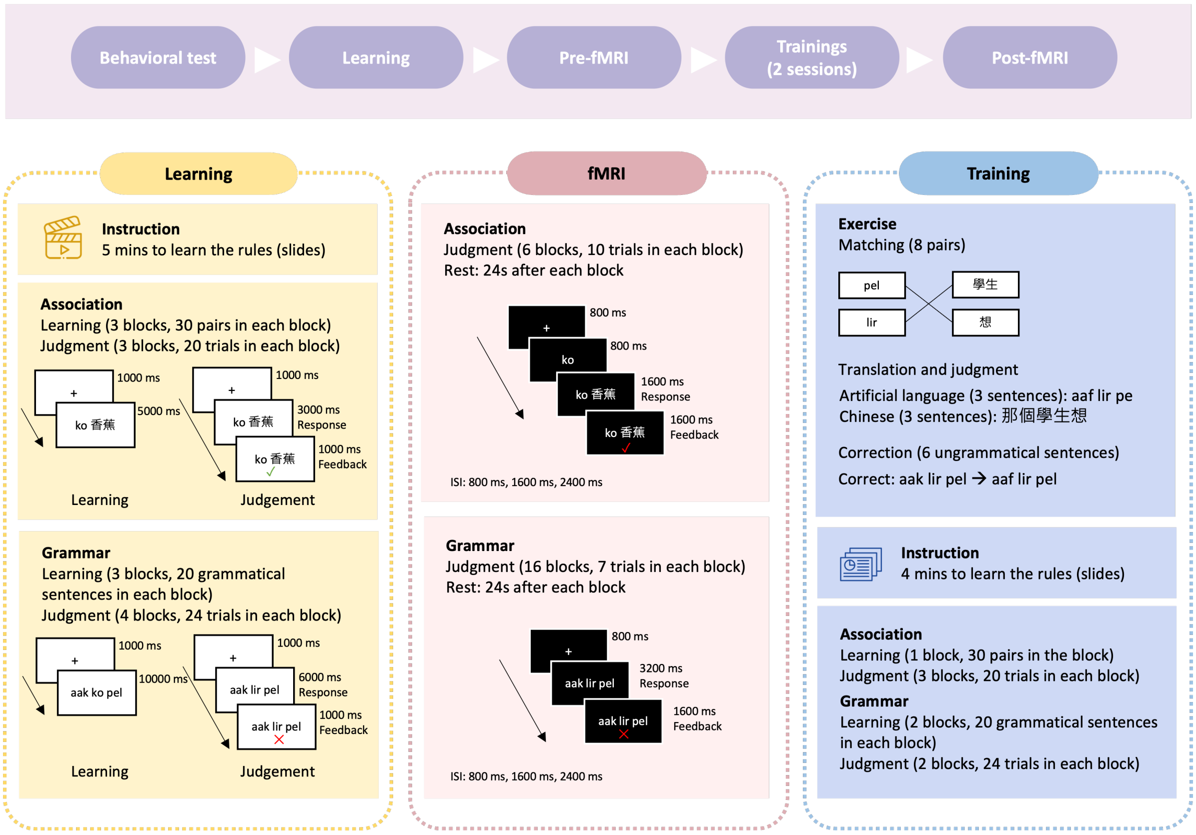

Figure 3.5: Experimental design for the longitudinal experiment (Cohort 2). In the learning session, participants were first instructed to learn the association and grammar rules explicitly. Then, participants completed four tasks. (1) In Associative Learning, participants learned the association of artificial words and Chinese meanings. (2) In Associative Judgment, participants judged whether the Chinese meanings and artificial words were matched correctly through a button press. (3) In Grammar Learning, participants were presented with grammatically correct sentences and were instructed to extract the underlying grammatical rules. (4) In Grammar Judgment, participants judged whether a sentence was grammatical through a button press. Feedback on whether the response was correct or incorrect was provided immediately after the button was pressed. In fMRI sessions, participants completed Association Judgment and Grammar Judgment tasks. Feedback on word association or sentence grammaticality was provided after every trial. Positive feedback refers to feedback that is consistent with the participant's response and vice versa. The training sessions included an exercise where participants were tasked with completing matching, translation, and correction exercises before the instruction and artificial language tasks.

mode = 120°, voxel size = $0.8 \times 0.8 \times 0.8\,\text{mm}^3$, slice thickness = 0.8 mm, and GRAPPA acceleration factor = 2).

3.4.2 Power Analysis

A power analysis was conducted to determine the minimum sample size required to test the hypothesis of a significant change in neural activity between the two fMRI scanning sessions within the same condition. The analysis was performed using G*Power software (Faul et al., 2007). The analysis for t-test indicated that a total sample size of N = 17 participants would be sufficient to achieve 80% power (effect size = 0.65, alpha level = 0.05). To ensure a robust margin for potential data loss (e.g., excessive motion, technical artifacts) and to exceed the minimum power threshold, the sample size was increased. Consequently, a final cohort of N = 18 participants was recruited for between-session comparison and Pre-fMRI investigation, and a cohort of N = 38 was used for Post-fMRI investigation.

3.4.3 Behaviour Data Analysis

The data was organised using Python (Spyder version 5.3.3 [5] in Anaconda[6]) and analysed by R (RStudio version 2023[7]). Statistical significance was determined using a threshold of $p < .05$. Learning performance was assessed using the d-prime in learning, training, and fMRI sessions.

To summarize the overall degree of cognitive and language abilities, we entered the measures from individual tests into a Principal Component Analysis (PCA) using R. The test scores were normalized by converting them to z-scores, controlling for the scale differences between the various tests. To ensure higher scores reflect better ability, we inverted the WCST perseverative error and WCST reaction time values by taking their negatives. We conducted two PCA analyses based on selected cognitive or language ID factors. We expected that the first principal component (PC1) returned from PCA would serve as an overall measurement of the two domains, ensuring parsimony while capturing most of the variance without overfitting.

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[5] https://www.spyder-ide.org

[6] https://www.anaconda.com

[7] https://posit.co/download/rstudio-desktop/

3.4.4 Imaging Data Preprocessing and Denoising

Functional images were preprocessed and analysed using SPM12 software (Wellcome Trust for Neuroimaging, Institute of Neurology, University College, London, UK) with the Conn toolbox (Whitfield-Gabrieli & Nieto-Castanon, 2012) in MATLAB (version 2021b[8]).

Functional and anatomical data were preprocessed using the default Conn preprocessing pipeline, including realignment with correction of susceptibility distortion interactions, slice timing correction, outlier detection, direct segmentation, MNI-space normalisation, and smoothing. Functional data were realigned using the SPM realign and unwarp procedure with coregistration to the first scan and b-spline interpolation. Slice-timing correction used sinc interpolation to align slice times. Outliers were identified with Artifact Detection Tools (ART) based on framewise displacement and blood oxygenation level-dependent (BOLD) signal changes. Data were normalised to MNI space and segmented into tissue classes with unified segmentation. Finally, functional data were smoothed using spatial convolution with a Gaussian kernel of 6 mm full-width at half-maximum (FWHM). For activation analysis, smoothed functional images were entered into a first-level analysis to regress out six motion parameters, and a 128-second high-pass filter was applied to remove low-frequency signals.

In addition, for functional connectivity analysis, functional data were denoised using a pipeline that regressed out confounding effects: white matter and CSF Component-based Noise Correction (CompCor) components (5 each), motion parameters and derivatives (12), outlier scans, session/task effects and derivatives (12), and linear trends (2). This was followed by bandpass filtering between 0.008 Hz and 0.09 Hz. CompCor components were calculated using the average BOLD signal and principal components from eroded segmentation masks. The effective degrees of freedom post-denoising ranged from 79.4 to 90.4, with a mean of 89.3 across participants.

3.4.5 Imaging Data Analysis

3.4.5.1 ROI selection

The internal-model hypothesis posits that cognitive tasks elicit simultaneous activation of the cerebellum, prefrontal cortex, and temporoparietal cortex (Ito, 2008). Accordingly, we expect language-related regions in the cerebellum and cerebrum to be co-activated dur-

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[8] https://www.mathworks.com/products/matlab.html

ing artificial-language acquisition. Because subcortical structures are integral to cerebello-cerebral communication, we also examined these regions. We conducted both activation and functional connectivity analyses within predefined ROIs.

ROIs were selected based on prior literature (see Table 3.3 for the full list). The superior frontal gyrus (SFG), broadly implicated in higher cognition and executive control, is recruited during linguistic planning (Kulik et al., 2023). Semantic processing supports associative learning, whereas syntactic processing supports grammar learning. Semantic processing engages the language-comprehension network, including the IFG, MFG, inferior parietal lobule (IPL), and left MTG (Binder et al., 2009; Jackson et al., 2016; Matchin et al., 2022; Molinaro et al., 2015). In addition, the IFG, left superior temporal gyrus (STG), left MTG, and IPL are key for processing syntactic structure (Chen et al., 2019; Matchin et al., 2017; Matchin & Hickok, 2020; Skeide et al., 2015). Posterolateral cerebellar regions, particularly Crus I/II, also contribute to syntactic and semantic processing (Nakatani et al., 2022; Saadon-Grosman et al., 2024; Schmahmann, 2019).

From the perspective of cerebello-cerebral loops, the cerebellum modulates cerebral activity via thalamic relays, including pathways to the right IFG and to BG structures such as the caudate nucleus (Yuan et al., 2022). The thalamus, a key relay between the cerebrum and cerebellum, plays an important role in language processing (Bulut & Hagoort, 2024). The cerebellum also interacts with the IFG and with subcortical nuclei of the BG–the caudate, pallidum, and putamen–which have been implicated in procedural learning (Ullman, 2004). Moreover, the hippocampalneocortical interactions framework holds that coordinated activity between the hippocampal formation and neocortex supports memory encoding, consolidation, and storage (Morris, 2006; S.-H. Wang & Morris, 2010). Consistent with this account, the hippocampal system and prefrontal cortex are critical in early L2 acquisition, particularly for learning new vocabulary and grammar (Breitenstein et al., 2005; Kepinska et al., 2018).

3.4.5.2 Neural activation analysis

Individual-level analysis. The neural activation analysis was performed using SPM12. For the Pre-fMRI analysis, we used only data from Cohort 2, whereas for the Post-fMRI investigation, we combined data from Cohorts 1 and 2. In the individual-level analysis, we constructed general linear models (GLM) to explore the neural activations associated with AJ and GJ.

The AJ GLM contained conditions of four POS, including noun, adjective, adverb, and verb. For the examination of automatic versus controlled processing, we created another

Region	**ROI**
Prefrontal cortex	Inferior frontal gyrus (Frontal_Inf_Oper_L, Frontal_Inf_Oper_R, Frontal_Inf_Tri_L, Frontal_Inf_Tri_R, Frontal_Inf_Orb_L, Frontal_Inf_Orb_R), Middle frontal gyrus (Frontal_Mid_L, Frontal_Mid_R, Frontal_Mid_Orb_L, Frontal_Mid_Orb_R), Superior frontal gyrus (Frontal_Sup_L, Frontal_Sup_R, Frontal_Sup_Orb_L, Frontal_Sup_Orb_R)
Temporal cortex	Left superior temporal gyrus (Temporal_Sup_L), Left middle temporal gyrus (Temporal_Mid_L)
Parietal cortex	Inferior parietal lobe (Angular_L, Angular_R, SupraMarginal_L, SupraMarginal_R)
Subcortical regions	Basal ganglia (Caudate_L, Caudate_R, Putamen_L, Putamen_R, Pallidum_L, Pallidum_R), Thalamus (Thalamus_L, Thalamus_R), Hippocampus (Hippocampus_L, Hippocampus_R), Parahippocampal (Parahippocampal_L, Parahippocampal_R)
Cerebellar regions	Crus I (Cerebellum_Crus1_L, Cerebellum_Crus1_R), Crus II (Cerebellum_Crus2_L, Cerebellum_Crus2_R)

Table 3.3: ROIs for imaging data analysis. ROIs were defined by AAL using the WFUPick-Atlas toolbox. L = Left, R = Right, Inf = Inferior, Sup = Superior, Mid = Middle, Orb = Orbital, Oper = Opercular, Tri = Triangular.

GLM containing six regressors (i.e., conditions): Fixation, judgment of matched word pairs (Word_mat), judgment of mismatched word pairs (Word_mis), Feedback_word, Rest, and ISI. The judgment condition does not include the presentation of artificial words. The six movement parameters were included in the design matrix as regressors of no interest. Moreover, three contrasts were defined: Word (Word_mat + Word_mis) > Rest, Feedback_word > Rest, and Word_mat > Word_mis.

The GJ GLM contained conditions of four grammar types. Moreover, for automatic versus controlled processing, we created another GLM that included six regressors: Fixation, judgment of grammatical sentence (Sentence_gra), judgment of ungrammatical sentence (Sentence_ung), Feedback_sen, Rest, and ISI. The six movement parameters were also included in the design matrix. Three contrasts were defined: Sentence (Sentence_gra + Sentence_ung) > Rest, Feedback_sen > Rest, and Sentence_gra > Sentence_ung. To examine the correct-related and error-related processing, we also created a GLM based on the correctness of judgment and the information of feedback. Positive/negative feedback is defined as the feedback in correct/incorrect trials. We created two contrasts: Sentence_cor > Sentence_inc, and Feedback_pos > Feedback_neg. The incorrect trials include missed trials.

Group-level analysis. For the group-level analysis, ROI analysis was performed to explore the cerebro-subcortical-cerebellar network. The ROIs were defined by automated anatomical labelling (AAL) using WFUPickAtlas toolbox[9] (ANSIR Laboratory, Wake Forest University School of Medicine, Winston-Salem, NC, USA). For the investigation of automatic and controlled processing, as well as learning- and error-related processing, we used whole-brain analysis. The whole cerebellum mask was applied when examining cerebellar activation. For the cerebrum, uncorrected $p < .001$ at voxel level and FDR-corrected $p < .05$ at cluster level were considered to be statistically significant. For the cerebellum, uncorrected $p < .001$ at voxel level and voxel > 20 at cluster level were considered to be statistically significant. For visualisation, spatially unbiased atlas template of the cerebellum and brainstem (SUIT) flatmap [10], BrainNet Viewer[11] (Xia et al., 2013), and MRIcroGL[12] were used.

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[9] https://www.nitrc.org/projects/wfu_pickatlas/

[10] https://www.diedrichsenlab.org/imaging/suit.htm

[11] https://www.nitrc.org/projects/bnv/

[12] https://www.nitrc.org/projects/mricrogl

3.4.5.3 Functional connectivity analysis

Individual-level analysis. The functional connectivity analysis was performed using the Conn toolbox. The psychophysiological interaction analyses (gPPI) were used to study the changes in functional connectivity across the same participant samples and contrasts as in the neural activation analysis. The field map was estimated and used for susceptibility distortion correction. For each seed-target pair, a gPPI model was defined using seed BOLD signals as physiological factors, task boxcar signals convolved with an SPM hemodynamic response function as psychological factors, and their outcome as gPPI terms. The default atlas of the Conn toolbox was used. This atlas was created based on the Harvard-Oxford cortical and subcortical areas atlas and the AAL cerebellar areas atlas.

Group-level analysis. The group-level analysis was performed using GLMs. Then, the ROI-to-ROI connectivity analysis was first performed to investigate the cerebro-subcortical-cerebellar network, using bilateral Crus I/II as seed regions. For each voxel, a separate GLM was estimated with connectivity measures as dependent variables and group identifiers as independent variables. Results were thresholded using uncorrected $p < .001$. To investigate automatic versus controlled and learning-related versus error-related processing, the gPPI analysis was then conducted on the whole-brain level, assessing seed-to-voxel connectivity using bilateral Crus I/II as seed regions. Results were thresholded using uncorrected $p < .001$ at voxel level and FDR-corrected $p < .05$ at cluster level.

3.4.5.4 Representational Similarity Analysis

We conducted the RSA using the Decoding Toolbox (Hebart et al., 2015). For AJ, we used non-normalised and unsmoothed data of each participant and included the following conditions: (1) noun; (2) adjective; (3) adverb; and (4) verb. For GJ, we used (1) Sentence_ung_type1; (2) Sentence_ung_type2; (3) Sentence_ung_type3; and (4) Sentence_gra. This approach avoids the loss of spatial information that normalisation or smoothing might introduce. RDMs were computed for each participant separately for each of the abovementioned ROIs. In each subject and for each ROI, the RDMs (1 Pearson's similarity score) were calculated for brain activity patterns elicited by grammaticality conditions. ROIs were coregistered for each participant to ensure that the neural activity patterns were aligned with the individual's brain anatomy. To generalise findings across participants, RDMs were averaged across subjects for each ROI. Furthermore, we compared the RDMs using multidimensional scaling (MDS) and hierarchical clustering.

3.4.5.5 Dynamic causal modeling

ROI selection and extraction. We used SPM12 to conduct DCM to explore the differences in automatic and controlled processing. To apply DCM, cerebellar ROIs representing associative and grammar learning processing were taken from Nakatani et al. (2022), involving the right Crus I (28 -74 -28) and right Crus II (16 -88 -36). For cerebrum ROIs, the left IFG was identified in the semantic network (Binder et al., 2009) and grammar network (Petersson et al., 2012). Moreover, the thalamus serves as the key intermediary structure in the cerebral-cerebellar loop (Buckner, 2013; Habas, 2021). The right Crus I/II sends its output via the deep cerebellar nuclei, particularly the dentate nucleus, crosses to the left thalamus, and the cerebral cortex. Therefore, left IFG (-44 10 28) and left thalamus (-8 -16 6) were selected as ROIs and they were centred around the mean MNI coordinates reported in the meta-analyses by Bulut and Hagoort (2024).

For each participant, ROIs were created by extracting the time series using the eigenvariate within a sphere with a radius of 8 mm (cerebrum) or 5 mm (cerebellum) after setting a whole-brain threshold of the contrast Word > Rest or Sentence > Rest at $p < .001$ (uncorrected). The sphere center of each ROI was moved to the closest supra-threshold voxel within the boundaries of the functional ROI as assessed by the AAL atlas. All voxels contributing to the ROIs were adjusted for the effects of interest (i.e., matched vs. mismatched and grammatical vs. ungrammatical) for exploring automatic and controlled processing. The ROIs were successfully defined in all 38 participants (Pre-fMRI: n = 18, Post-fMRI: n = 38).

Individual-level analysis. To specify task-induced changes in directional information flow among the cerebro-subcortical-cerebellar network, we performed DCM analysis based on the selected ROIs. We created the automatic model and the controlled model (Figure 3.6) for both Pre-fMRI and Post-fMRI. We used the deterministic bilinear DCM to describe the neuronal dynamics of the artificial language learning network:

$$dx/dt = (A + uB)x + Cu \tag{3.2}$$

Here, vector x represents the state (associative or grammar judgment > rest), and vector u represents external input. DCMs were specified for each of the fMRI sessions (Pre-AJ, Pre-GJ, Post-AJ, and Post-GJ) separately using SPM12. To specify task-induced changes, we created automatic and controlled DCMs based on the full model, differing solely in their modulatory effects. The A matrix represents the fixed or intrinsic connectivity (context-independent). We assumed bidirectional connections between all ROIs.

The B matrix represents the modulatory effects of association or grammaticality on connections (context-dependent). The full model assumed the modulatory effects of automatic or controlled conditions on all connections. For the automatic model, we predicted that matched or grammatical conditions strengthen cerebellar-driven automatic processing (right Crus I/II → left thalamus → left IFG and right Crus I/II → left IFG) and the intrinsic right Crus I/II connection. On the contrary, mismatched or ungrammatical conditions may enhance top-down control (left IFG → left thalamus → right Crus I/II and left IFG → right Crus I/II) and the intrinsic left IFG connection, as the IFG drives the network to handle semantic or syntactic incongruity. For the controlled model, we predicted that matched or grammatical conditions would enhance forward processing and the intrinsic left IFG connection, while mismatched or ungrammatical conditions would increase cerebellar feedback and the intrinsic right Crus I/II connection due to prediction errors or grammatical violations. The C matrix specifies the driving inputs. We predicted that the left IFG is the entry point for language stimuli.

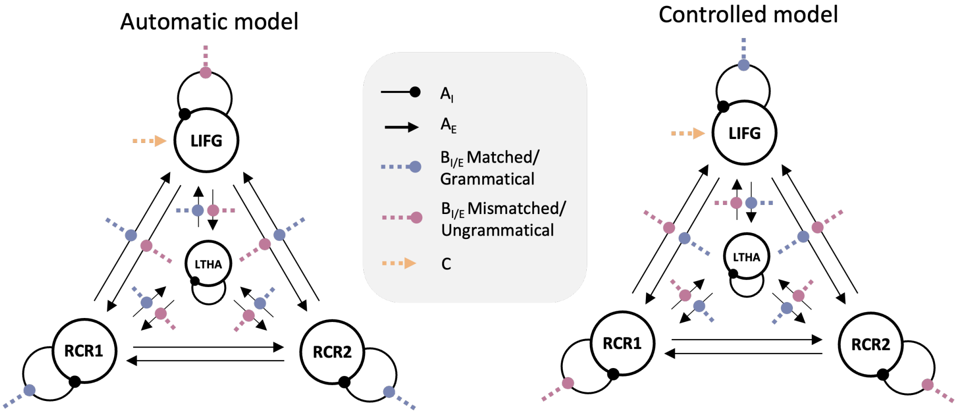


Figure 3.6: DCM design for automatic and controlled processing. The models mainly differ in where the modulatory effects of associativity or grammaticality had effects. A = fixed or intrinsic connectivity. B = modulatory effects of association or grammaticality. C = driving input. I = internal; E = external. IFG = inferior frontal gyrus. THA = thalamus. CR1 = Crus I. CR2 = Crus II. L = left. R = right.

Group-level analysis. To determine which model best explains the observed pattern, we constructed parametric empirical Bayes (PEB) models for the whole group of participants with d-prime as a covariate. This approach enables the estimation of effective connectivity averaged across all participants, taking into account participant variability in the connectivity parameters. Then, we compared the evidence for the automatic and controlled models using Bayesian model comparison (BMC). The threshold for the significant effective connectivity was set at posterior probabilities greater than 95% ($P > .95$).

3.4.5.6 Individual difference effects

The individual difference investigation was based on the contrast between automatic versus controlled and learning-related versus error-related processing (Pre-fMRI: n = 18, Post-fMRI: n = 38). Based on the behavioural results, 12 individual difference factors were selected: Interference control, digit span, reading span, Raven's SPM score, WCST perseverative error, WCST reaction time, Chinese DSE grade, English DSE grade, LLAMA_B score, LLAMA_F score, L1 immersion, and multilingual language diversity. These factors were summarized in the Cognitive PC1 and Language PC1 measures, with higher values reflecting better abilities. Furthermore, fMRI task d-primes and reaction times were investigated as proficiency factors for RQ 1 and 2. The d-prime score is a measure of sensitivity in signal detection theory, used to quantify the ability to distinguish between signal and noise. The equation is given by:

$$d' = Z(H) - Z(F) \tag{3.3}$$

where: H is the hit rate, the proportion of correct responses to signal trials. F is the false alarm rate, the proportion of incorrect responses to noise trials, not including missed trials. $Z()$ is the z-score function, converting a proportion to a standard normal deviate.

Neural activation analysis. The analysis of neural activation was performed using SPM12. We employed a multiple regression model within a factorial design framework to investigate the relationships between neural responses and individual difference measurements. For each contrast, each individual difference factor was entered as a predictor to account for variability across participants. We only examined whether individual difference factors would affect cerebellar activation, applying a whole cerebellum mask and setting the threshold as uncorrected $p < .001$ at voxel level and voxel > 20 at cluster level.

Functional connectivity analysis. The Conn toolbox was used for the functional connectivity analysis of individual difference effects. Between-subject effects were identified as the second-level covariates. Then, the individual difference effects were examined using the ROI analysis, with bilateral Crus I/II as seed regions. The threshold for statistical significance was set to FDR-corrected $p < .05$.

CHAPTER

4

RESULTS

This chapter presents thesis results. Firstly, we examined behavioural outcomes to evaluate learning performance in artificial language tasks and explore how individual differences correlate with task performance. Subsequently, we analysed fMRI data to address three aspects of the RQs. For RQ1 or RQ2, to investigate the cerebro-subcortical-cerebellar network, we assessed neural activation and functional connectivity patterns using ROI analysis. To explore differences in automatic and controlled processing, we used whole-brain analysis to examine how task proficiency influences these patterns under automatic versus controlled conditions and analysed information flow among the cortical-subcortical-cerebellar network. To investigate correct-related and error-related activity, we examined neural patterns of correct and incorrect judgment, as well as positive and negative feedback during grammar processing, using the whole-brain analysis. For RQ3, we explored individual difference influences based on whole cerebellum activation analysis and ROI-to-ROI functional connectivity analysis.

4.1 BEHAVIOURAL RESULTS

Our behavioural analyses first assessed whether participants successfully acquired the artificial language. We then examined how associativity and grammaticality affected performance.

To relate individual differences to learning outcomes, we conducted correlation and regression analyses linking cognitive and language abilities to task d-primes. We identified the factors that best predicted d-primes and used them as individual difference factors in subsequent neural activation and functional connectivity analyses.

4.1.1 Learning Performance

4.1.1.1 Proficiency

Overall improvement. Figure 4.1 shows the overall improvement during artificial language learning. There was an overall increase in d-prime and a decrease in reaction time. Note that the fMRI sessions had a shorter response window than the learning and training sessions, resulting in significantly shorter reaction times during fMRI sessions compared to other sessions.

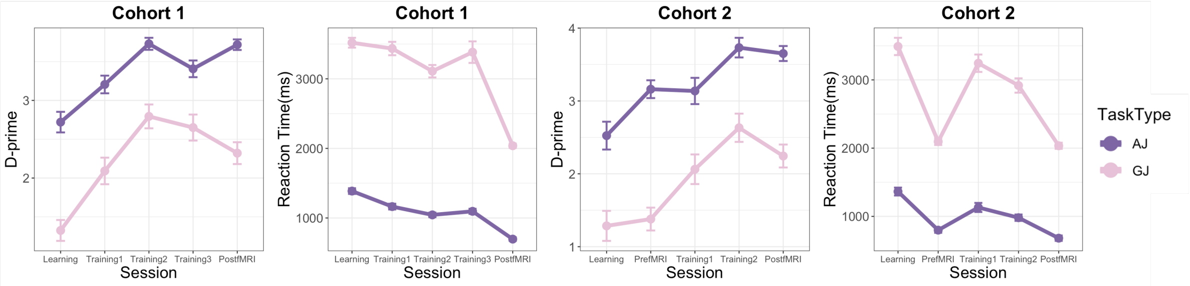


Figure 4.1: Overall improvement of artificial language learning. D-prime and reaction time change in learning, training, and fMRI sessions.

Task difference (AJ and GJ). The mean d-prime for Pre-fMRI AJ (Pre-AJ), Pre-fMRI GJ (Pre-GJ), Post-fMRI AJ (Post-AJ), and Post-fMRI GJ (Post-GJ) were 3.16 (SD = 0.52), 1.38 (SD = 0.67), 3.72 (SD = 0.40), and 2.33 (SD = 0.84), respectively. The mean reaction times for the four tasks were 798 ms (SD = 165), 2096 ms (SD = 210), 691 ms (SD = 155), and 2035 ms (SD = 182), respectively.

In Pre-AJ, participants showed higher d-primes ($t(17) = 11.23, p < .001$) and lower reaction time ($t(17) = -21.65, p < .001$) than Pre-GJ. In Post-AJ, participants also showed higher d-primes ($t(37) = 12.05, p < .001$) and lower reaction time ($t(37) = -42.46, p < .001$) than post-GJ. These results suggest that the GJ task is more complex than the AJ task.

Stage difference. There was a main effect of session in terms of d-prime (Cohort 1: $F(2.62, 49.80) = 12.95$, $p < .001$, $\eta_p^2 = .288$; Cohort 2: $F(2.91, 50.41) = 18.95$, $p < .001$, $\eta_p^2 = .329$) and reaction time (Cohort 1: $F(3.00, 57.07) = 89.46$, $p < .001$, $\eta_p^2 = .568$; Cohort 2: $F(2.96, 50.30) = 83.12$, $p < .001$, $\eta_p^2 = .568$).

Both Cohort 1 and Cohort 2 attained a relatively proficient level of mastery in the artificial association and grammar by the end of the experiment (d-prime > 2). Furthermore, paired sample t-tests showed that Cohort 2 participants demonstrated higher d-primes in Post-AJ ($t(17) = -4.92, p < .001$) and Post-GJ ($t(17) = -5.07, p < .001$). They also showed lower reaction time in Post-AJ ($t(17) = 4.64, p < .001$) but not in Post-GJ ($t(17) = 0.92, p = .366$). These results suggest that Cohort 2 demonstrated significant improvement from the early to the late stage of acquisition. Given the already brief response window for the GJ task, it is reasonable that participants did not exhibit significantly decreased reaction times in the late stage.

4.1.1.2 Associativity and grammaticality

Figure 4.2 shows the behavioural results of associativity and grammaticality. In Pre-AJ, participants showed higher accuracy when judging matched associations compared with mismatched associations ($t(17) = -2.41, p = .028$), but this difference was not observed in Post-AJ ($t(36) = 1.16, p = .253$). Moreover, no significant results were found for reaction time in both stages (Pre-AJ: $t(17) = 1.21, p = .242$; Post-AJ: $t(37) = -1.84, p = .073$).

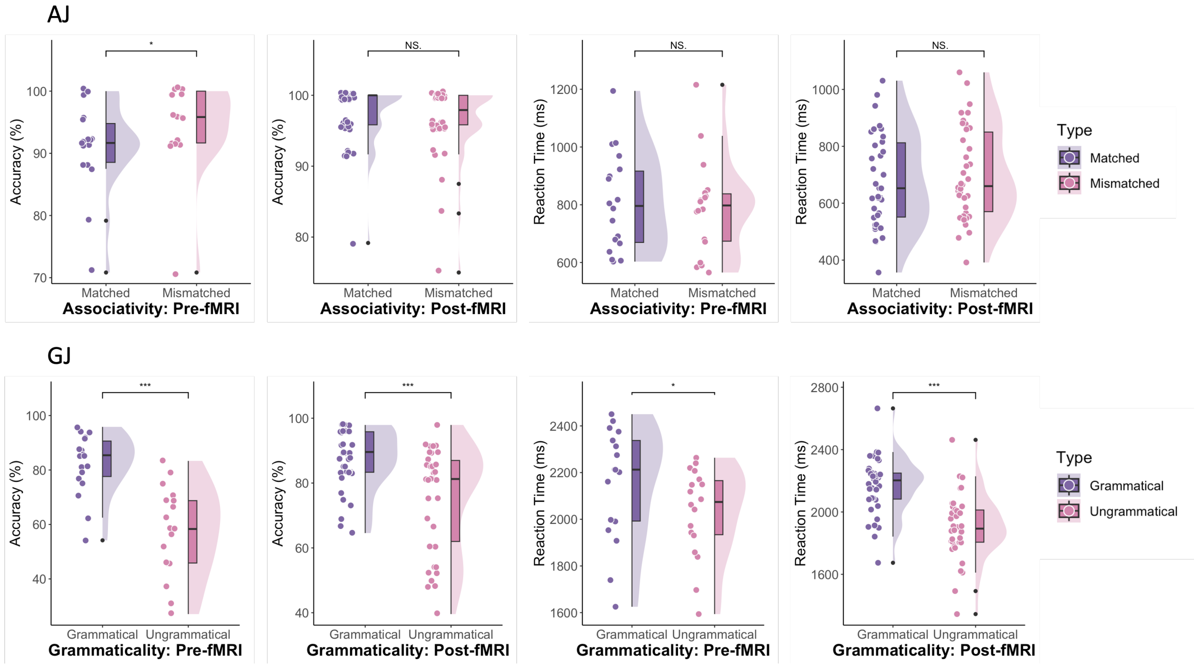


Figure 4.2: Behavioural results of associativity and grammaticality. Accuracies and reaction times for automatic (i.e., matched and grammatical) and controlled (i.e., mismatched and ungrammatical) conditions. The top and bottom panels include the results for Associative Judgment and Grammar Judgment, respectively. $*p < .05; **\ p < .01; ***p < .001; NS. p > .05$.

In both Pre-GJ and Post-GJ, the accuracies of grammatical sentence judgment were higher than ungrammatical sentence judgment (Pre-GJ: $t(17) = 6.49, p < .001$; Post-GJ: $t(37) = 6.44, p < .001$). However, it took longer for the participants to judge grammatical sentences compared with ungrammatical sentences (Pre-GJ: $t(17) = 5.06, p < .001$; Post-GJ: $t(37) = 13.56, p < .001$).

Due to ceiling effects in the AJ task, participants showed no significant difference in performance between matched and mismatched association judgments. However, they exhibited higher accuracy in judging grammatical sentences, albeit with greater cognitive effort.

4.1.2 Individual Difference

4.1.2.1 Selection of factors

To examine the effects of individual differences, participants underwent a series of cognitive and language assessments. We selected individual difference factors based on correlation and stepwise regression analyses. Due to the multicollinearity concern of the regression analysis, several factors of WCST and LHQ (i.e., WCST accuracy, WCST non-perseverative error, L1 proficiency, L2 proficiency, L1 immersion, L1 dominance, L1 to L1 dominance ratio, and L2 to L1 dominance ratio) were excluded based on the alias variable and variance inflation factor (VIF). Table 4.1 summarises all cognitive and language ability factors for selection.

Cognitive domain	**Factors**
Interference control	Stroop score
Memory	Digit span, reading span
Intelligence	Raven's SPM score
Cognitive flexibility	WCST perseverative error, reaction time
Language domain	**Factors**
Language proficiency	Chinese DSE grade, English DSE grade
Language experience	L2 immersion, L2 dominance, multilingual language diversity
Language analytical ability	LLAMA_B score (vocabulary), LLAMA_F score (grammar)

Table 4.1: Included individual difference factors for behavioural analysis. In total, 26 factors were extracted from the assessment results. Included factors were selected based on the VIF analysis.

Figure 4.3 shows the correlations between task d-primes and individual difference factors. Significant positive correlations were observed between Pre-GJ d-prime and Raven score ($r = .53, p = .022$).

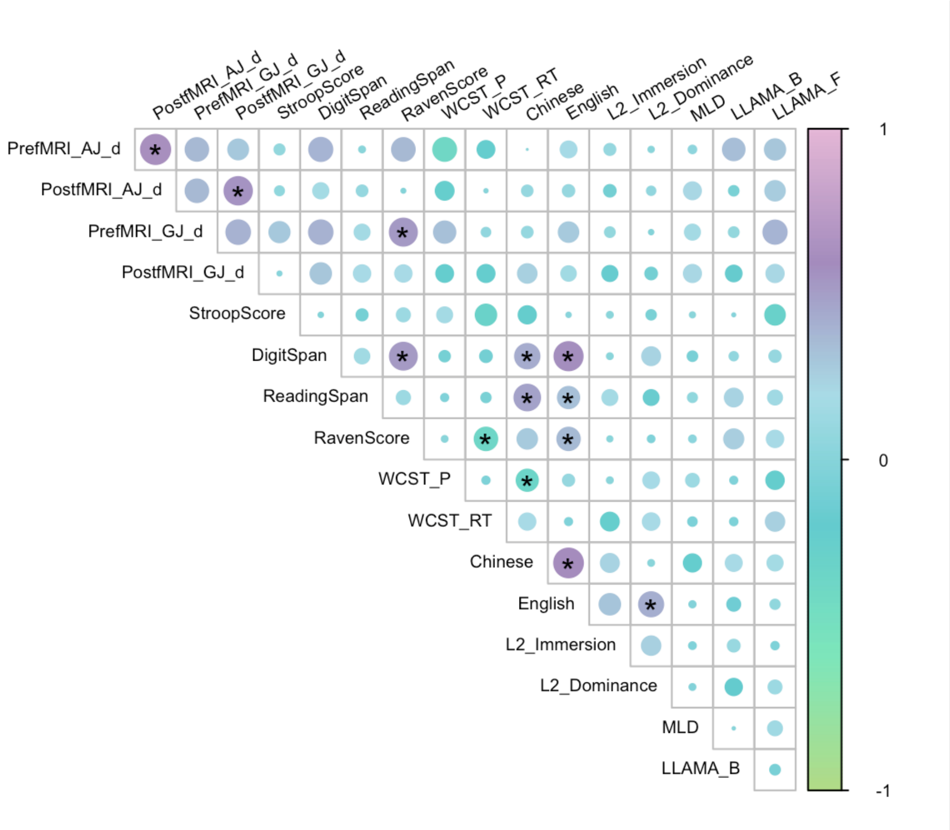


Figure 4.3: Correlations between task d-primes and individual difference factors. The size of circles corresponds to the absolute value of the correlation coefficient. The colour of circles represents the sign and magnitude of the correlation coefficient. WCST_P = WCST non-perseverative error, WCST_RT = WCST reaction time, MLD = multilingual language diversity.

Furthermore, stepwise regression selection was conducted using Akaike Information Criterion (AIC) to identify the most relevant individual difference predictors for task d-primes. We created cognitive models and language models to investigate which domain factors can better predict the task d-primes.

For Pre-AJ, DigitSpan ($b = .51, t = 1.96, p = .069$) and reading span ($b = .48, t = 1.92, p = .074$) were retained in the final cognitive stepwise model ($R^2 = .321$, Adjusted $R^2 = .231$, $F(2,15) = 3.55,\ p = .055$). LLAMA_B ($b = .47, t = 2.35, p = .037$), LLAMA_F ($b = .36, t = 1.87, p = .086$), English ($b = .83, t = 2.51, p = .028$), and Chinese ($b = -.92, t = -2.47, p = .030$) were retained in the final language stepwise model ($R^2 = .486$, Adjusted $R^2 = .271$,

$F(5,12) = 2.27$, $p = .114$). The cognitive model outperformed the language model, as it had a better model fit ($AIC = 51.08$) compared to the language model ($AIC = 52.09$).

For Post-AJ, WCST perseverative error ($b = -.24, t = -1.46, p = .153$) was retained in the final cognitive stepwise model ($R^2 = .056$, Adjusted $R^2 = .030$, $F(1,36) = 2.13$, $p = .153$). LLAMA_F ($b = .28, t = 1.75, p = .089$) was retained in the final language stepwise model ($R^2 = .078$, Adjusted $R^2 = .053$, $F(1,36) = 3.05$, $p = .089$). The language model ($AIC = 109.73$) outperformed the cognitive model ($AIC = 110.64$).

For Pre-GJ, Stroop score ($b = .57, t = 2.72, p = .017$), Raven's SPM score ($b = .35, t = 1.77, p = .099$), and WCST reaction time ($b = .56, t = 1.69, p = .114$) were retained in the final cognitive stepwise model ($R^2 = .445$, Adjusted $R^2 = .325$, $F(3,14) = 3.73$, $p = .037$). LLAMA_F ($b = .53, t = 2.71, p = .019$), English ($b = .73, t = 2.32, p = .039$), Chinese ($b = -.48, t = -1.39, p = .190$), and multilingual language diversity ($b = .35, t = 1.25, p = .236$) were retained in the final language stepwise model ($R^2 = .491$, Adjusted $R^2 = .279$, $F(5,12) = 2.31$, $p = .109$). The cognitive model ($AIC = 49.47$) outperformed the language model ($AIC = 51.91$).

For Post-GJ, Digit span ($b = .31, t = 1.95, p = .059$) was retained in the final cognitive stepwise model ($R^2 = .095$, Adjusted $R^2 = .070$, $F(1,36) = 3.80$, $p = .059$). LLAMA_B ($b = -.24, t = -1.57, p = .126$), Chinese ($b = .42, t = 2.62, p = .013$), L2 Immersion ($b = -.24, t = -1.52, p = .138$), and multilingual language diversity ($b = .30, t = 1.96, p = .058$) were retained in the final language stepwise model ($R^2 = .257$, Adjusted $R^2 = .167$, $F(4,33) = 2.85$, $p = .039$). The cognitive model ($AIC = 49.47$) outperformed the language model ($AIC = 51.91$).

Overall, cognitive factors can better predict task d-primes than language factors, except for the Post-AJ task. Combining correlation and regression results, L2 dominance was excluded from the following activation and functional connectivity analyses.

4.1.2.2 Summary of factors

To summarise the overall degree of cognitive and language abilities, we entered the measures from individual tests into a Principal Component Analysis (PCA). The test scores were normalised by converting them to z-scores, controlling for the scale differences between the various tests. To ensure higher scores reflect better ability, we inverted the WCST perseverative error and WCST reaction time values by taking their negatives. We conducted two PCA analyses based on selected cognitive or language ID factors. We expected that the first principal component (PC1) returned from PCA would serve as an overall measurement of the two domains, ensuring parsimony while capturing most of the variance without overfitting.

As shown in Figure 4.4, PCA was conducted separately to reduce dimensionality for the comparison of cognitive and language individual differences. In the cognitive domain, higher PC1 values primarily represented lower general abilities, as most loadings were negative, except for the inverted WCST perseverative error (loading = .04). This PC accounted for 30.1% of the variance. For the language domain, higher PC1 values reflected overall higher specific language abilities, as most loadings were positive except for multilingual language diversity (loading = -.18). This PC explained 30.9% of the variance. For the following neural analyses, we took the negative of the cognitive domain's PC1 scores (Cognitive PC1) to align their direction with the language domain's PC1 (Language PC1), so that higher values in both represent higher abilities. Cognitive PC1 and Language PC1 were positively correlated ($r = .378$, $p = .019$).

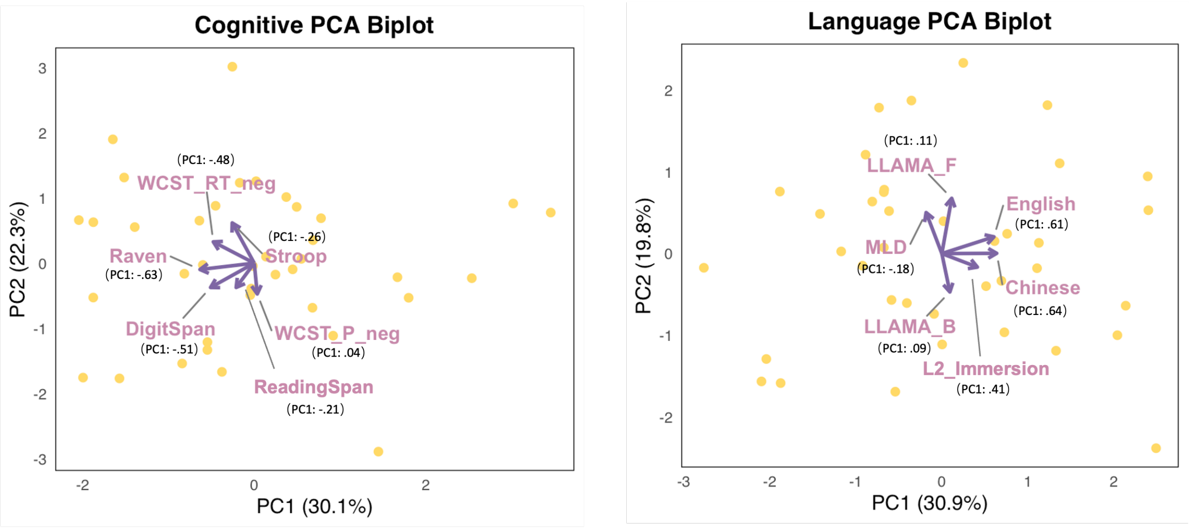


Figure 4.4: PCA biplots of cognitive and language IDs. Two PCs are presented for visualisation purposes. WCST_P = WCST non-perseverative error, WCST_RT = WCST reaction time, MLD = multilingual language diversity.

Furthermore, we used Cognitive PC1 and Language PC1 to correlate d-prime and reaction time of AJ and GJ. We found that only Cognitive PC1 was significantly correlated with task performance. To be more specific, Cognitive PC1 was associated with d-prime in Pre-AJ ($r = .488$, $p = .043$).

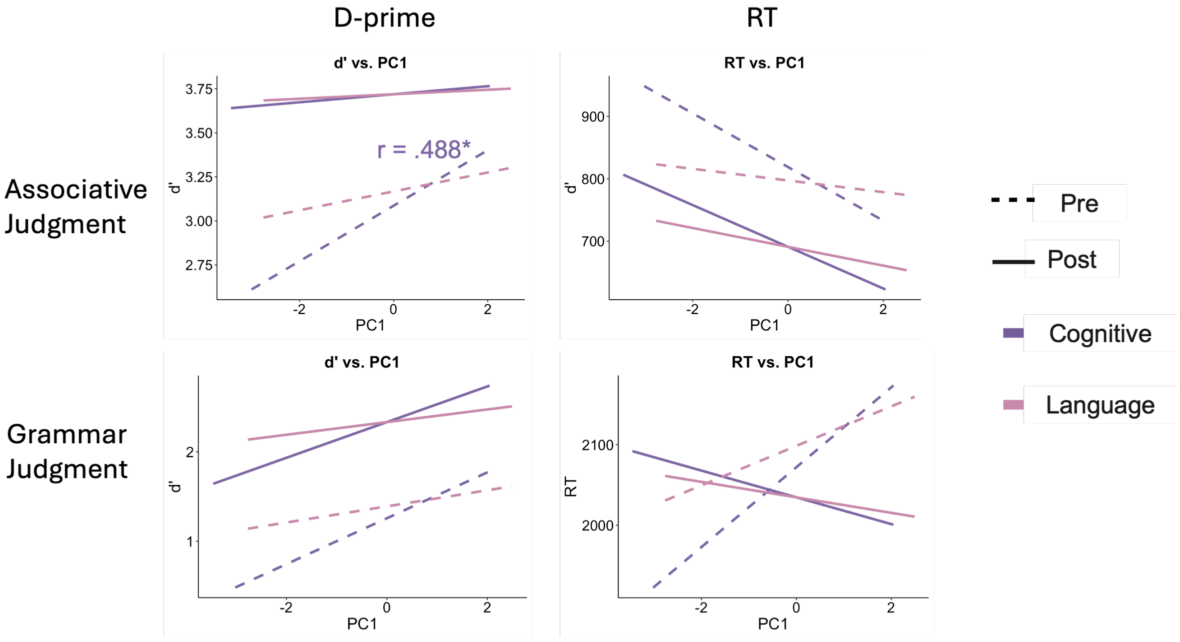


Figure 4.5: PCA biplots of cognitive and language IDs. Two PCs are presented for visualisation purposes. WCST_P = WCST non-perseverative error, WCST_RT = WCST reaction time, MLD = multilingual language diversity.

4.2 THE CEREBELLUM'S ROLE IN LANGUAGE LEARNING

Based on the internal model hypothesis, we explored three aspects to investigate the cerebellum's role in language learning. Firstly, we examined the cerebro-subcortical-cerebellar cooperative network to explore if the cerebellum Crus I/II, known for its significant role in language processing, co-activated with cortical and subcortical language-related areas during associative learning and grammar learning. Furthermore, we examined whether the cerebellum Crus I/II showed functional connectivity with cortical and subcortical language-related areas. Secondly, we investigated the different involvement of the cerebellum in automatic and controlled processing using activation and functional connectivity analysis. Thirdly, with the same analysis methods, we compared the cerebellum's contributions to correct-related and error-related processing.

4.2.1 Cerebro-Subcortical-Cerebellar Cooperative Network

The cooperative network was first examined to explore if the cerebellum Crus I/II contributes to artificial language learning in cooperation with cortical and subcortical regions. The ROI co-activation and functional connectivity analyses were assessed using the following contrasts: (1) Word > Rest; (2) Feedback_word > Rest; (3) Sentence > Rest; and (4) Feedback_sen > Rest. The ROIs are summarised in Table 3.3. For ROI activation analysis, we used the ROI anatomical mask to extract the data. For ROI-to-ROI gPPI functional connectivity analysis, we examined contrasts using bilateral Crus I/II as seed regions.

Furthermore, using the activation ROI analysis, the judgment-related and feedback-related activations in AJ and GJ were compared to investigate task differences. The following contrasts were assessed for both Pre- and Post-fMRI sessions: (1) Word versus Sentence; and (2) Feedback_word versus Feedback_sen.

Finally, we examined the ROI activation and changes in functional connectivity over time, specifically in judgment and feedback. The change contrasts include: (1) Pre-AJ Word versus Post-AJ Word; (2) Pre-AJ Feedback versus Post-AJ Feedback; (3) Pre-GJ Sentence versus Post-GJ Sentence; and (4) Pre-GJ Feedback versus Post-GJ Feedback. Moreover, to explore the effects of proficiency, we used d-prime improvement and reaction time improvement as individual difference variables to correlate with the results.

Whole-brain activation maps are summarised in Figure 4.6 to show the overall pattern. Areas of peak activation of the ROI analysis are summarised in Appendix B.1.1. Detailed results are provided in the following sections.

4.2.1.1 Associative Judgment

Activation. In Pre-AJ, compared to the rest baseline, associative judgment (Word > Rest) significantly activated a set of regions, including right IPL, bilateral IFG, bilateral SFG, left MFG, bilateral putamen, bilateral thalamus, bilateral Crus I, and bilateral Crus II. Furthermore, compared to the rest baseline, feedback (Feedback_word > Rest) activated the right MFG and left Crus I. In Post-AJ, associative judgment elicited activations in bilateral IFG, right SFG, bilateral putamen, right thalamus, and bilateral Crus I. Feedback elicited activations in left parahippocampus, right caudate, right hippocampus, and bilateral Crus I.

No significant cerebellar activation was observed in the F-test for the main effect of POS processing. A follow-up contrast comparing verb and noun processing specifically showed a trend of greater activation in Crus I/II for verbs, but this effect was not statistically significant.

Functional connectivity. In Pre-AJ, positive functional connectivity between Crus I/II and cortical regions was found for association judgment, including left Crus I-to-left MTG ($\beta = .53, T(17) = 4.05$) and left Crus II-to-right IFG ($\beta = .53, T(17) = 3.51$) connections. For feedback processing, positive connectivity was found between left Crus I-to-left STG ($\beta = .64, T(17) = 3.65$), left Crus II-to-left STG ($\beta = .41, T(17) = 3.20$), and left Crus II-to-left

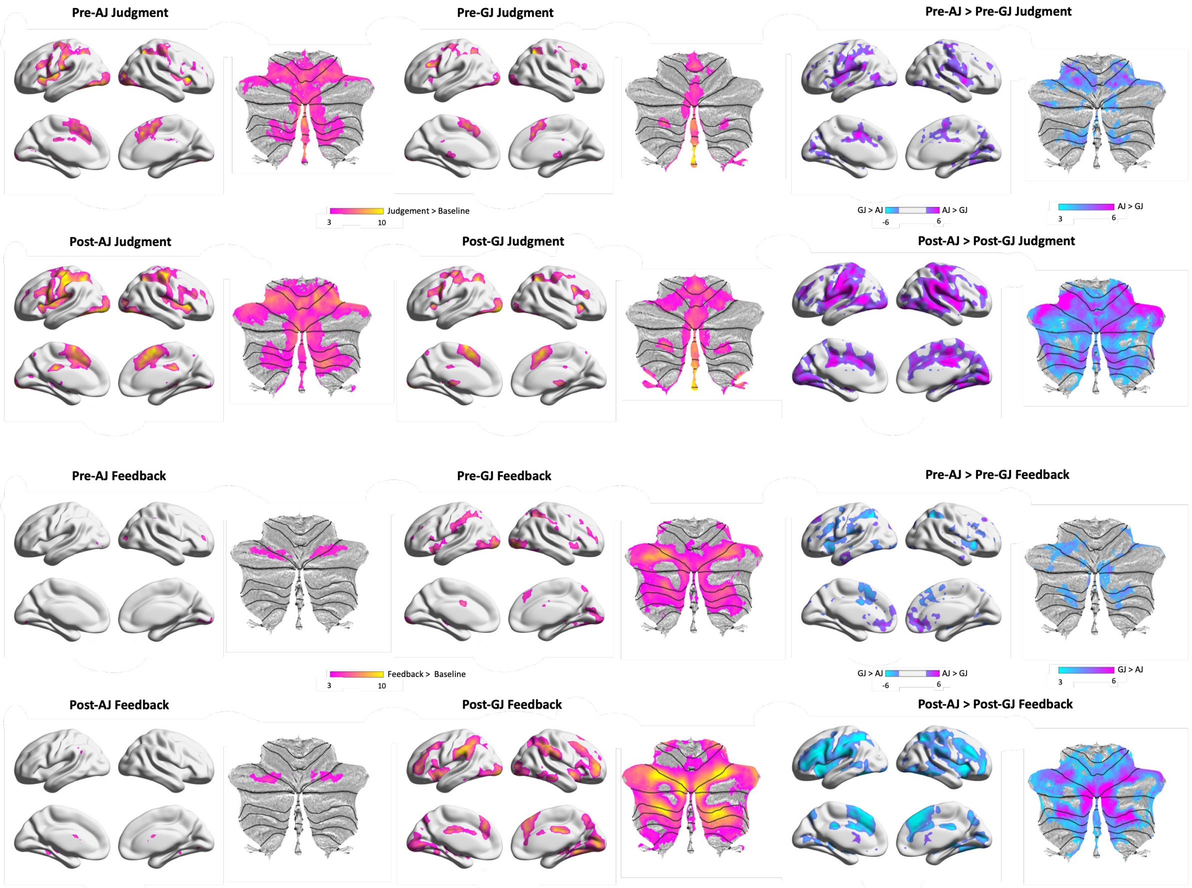


Figure 4.6: Judgment- and feedback-related activation maps in Pre-fMRI and Post-fMRI. A. Neural activations during judgment stimuli presentation. The rest sessions were defined as baselines. B. Neural activations during feedback stimuli presentation.

MTG ($\beta = .47, T(17) = 3.09$). In Post-AJ, no significant connectivity was found for association judgment. For feedback processing, the right Crus I showed positive connectivity with the right IFG ($\beta = 0.52, T(36) = 3.08$). In addition, the right Crus II also showed positive connectivity with the right IFG ($\beta = 0.54, T(37) = 3.08$).

4.2.1.2 Grammar Judgment

Activation. In Pre-GJ, compared to the rest baseline, grammar judgment (Sentence > Rest) was associated with significant activations in right IPL, bilateral IFG, bilateral MFG, left thalamus, bilateral caudate, right putamen, and bilateral Crus II. Feedback (Feedback_sen > Rest) was associated with significant activations in bilateral MFG, right IPL, left IFG, bilateral Crus I, and bilateral Crus II. In Post-GJ, grammar judgment elicited activations in bilateral IFG, right IPL, bilateral MFG, left thalamus, right putamen, bilateral pallidum, left

Crus I, and bilateral Crus II. Feedback elicited activations in right MFG, left IFG, right IPL, left MTG, left caudate, right thalamus, bilateral Crus I, and bilateral Crus II.

The *F*-test contrasting the three violation types revealed significant activation in Crus I/II and vermis IX. Notably, these regions exhibited distinct activation profiles (Figure 4.7). In Crus I/II, activations for Type 3 violations were consistently stronger than for Type 2, both before and after training. Conversely, vermis IX showed the opposite pattern, with stronger activation for Type 2 violations. This region difference may arise because the cerebellar hemispheres and the vermis connect to distinct regions of the cerebrum.

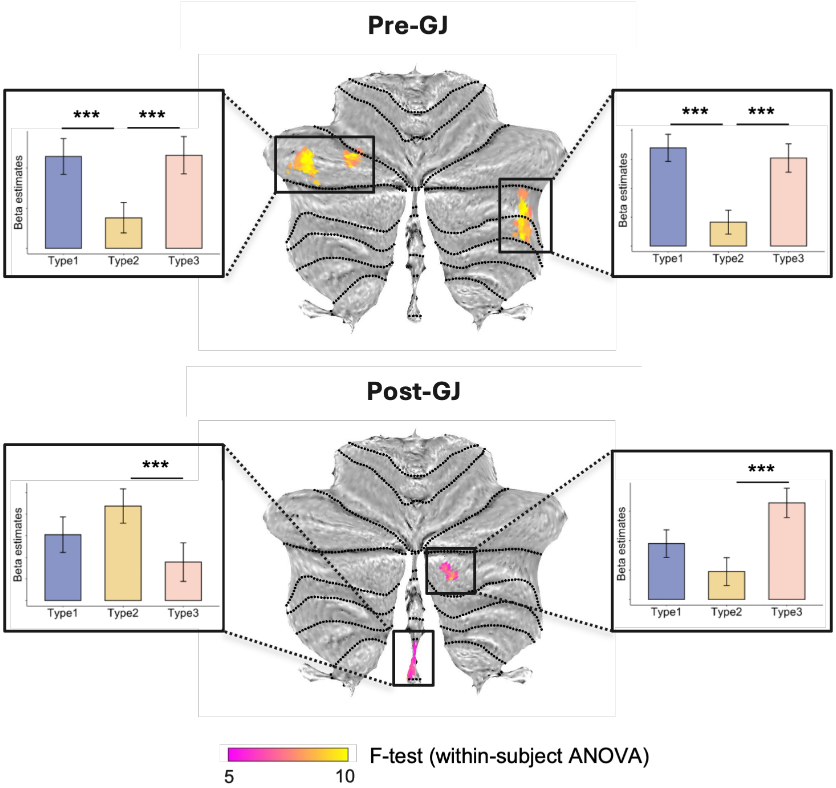


Figure 4.7: Cerebellar grammar violation specific patterns. Pre = fMRI session before training; Post = fMRI session after training; AJ = associative judgment. ***$p < .001$

Functional connectivity. In Pre-GJ, the left Crus I showed positive connectivity with left putamen ($\beta = 2.27, T(17) = 3.49$), right putamen ($\beta = 2.21, T(17) = 3.50$), and right caudate ($\beta = 2.30, T(17) = 3.07$) during grammar judgment (Sentence > Rest). During this procedure, the left Crus II showed positive connectivity with the right thalamus ($\beta = 1.55, T(17) = 3.02$). Moreover, the left Crus I showed negative connectivity with the left parahippocampus ($\beta = -7.59, T(17) = -3.30$) during feedback processing (Feedback > Rest). In Post-GJ, no significant connectivity was found for grammar judgment and feedback processing.

4.2.1.3 Task difference

In Pre-fMRI, stronger activations were observed during association judgment compared to grammar judgment in bilateral SFG, bilateral MTG, bilateral IFG, left MFG, left putamen, right pallidum, and bilateral Crus I. However, no stronger activation was observed for grammar judgment. Furthermore, while bilateral SFG, left MTG, and left IFG showed significant activations for the contrast Feedback_word > Feedback_sen, a broader range of regions exhibited significant activations for Feedback_sen > Feedback_word. These regions include the right IPL, bilateral IFG, bilateral MFG, left MTG, right pallidum, bilateral putamen, right thalamus, and bilateral Crus I.

In Post-fMRI, association judgment was associated with stronger activations in bilateral IFG, left STG, left MFG, right IPL, right hippocampus, left putamen, bilateral Crus I, and bilateral Crus II. Similar to Pre-fMRI, no regions showed stronger activation during grammar judgment. Moreover, feedback for association judgment correlated with greater activations in bilateral hippocampus, bilateral caudate, and right Crus I. Feedback for grammar judgment correlated with greater activations in bilateral IFG, right IPL, left MTG, right hippocampus, left putamen, bilateral Crus I, and bilateral Crus II.

4.2.1.4 Change

The ROI analysis revealed no significant difference in the cerebellum between Pre-fMRI and Post-fMRI judgment and feedback (Figure 4.8). However, the activations in the left caudate and right IFG decreased from Pre-GJ to Post-GJ during judgment, whereas the activations in the bilateral IPL and right MTG increased during feedback processing.

Effects of d-prime. The d-prime change was calculated as the difference between Post-fMRI minus Pre-fMRI d-prime scores. For participants with greater d-prime improvement, there was a reduction of activation in left STG, right Crus II, and left Crus I during association judgment from Pre-AJ to Post-AJ. In contrast, the left IFG and bilateral MTG demonstrated increased activations during feedback processing. As for GJ, the bilateral right pallidum and left MTG showed increased activations from Pre-GJ to Post-GJ during feedback processing.

Effects of reaction time. The reaction time change was calculated as the difference between Pre-fMRI minus Post-fMRI reaction times. No effect was observed in ROIs.

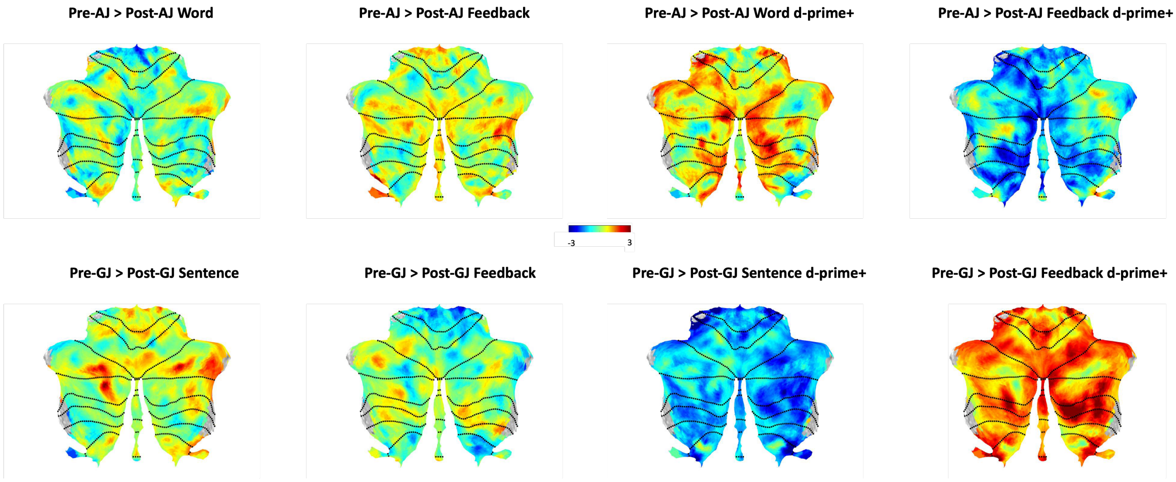


Figure 4.8: Judgment- and feedback-related change activation maps. Unthresholded whole-cerebellum maps are displayed for visualisation purposes. Pre = fMRI session before training; Post = fMRI session after training; AJ = associative judgment.

4.2.1.5 Summary

Overall, Crus I/II exhibited co-activation with cortical and subcortical language-related regions during association and grammar judgment, as well as feedback processing. Additionally, Crus I/II demonstrated positive functional connectivity with cortical regions during Pre-AJ judgment and feedback processing, as well as Post-AJ feedback processing. However, Crus I/II showed positive connectivity with subcortical regions during Pre-GJ judgment but negative connectivity with subcortical regions during Pre-GJ feedback. These results suggest that Crus I and Crus II contribute to association and grammar learning in cooperation with cortical and subcortical areas, although through different patterns. Interestingly, although no clear lateralisation pattern emerged in the activation patterns, the majority of significant connections originated from the left Crus I/II.

As for the task difference, bilateral Crus I/II, especially the lateral Crus I, along with several cortical and subcortical language-related regions, showed greater engagement during association judgment than grammar judgment in both Pre-fMRI and Post-fMRI. However, the lateral Crus I was found to be associated with working memory (Nettekoven et al., 2024), which is more related to grammar learning. In contrast, bilateral Crus I/II, together with multiple cortical and subcortical language-related regions, exhibited greater engagement during grammar feedback processing in both Pre-fMRI and Post-fMRI. Only a small number of regions were more engaged in association feedback processing. Despite the task content difference, the different complexity of the tasks might also contribute to this difference. From activation maps and T values of the contrasts, it seems that the Word > Sentence and Feedback_sen > Feedback_word differences were more pronounced in the Post-fMRI than Pre-fMRI, but this may be due to the sample size difference (i.e., Pre-fMRI n = 20 < Post-fMRI n = 38).

Moreover, our findings align with previous research (LeBel et al., 2021) in demonstrating cerebellar involvement in high-level (i.e., grammatical violation but not in low-level (i.e., POS) processing. Two primary explanations have been proposed for this dissociation: task difficulty and conceptual representation. The task-difficulty account posits that the cerebellum responds to increased cognitive load, which would predict stronger activation for more challenging conditions. However, our data contradict this, as we found stronger Crus I/II activation in conditions with higher behavioural accuracy. On the other hand, recent studies also reported that the cerebellum is not only involved in simple and automatic tasks (Tao et al., 2024). Therefore, the cerebellar involvement does not solely depend on task difficulty. The conceptual account suggests the cerebellum represents language at a purely conceptual level, but our results show its engagement in formal, language-specific grammar processing that is not purely conceptual. Instead, we propose that the key factor is the computational nature of the task. Grammatical violation detection inherently requires sequence processing, prediction, and error correctionfunctions perfectly aligned with the cerebellum's role in building internal models. In contrast, basic POS processing does not rely on these specific predictive and error-based learning mechanisms.

Participants with greater improvements in d-prime exhibited reduced activations in Crus I/II during AJ judgment. Based on the unthresholded maps, there was an opposite pattern for AJ feedback. Interestingly, Crus I/II demonstrated an increasing pattern during GJ judgment, while a decreasing pattern was observed during GJ feedback. However, further analysis is required to confirm this pattern.

4.2.2 Automatic and Controlled processing

For the second aspect, we explored the cerebellum's role in automatic and controlled processing. To investigate activation and functional connectivity patterns, we performed the activation analysis with the whole cerebellum mask and gPPI seed-to-voxel whole-brain analysis with bilateral Crus I/II as seed regions. The distinction between automatic and controlled conditions depends on whether the presented stimuli align with or violate the knowledge (predictions) of the artificial language. Matched associations and grammatical sentences are classified as automatic conditions, whereas mismatched associations and ungrammatical sentences are classified as controlled conditions.

In terms of engagement, we first examined activation and functional connectivity patterns of two contrasts in both Pre-fMRI and Post-fMRI: (1) Word_mat > Word_mis; and (2) Sentence_gra > Sentence_ung. Furthermore, we used d-prime and reaction time to correlate with the contrast results to explore the proficiency effects. In terms of change, we examined the differences in activation and functional connectivity between early and late stages of acquisition (i.e., Pre-fMRI and Post-fMRI) based on the Cohort 2 data, and we examined the interaction effect between processing type and stage. Furthermore, we also examined whether participants with greater proficiency improvements in d-prime and reaction time showed larger differences in activation or functional connectivity contrasts.

4.2.2.1 Engagement in automatic and controlled processing

As shown in Figure 4.9, direct comparison of automatic and controlled conditions revealed significant effects in lobules V, VI, and VIII, which are linked to motor functions, especially finger press (King et al., 2019). The automatic conditions, compared with controlled conditions, were associated with activations in the right hemisphere, while the controlled conditions were associated with left-lateralised activations. This limitation stems from the task design, where participants consistently pressed the right button to indicate a matched association or grammatical sentence and the left button otherwise. However, it should be noted that the mismatched judgment in Pre-AJ was associated with greater activations in the right Crus I compared with the matched judgment, and the right Crus I/II were more active during ungrammatical judgment in Post-GJ. This indicates potential cognitive differences between these processing types.

Moreover, the functional connectivity analysis revealed that Crus I/II showed positive connectivity with cognitive-related regions for the automatic > controlled contrasts. Specifically, the left Crus II showed positive connectivity with the left MFG for Word_mat > Word_mis in Post-AJ. Furthermore, a positive left Crus I-to-left MFG connection was found for Sentence_gra > Sentence_ung in Pre-GJ, and a positive right Crus I-to-left IFG connection was found for the same contrast in Post-GJ (for more details, see Appendix B.1.2).

Therefore, we further examined the effects of proficiency on these differences. To investigate whether the difference between automatic and controlled would be greater among more proficient participants, we used d-prime and reaction time as measurements to correlate the contrast results.

Effects of d-prime. The left lobule VI and right Crus I showed positive correlations with d-primes for Word_mis > Word_mat during Pre-AJ and Post-AJ, respectively. The right lobule VI and V demonstrated positive correlations with d-primes for Sentence_gra > Sentence_ung during Pre-GJ, and the lobule VI exhibited the same pattern during Post-GJ.

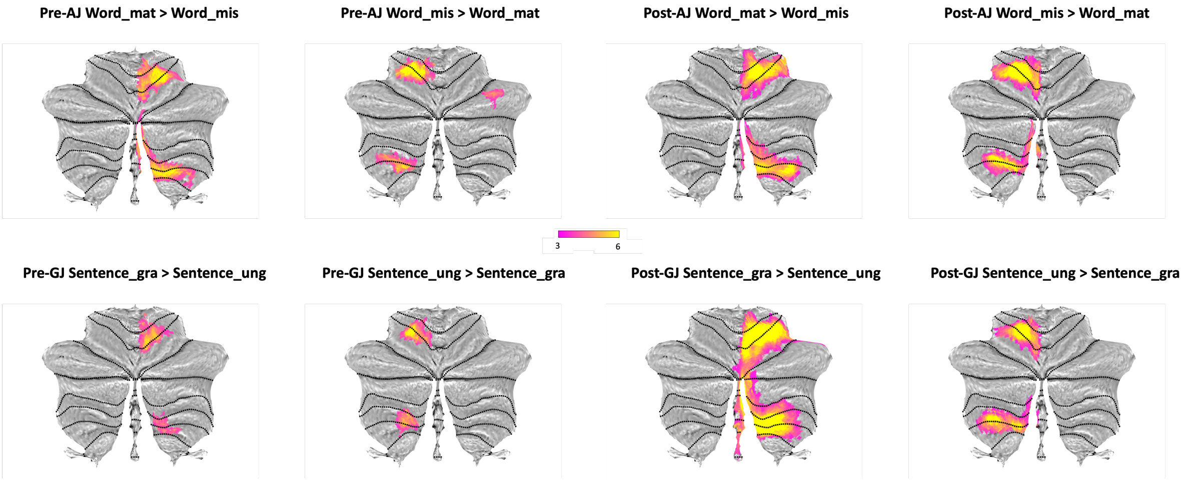


Figure 4.9: Cerebellar automatic and controlled processing activations. Pre = fMRI session before training; Post = fMRI session after training; AJ = associative judgment; GJ = grammar judgment; Word_mat/mis = judgment of matched or mismatched associations. Sentence_gra/ung = judgment of grammatical or ungrammatical sentences.

As for functional connectivity, for the contrast Word_mat > Word_mis, in Pre-AJ, higher task d-primes correlated with positive connectivity between Crus/II and regions associated with cognitive (i.e., bilateral MFG, right MTG, left thalamus, bilateral insula, and cingulate gyrus) and sensorimotor (i.e., bilateral central opercular cortex) processing. Higher d-primes also correlated with a negative left Crus I-to-right inferior temporal gyrus connection. In Post-AJ, on the contrary, higher task d-primes correlated with negative connectivity between Crus/II and regions relating to cognition and sensory (i.e., bilateral SFG, left precuneus, and left IPL).

Furthermore, for the contrast Sentence_gra > Sentence_ung, in Pre-GJ, higher task d-primes were associated with positive connectivity between the right Crus I and the right precuneus, as well as between the left Crus I and the left postcentral gyrus. Contrary effects were observed in Post-GJ, with higher task d-primes associated with negative connections between Crus I/II and sensory-related regions (e.g., right cuneus and left postcentral gyrus).

Effects of reaction time. As for reaction time effects, left lobule VIIb, right Crus I, and left lobule VI showed negative correlations with Post-AJ reaction time for the contrast Word_mis > Word_mat. This result is consistent with d-prime results. Moreover, the right vermis VIII showed negative correlations with Pre-GJ reaction time for the contrast Sentence_ung > Sentence_gra.

For the contrast Word_mat > Word_mis, in Pre-AJ, increased reaction time was correlated with positive left Crus I-to-right SFG, left Crus I-to-left MFG, and right Crus II-to-

IPL connections. These connected cortical regions are responsible for cognitive processing. However, no significant effect was found in Post-AJ.

For the contrast Sentence_gra > Sentence_ung, in Pre-GJ, increased reaction time was correlated with the negative connectivity between the left Crus II and the right cingulate gyrus. In the post-GJ, the reaction time effects were observed in three negative functional connections: left Crus I with right precuneus, right Crus I with right IFG, and left Crus II with MTG. In addition, the increased reaction time was correlated with the positive connectivity between Crus II and the left MTG.

4.2.2.2 Change in automatic and controlled processing

The stage difference activation analysis revealed no significant cerebellar difference between Pre-AJ Word_mat versus Post-AJ Word_mat and Pre-AJ Word_mis versus Post-AJ Word_mis. However, the interaction analysis of processing type and stage revealed that, compared with Pre-AJ, the difference between matched and mismatched judgment in right Crus I was stronger in Post-AJ ((Post-AJ Word_mat > Word_mis) > (Pre-AJ Word_mat > Word_mis)), whereas no significant effect was found for the contrast (Pre-AJ Word_mat > Word_mis) > (Post-AJ Word_mat > Word_mis). In terms of GJ, although there was no cerebellar activation difference in grammatical sentence judgment between Pre-GJ and Post-GJ, the left Crus II showed stronger activation during ungrammatical sentence judgment in Pre-GJ than Post-GJ. However, no interaction effect was found between processing type and stage.

Functional connectivity analysis revealed that, compared with Post-AJ, the left Crus I showed greater connectivity with left STG and right insula during Pre-AJ matched association judgment. Moreover, the right Crus II showed greater connectivity with the right precentral gyrus during Pre-AJ mismatched association judgment. There was no interaction effect between processing type and stage. In terms of GJ, no stage difference was found for grammatical and ungrammatical sentence judgment. However, the interaction analysis showed that bilateral Crus I/II showed negative connectivity with the middle occipital gyrus or cuneus for the contrast (Pre-GJ Sentence_gra > Sentence_ung) > (Post-GJ Sentence_gra > Sentence_ung). Detailed activation and functional connectivity results are summarised in Appendix B.1.2.

Effects of d-prime. Participants with greater d-prime improvement exhibited stronger activity in the left lobule VI during Pre-AJ matched association judgment compared to Post-AJ matched association judgment. The right lobule VI was more active during Pre-AJ mismatched association judgment than Post-AJ mismatched association judgment. No interaction effect was observed. As for GJ, the d-prime effect was only observed in lobule VI, where the difference Sentence_gra > Sentence_ung was greater in Post-GJ than Pre-GJ.

The functional connectivity analysis identified an interaction effect with d-prime change as the between-subject effect factor, where the connection between the right Crus II and right caudate was stronger for the contrast (Pre-AJ Word_mat > Word_mis) compared to (Post-AJ Word_mat > Word_mis). Additionally, the left Crus I exhibited stronger connectivity with the left lingual gyrus and right caudate during Pre-GJ grammatical and ungrammatical sentence judgment compared to Post-GJ. The interaction effects were found in the positive connections between right Crus II and left hippocampus, as well as right Crus II and left MTG.

Effects of reaction time. The activation analysis showed no significant effect of reaction time on AJ or GJ.

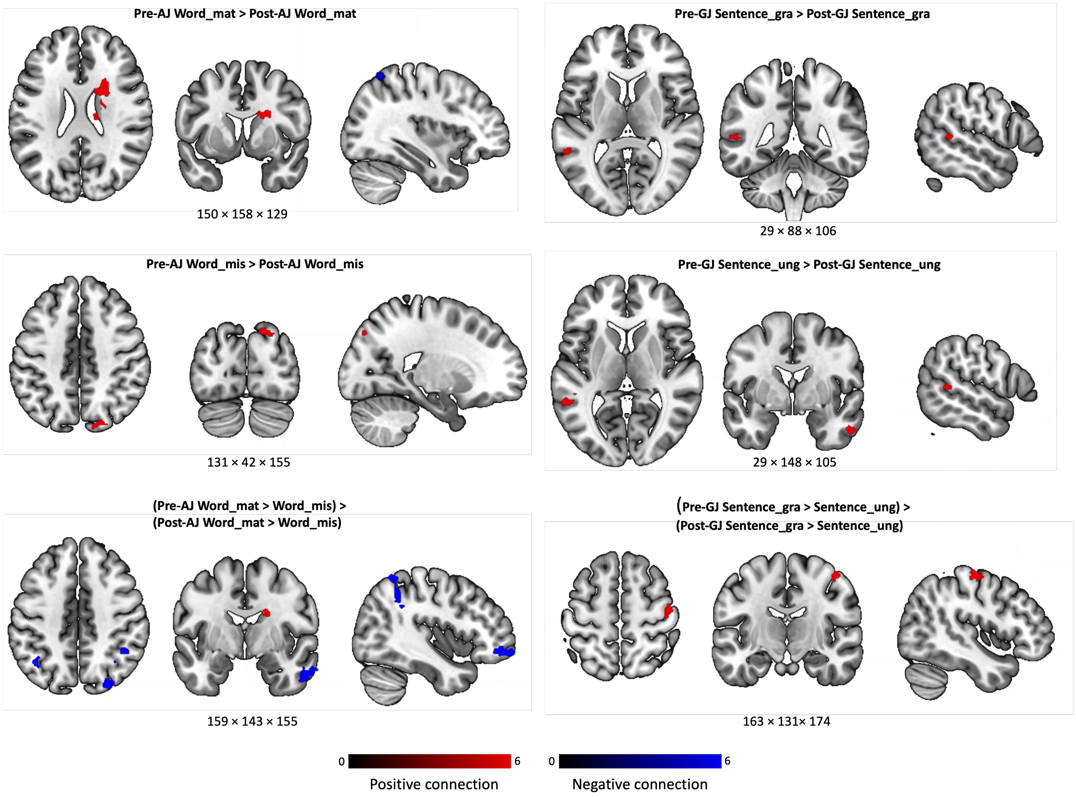


Figure 4.10: Reaction time change effects on functional connectivity change in automatic and controlled processing. The whole-brain functional connectivity analysis was performed using bilateral Crus I/II as seed regions. Pre = fMRI session before training; Post = fMRI session after training; AJ = associative judgment; GJ = grammar judgment; Word_mat/mis = judgment of matched or mismatched associations. Sentence_gra/ung = judgment of grammatical or ungrammatical sentences.

We further investigate the effects of changing reaction time on functional connectivity change. As shown in Figure 4.10, in Pre-AJ, bilateral Crus I and left Crus I showed increased connectivity with the right caudate during Pre-AJ matched association judgment compared with Post-AJ. However, the right Crus I showed weaker connections with the right superior parietal lobe and right MTG for the same contrast. Additionally, the left Crus II demonstrated enhanced connectivity with the right cuneus during Pre-AJ mismatched association judgment compared to Post-AJ. The analysis also revealed interaction effects in a positive connection between the right Crus I and right caudate and a negative connection between the right Crus I and right MFG. Furthermore, the right Crus II exhibited reduced connectivity with several regions, including the bilateral MTG, right IPL, right SFG, and right frontal pole, for the interaction effects.

In contrast to Pre-GJ grammatical sentence judgment versus Post-GJ grammatical sentence judgment, the left Crus II exhibited stronger connectivity with the left MTG. Similarly, for the contrast of Pre-GJ ungrammatical sentence judgment versus Post-GJ ungrammatical sentence judgment, the left Crus II showed increased connectivity with the left MTG, while the right Crus II demonstrated stronger connectivity with the right MTG. Additionally, an interaction effect was observed in the positive connection between the right Crus II and the right precentral gyrus.

4.2.2.3 Summary

The activation analysis revealed that the right Crus I was more engaged in controlled processing during Pre-AJ, which is consistent with Lesage et al. (2017) and Moberget et al. (2014). Moreover, the right medial Crus I/II were more engaged in controlled processing in Pre-GJ. However, these patterns were not observed in Post-AJ and Post-GJ. As for stage difference, the right Crus I exhibited interaction effects between processing type and stage in AJ. In right Crus I, while matched association judgment activity demonstrated an increasing trend, mismatched association judgment showed a decreasing trend. The left Crus II showed decreased activity from the early to the late stage of grammar learning. Figure 4.9 summarised the contrast estimates of bilateral Crus I/II in AJ and GJ.

Given the differences in performance across subjects, we used d-prime and reaction time as measures of proficiency effect to correlate with the activation and functional connectivity results. We first investigated the cerebellar engagement in automatic and controlled processing. In individuals with greater proficiency, cerebellar regions were more engaged in controlled processing during AJ, whereas in individuals with less proficiency, cerebellar regions were more engaged in automatic processing during GJ. Analysis of proficiency effects on functional connectivity revealed that, in individuals with higher d-primes,

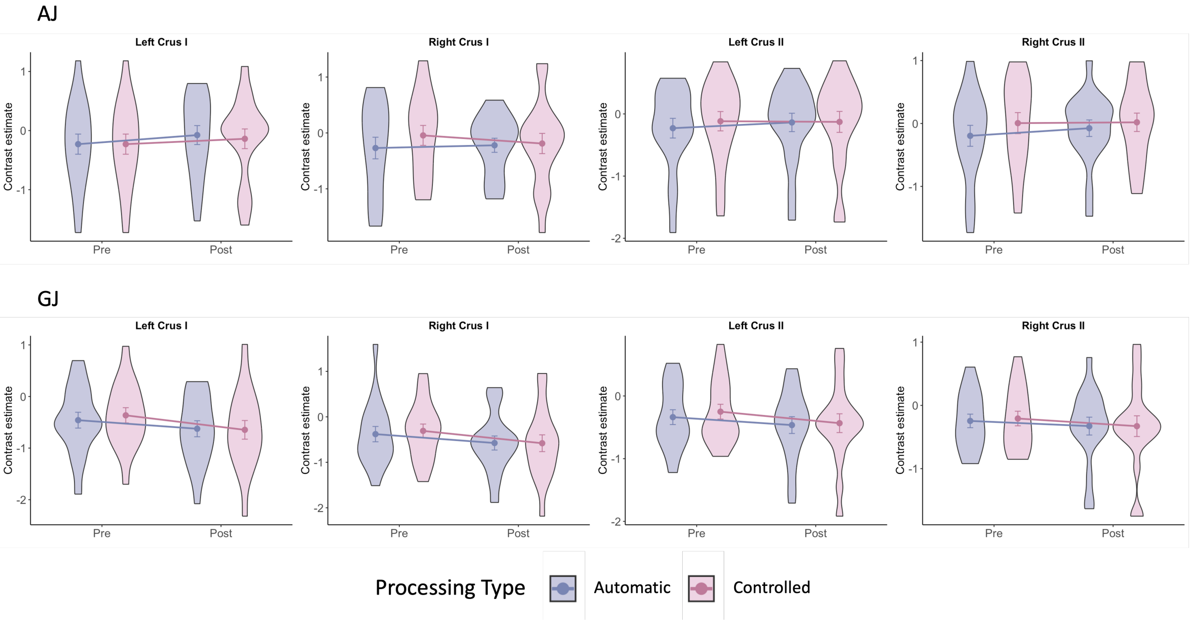


Figure 4.11: Crus I/II activities in automatic and controlled processing. Contrast estimates were extracted from each ROI. The top and bottom panels include the results for Associative Judgment and Grammar Judgment, respectively. Pre = fMRI session before training; Post = fMRI session after training.

Crus I and Crus II exhibited positive connectivity (i.e., automatic > controlled) with cortical and subcortical regions during the early stage, especially with the MFG. However, they displayed negative connectivity (i.e., controlled > automatic) with cortical and subcortical regions in the late stage. There was no clear functional connectivity pattern for reaction time effects.

Furthermore, we examined stage differences in automatic and controlled processing, as well as the interaction effect between processing type and stage, accounting for task proficiency. Among participants who showed greater improvement in d-primes, the lobule VI was found to be more active during Pre-AJ compared with Post-AJ. The same regions showed an interaction effect in GJ. Regarding functional connectivity change, the connection between Crus I/II and the right caudate was significantly modulated by processing type and stage. As for functional connectivity, in both AJ and GJ, among participants who showed greater progress, the connections between Crus I/II and the cerebrum ROIs were stronger in the early stage, with the difference being more pronounced for automatic processing. In other words, this difference in connection between automatic processing and controlled processing was greater in the early stage. When accounting for reaction times, cerebellum-cerebrum connectivity showed more diverse patterns. These findings suggest that the cerebellar-cerebrum connectivity showed different engagement and change in automatic and controlled processing.

In summary, we found that, when accounting for proficiency, cerebellar language-related regions still showed different engagement and change for automatic and controlled processing across tasks and stages. This suggests that the cerebellum may contribute to artificial language learning via the interplay between automatisation and error-tuning mechanisms.

4.2.3 Correct-Related and Error-Related Processing

The third aspect is the cerebellum's role in correct-related and error-related grammar processing. Similar to the second aspect, we examined the engagement and change pattern using inactivation and functional connectivity analysis. The entire analysis procedure remains the same, but the examined contrasts differ. In accordance with Balsters and Ramnani (2011), we distinguished correct-related and error-related activities based on whether participants successfully applied an internal grammar knowledge model. Furthermore, considering the update of the internal model, we also examined the difference in feedback processing.

In terms of engagement, we examined two correct-related > error-related contrasts in Pre-GJ and Post-GJ: (1) Sentence_cor > Sentence_inc; and (2) Feedback_pos > Feedback_neg. Furthermore, we correlated contrast differences with participants d-primes and reaction times to account for the individual proficiency difference. In terms of change, we compared changes in the two activities between stages and examined the interaction between processing type and stage. We also explored the effect of proficiency on change.

4.2.3.1 Engagement in correct-related and error-related processing

As shown in Figure 4.12, the cerebellum, especially bilateral Crus I/II, showed stronger activations in correct sentence judgment and positive feedback processing in Pre-GJ. In Post-GJ, a broad region of the cerebellum was more active during correct sentence judgment, whereas only bilateral lobule VIII was more active during positive feedback processing. In contrast, bilateral lobule VI extending to later Crus I, medial Crus I extending to Crus II, and lobule IX were more associated with negative feedback processing. Detailed results are summarised in Appendix B.1.3

The functional connectivity analysis revealed that, in Pre-GJ, the right Crus I showed increased connectivity with the right cuneus during correct sentence judgment compared with incorrect sentence judgment. No significant difference was found between positive and negative feedback. Moreover, in Post-GJ, the left Crus I showed decreased connectiv-

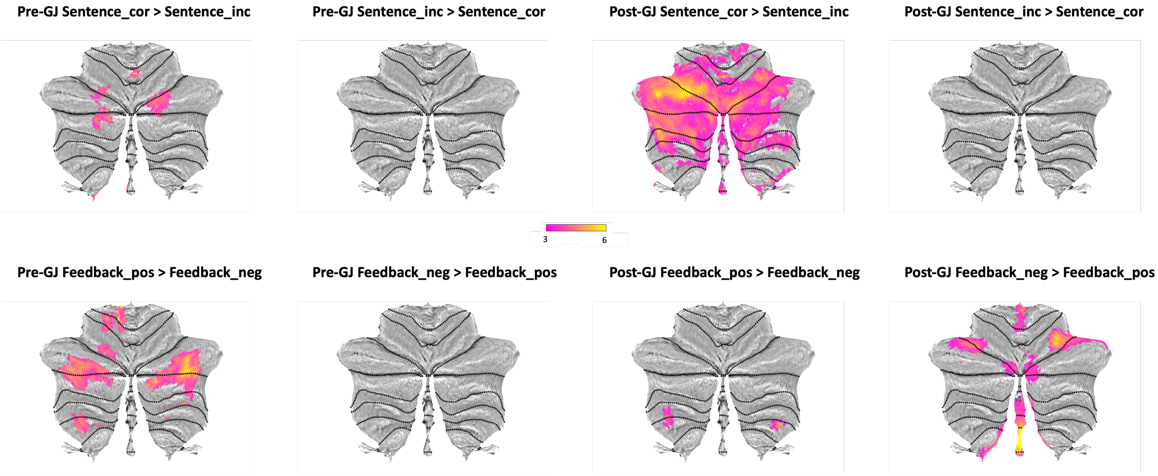
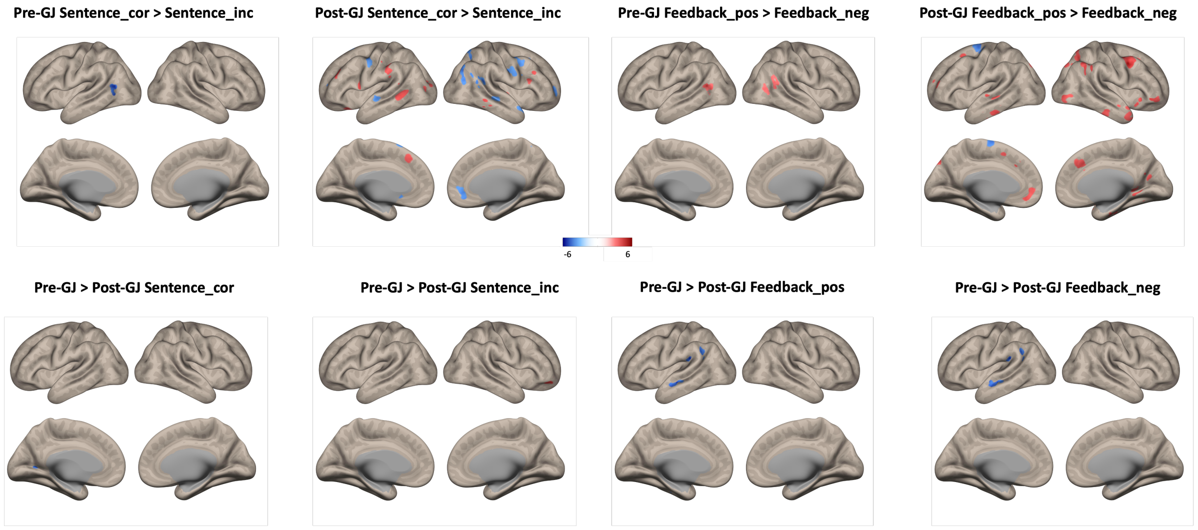


Figure 4.12: Correct-related and error-related processing activation in Pre-GJ and Post-GJ. The top panel and bottom panel include results for contrast between correct and incorrect judgment, as well as positive and negative feedback, respectively. Pre = fMRI session before training; Post = fMRI session after training; GJ = grammar judgment; Sentence_cor/inc = correct or incorrect sentence judgment; Feedback_pos/neg = positive or negative feedback.

ity with the left cingulate gyrus during correct sentence judgment. In addition, the connections between Crus I/II and a wide range of cortical and subcortical language-related regions (i.e., bilateral MFG, right SFG, left thalamus, left IPL, and left IFG) were stronger during positive feedback compared with negative feedback.

Effects of d-prime. In Pre-GJ, no significant d-prime effect was observed. In Post-GJ, participants with higher d-primes showed increased activation in left Crus II, right Crus I, and vermis VI during negative feedback processing compared to positive feedback processing.

As for the functional connectivity, as shown in Figure 4.13, in Pre-GJ, the higher d-primes were associated with a positive connection between the right Crus II and left MTG for the contrast Sentence_cor > Sentence_inc. Moreover, they were associated with negative right Crus I-to-right MFG, positive right Crus II-to-right IPL, and positive right Crus II-to-left lateral occipital cortex connections for the contrast Feedback_pos > Feedback_neg. In Post-GJ, among those with higher d-primes, Crus I/II were negatively connected to cortical regions such as right MFG, right cingulate gyrus, right precuneus, right angular gyrus, right MFG, right SFG, and right STG for the contrast Sentence_cor > Sentence_inc. On the contrary, they were positively correlated with regions such as the left MTG, left IPL, left MFG, left cuneus, right putamen, and right IFG for the same contrast. In addition, Crus I/II showed stronger connectivity with a wide range of language-related regions, such as right



Pre-GJ Sentence_cor > Sentence_inc

Post-GJ Sentence_cor > Sentence_inc

Pre-GJ Feedback_pos > Feedback_neg

Post-GJ Feedback_pos > Feedback_neg

Pre-GJ > Post-GJ Sentence_cor

Pre-GJ > Post-GJ Sentence_inc

Pre-GJ > Post-GJ Feedback_pos

Pre-GJ > Post-GJ Feedback_neg

Figure 4.13: D-prime effects on functional connectivity in correct-related and error-related processing. The top panel and bottom panel include results for engagement and change, respectively. Pre = fMRI session before training; Post = fMRI session after training; GJ = grammar judgment; Sentence_cor/inc = correct or incorrect sentence judgment; Feedback_pos/neg = positive or negative feedback.

MFG, right IPL, right SFG, left STG, left MTG, and left caudate, during positive feedback processing compared with negative feedback processing, whereas they showed weaker connections with left SFG, left thalamus, and left cingulate gyrus.

Effects of reaction time. Activation analysis showed no significant effect of reaction time. As for the functional connectivity, higher reaction times were associated with the negative connectivity between the right Crus II and right postcentral gyrus for the contrast Sentence_cor > Sentence_inc. No other significant connections were observed.

4.2.3.2 Change in correct-related and error-related processing

The change activation analysis revealed that the left Crus I/II and right Crus I showed decreased activation during correct sentence judgment in Post-GJ compared with Pre-GJ. Moreover, there was an interaction effect between feedback processing type and stage ((Pre-GJ Feedback_pos > Feedback_neg) > (Post-GJ Feedback_pos >Feedback_neg)) in the bilateral medial Crus II extending to right medial Crus I, right lobule VI extending to lateral Crus I, left lobule VIII, bilateral lobule IX, and vermis III.

No significant change effect in functional connectivity was observed in correct sentence judgment. However, for the Sentence_inc > Sentence_cor contrast, Pre-GJ compared to Post-GJ revealed increased connectivity between the right Crus I and the left lingual gyrus, as well as between the left Crus II and the left IPL. There was decreased connectivity between the left Crus II and the left cuneus. Additionally, several regions showed significant interaction effects between processing type and stage ((Pre-GJ Sentence_cor > Sentence_inc) > (Post-GJ Sentence_cor > Sentence_inc)). Specifically, the left Crus I exhibited increased connectivity with the cuneus, while the right Crus I showed increased connectivity with the right IPL. The left Crus II was more strongly connected with the right occipital lobe, and the right Crus II displayed increased connectivity with multiple regions, including the right lingual gyrus, left precentral gyrus, left postcentral gyrus, left STG, and right IPL.

For both positive and negative feedback, the right Crus I exhibited reduced connectivity with the right SFG in Pre-GJ compared to Post-GJ. For the interaction effect (i.e., (Pre-GJ Feedback_pos >Feedback_neg) > (Post-GJ Feedback_pos >Feedback_neg)), there was stronger negative connectivity between the right Crus II and the left lateral occipital cortex. The results are summarised in Appendix B.1.3.

Effects of d-prime. No significant effect was found for judgment. Furthermore, bilateral lobule VIII, vermis IV and V, left Crus I, and right lobule VI were positively correlated with d-prime improvement for the contrast Pre-GJ Feedback_pos > Post-GJ Feedback_pos. The left Crus II showed an interaction effect for the contrast (Pre-GJ Feedback_pos > Feedback_neg) > (Post-GJ Feedback_pos > Feedback_neg).

Figure 4.13 shows functional connectivity change associated with d-prime changes in correct- and error-related processing. The left Crus I showed significant connectivity changes with the right caudate, left lingual gyrus, and right MFG in both correct and incorrect sentence judgment, with a mix of increased and decreased connectivity in Pre-GJ compared to Post-GJ. For the interaction effect, the left Crus I exhibited stronger connectivity with the left MFG, while the right Crus I showed reduced connectivity with the left precuneus in Pre-GJ than Post-GJ. As for feedback processing, the Crus I/II showed reduced connectivity with left MTG and left IPL in Pre-GJ correct and incorrect sentence judgment than Post-GJ. No interaction effect was observed.

Effects of reaction time. No significant activation result was found for the effects of reaction time. In terms of functional connectivity change in correct sentence judgment, among participants with greater reaction time improvement, left Crus II-to-left MTG and right Crus II-to-right MTG connectivity increased from Pre-GJ to Post-GJ. Increased connectivity was also observed in incorrect sentence judgment, including left Crus I-to-left SFG, left Crus II-to-left MTG, and right Crus II-to-right MTG connections. For the interaction effect, the left Crus I showed enhanced connectivity with the left postcentral gyrus for the contrast Pre-GJ Sentence_cor > Sentence_inc) > (Post-GJ Sentence_cor > Sentence_inc). In contrast, the right Crus II exhibited two distinct patterns: negative connectivity with the right postcentral gyrus and positive connectivity with the right MFG for the same contrast.

4.2.3.3 Summary

In both the early and late stages of grammar learning, the cerebellum was more involved in correct sentence judgment than incorrect judgment, especially in bilateral Crus I/II. The left Crus I/II and right Crus II showed decreased activity during correct judgment over time, which is in line with Balsters and Ramnani (2011), but this decrease was not correlated with proficiency. However, no significant change effects in activation were observed for incorrect judgments, nor was there a significant interaction between stage and processing type. A significant interaction effect was found in right Crus II-to-left STG and right Crus II-to-right IPL functional connectivity, with more involvement in correct judgment at the early stage.

During feedback processing, Crus I, Crus II, and lobule VI exhibited greater activation in response to positive feedback during the early stage, but increased activation in response to negative feedback during the late stage. These regions also exhibited interaction effects, indicating that while positive feedback-related activity decreased over time, negative feedback-related activity increased, which is in line with Peterburs et al. (2018). The functional connectivity between Crus I/II and cerebral language-related regions was stronger during positive feedback in the late stage. Additionally, the right Crus I-to-right SFG connection exhibited change, with increased connectivity over time for both positive and negative feedback.

We further investigated the effects of d-prime and reaction time. Reaction time had a weaker influence on neural patterns compared to d-prime. As confirmed by behavioural results, participants showed no significant improvement in reaction time from the early to the late stage. Although cerebellar activation analysis showed no significant d-prime effect on sentence judgments, functional connectivity between Crus I/II and cerebral regions was modulated by processing type, stage, and their interaction. Among the participants who showed greater improvement in d-prime, the cerebellum demonstrated change in processing positive but not negative feedback. Interestingly, the left Crus II showed an interaction effect, suggesting that while the positive feedback processing becomes unconscious and less effortful, the error-related model still requires continuous updating, especially among those who showed greater improvement.

Furthermore, we found different d-prime effects on cerebellum-cerebrum functional connectivity during the processing of positive and negative feedback. These results suggest that cerebellar engagement and change in correct-related and error-related processing are different.

4.3 CORTICAL, SUBCORTICAL, AND CEREBELLAR CONTRIBUTION DIFFERENCE

The cerebellum's contribution to language should be investigated in conjunction with cerebrum patterns. Therefore, our second RQ is how the cerebellar internal model contributes to language learning differently from the cerebral cortex and subcortical areas. Following the investigation of the cerebellum, we also compared cortical and subcortical activations in automatic versus controlled processing, as well as correct- and error-related processing, focusing on engagement and change. The analysis mirrors the procedures used for cerebellar analysis. Furthermore, we also conducted DCM analysis to explore the effects of automatic and controlled processing on the cerebrum-cerebellum connection. Lastly, we explored different contributions to automatic and controlled processing in GJ using RSA.

4.3.1 Automatic and controlled processing

4.3.1.1 Engagement in automatic and controlled processing

As shown in Figure 4.14, the contrast between automatic and controlled consistently elicited lateralised activations in cerebrum sensorimotor areas (e.g., postcentral gyrus) as in the cerebellum. This is due to the unbalanced design of the button press. However, in Pre-AJ, we found that matched judgment was associated with higher activations in the left thalamus and left SFG, while mismatched judgment was associated with right SFG and right putamen. In Post-AJ, the left thalamus and left putamen were more engaged in matched judgment, whereas right MFG, right pallidum, right thalamus, bilateral IFG, and left MTG were more engaged in mismatched judgment. Furthermore, in Pre-GJ, the right SFG and bilateral IFG were more active during ungrammatical sentence judgment. In Post-GJ, the left thalamus, left putamen, left SFG, and left STG were more involved in grammatical sentence judgment, while right SFG, right thalamus, bilateral IFG, bilateral IPL, left MTG, right putamen, and left MFG were more active during ungrammatical sentence judgment. These results suggest cognitive differences between automatic and controlled processing.

Effects of d-prime. No significant d-prime effect was found in AJ. In Pre-GJ, the left SFG showed positive correlations with d-primes for the contrast Sentence_gra > Sentence_ung. In contrast, in Post-GJ, the left cingulate gyrus showed negative correlations with d-prime

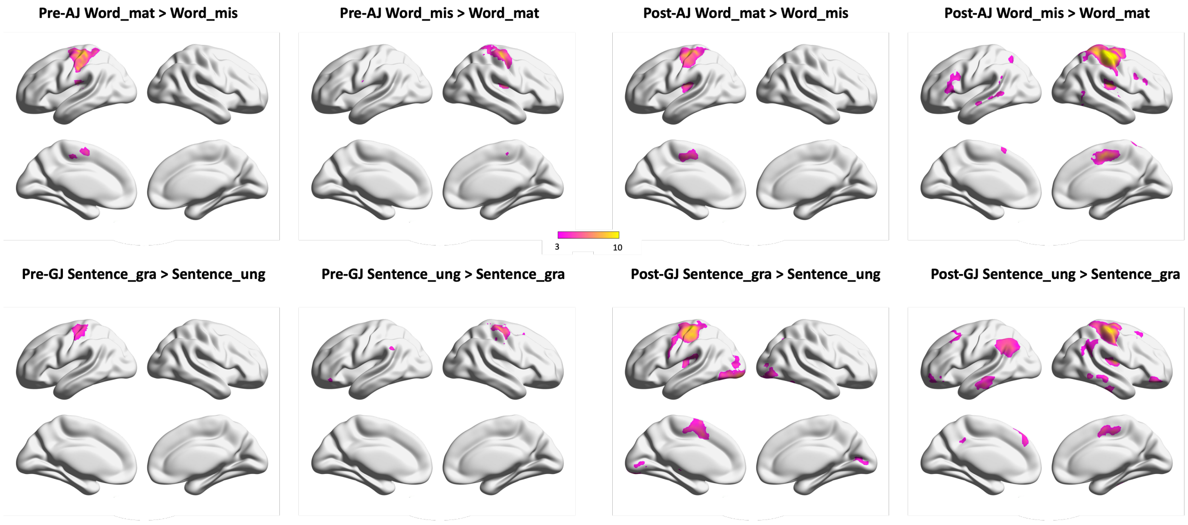


Figure 4.14: Whole-brain automatic and controlled processing activations. Pre = fMRI session before training; Post = fMRI session after training; AJ = associative judgment; GJ = grammar judgment; Word_mat/mis = judgment of matched or mismatched associations. Sentence_gra/ung = judgment of grammatical or ungrammatical sentences.

for the contrast Sentence_gra > Sentence_ung. Detailed results are summarised in Appendix B.2.1.

Effects of reaction time. In Post-AJ, the left MFG and left IFG showed negative correlations with d-primes for the contrast Word_mis > Word_mat. Moreover, in Pre-GJ, a wide range of cortical and subcortical areas showed negative correlations with d-primes for the contrast Sentence_gra > Sentence_ung, including right thalamus, right lingual gyrus, right cuneus, right precuneus, left precentral gyrus, right caudate, bilateral MTG, bilateral STG, and left IFG.

4.3.1.2 Change in automatic and controlled processing

The change analysis revealed that the left middle occipital gyrus showed decreased activity in matched association judgment from Pre-AJ to Post-AJ. Moreover, there was an interaction effect between processing type and stage in the left IPL and right MFG, where the difference between Word_mat >Word_mis was greater in Pre-AJ than Post-AJ. The left caudate and right MFG showed reduced activation in both types of processing from Pre-GJ to Post-GJ. Additionally, the right IFG demonstrated an interaction effect, where the difference in activation between Sentence_gra > Sentence_ung became more pronounced in Post-GJ than Pre-GJ. Further analysis showed that the right IFG demonstrated a greater increase in activity associated with grammatical sentence judgment compared with ungrammatical sentence judgment.

Effects of d-prime. Among the participants with greater d-prime improvement, the left MTG showed reduced activation from Pre-AJ to Post-AJ during both matched and mismatched association judgment. The right IFG was only associated with decreased activations in matched association judgment. In contrast, the left hippocampus demonstrated increased activations in matched association judgment. No significant interaction effect was observed between processing type and stage. As for GJ, the left cingulate gyrus and left putamen showed positive correlation with d-prime change for the contrast between Pre-GJ and Post-GJ grammatical sentence judgment. These regions were associated with enhanced activations from Pre-GJ to Post-GJ. In addition, the left parahippocampus demonstrated increased activations during ungrammatical sentence judgment. No significant interaction effect was observed.

Effects of reaction time. No significant effect was found for AJ. However, the left insula and right MFG showed negative correlations with reaction time change for the contrast (Post-GJ Sentence_gra >Sentence_ung) > (Pre-GJ Sentence_gra > Sentence_ung).

4.3.1.3 Neural representations of word and sentence

As for POS-specific patterns, the clustering analysis showed that Crus I/II showed dissimilar patterns with AG and subcortical regions 4.15. Moreover, in Pre-GJ, all ROIs demonstrated different neural patterns for three ungrammatical sentence types and grammatical sentences. Overall, these regions have similar patterns when processing sentence grammar. Interestingly, compared with grammatical versus ungrammatical, the differences between the three sentence types were greater. Although ROIs demonstrated similar patterns when processing sentence types, the hierarchical clustering analysis revealed that Crus I/II still demonstrated some different patterns with AG and subcortical ROIs in both Pre-GJ and Post-GJ.

We then compared RDMs of the ROIs (Figure 4.16). The results showed that AG showed a less dissimilar pattern, while subcortical regions (i.e., BG, hippocampus, parahippocampus, thalamus) showed more dissimilar patterns for different POS and grammar types.

4.3.1.4 Effective connectivity in automatic and controlled processing

We further performed DCM to specify the information flow among the left IFG, left thalamus, and right Crus I/II. In the tables, off-diagonal cell estimates represent rate constants, expressed in units of 1/s (Hz), indicating the rate at which activation in a source ROI influences the activation in a target ROI per second. Positive estimates reflect excita-

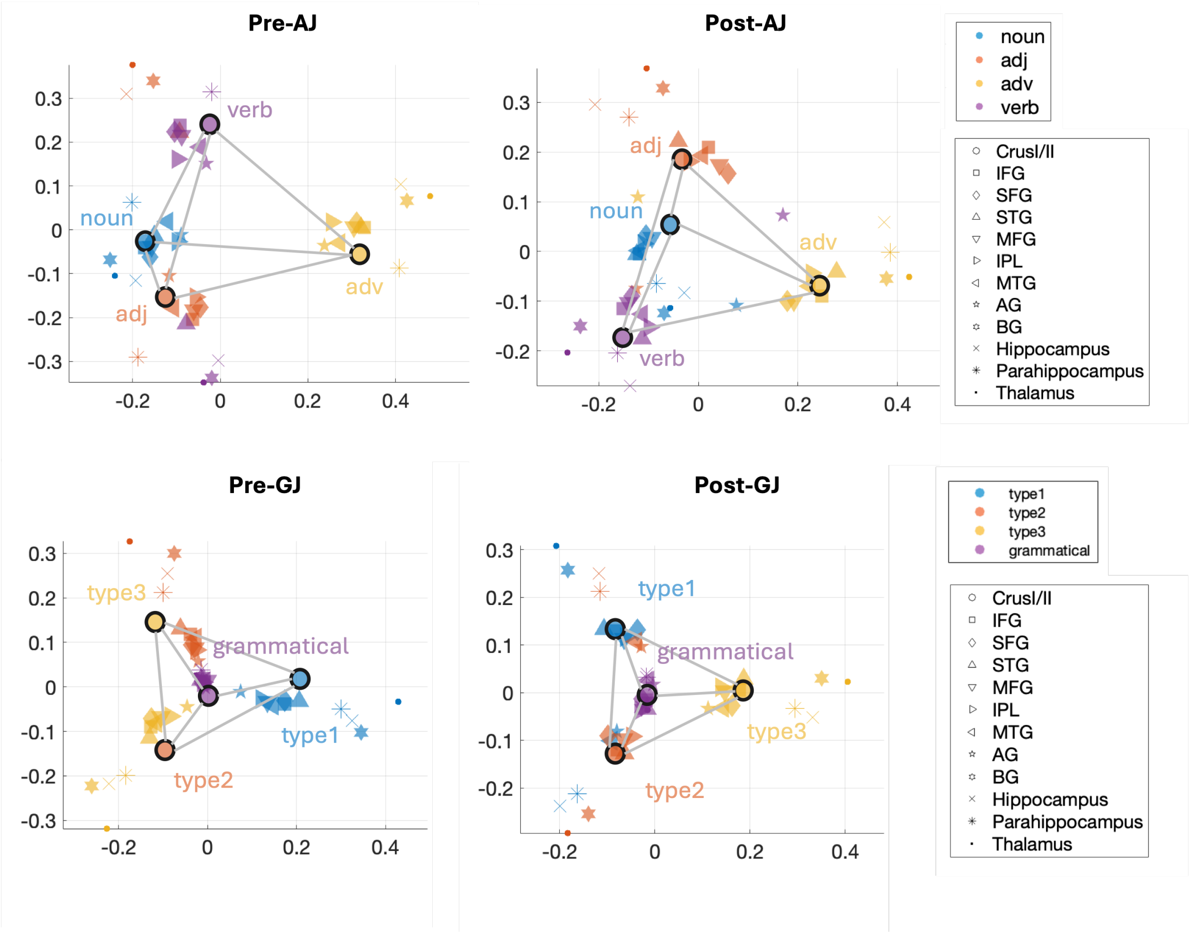


Figure 4.15: RSA results for AJ and GJ. The MDS plots showed how ROIs showed different representations for different POS or grammar types. The representations for Crus I/II were highlighted.

tory effects, while negative estimates indicate inhibitory effects. Diagonal cells represent self-connections.

Firstly, we examined the fixed connections, which are the intrinsic connectivity between brain regions in the absence of external inputs. As d-prime showed a stronger influence on activation and functional connectivity patterns compared to reaction time, we used d-prime as a covariate to measure the effect of proficiency. As shown in Figure 4.17, we found several closed loops between right Crus I and left IFG, right Crus I and left thalamus, and right Crus II and left thalamus. More closed loops were found in models with d-prime as the individual difference factor. All self-connections are negative from -.1 to -.6 hz, which represents the exponential decay rate of neural activity. There was no clear pattern of inter-regional connections.

Secondly, we compared automatic models and controlled models. As shown in Figure

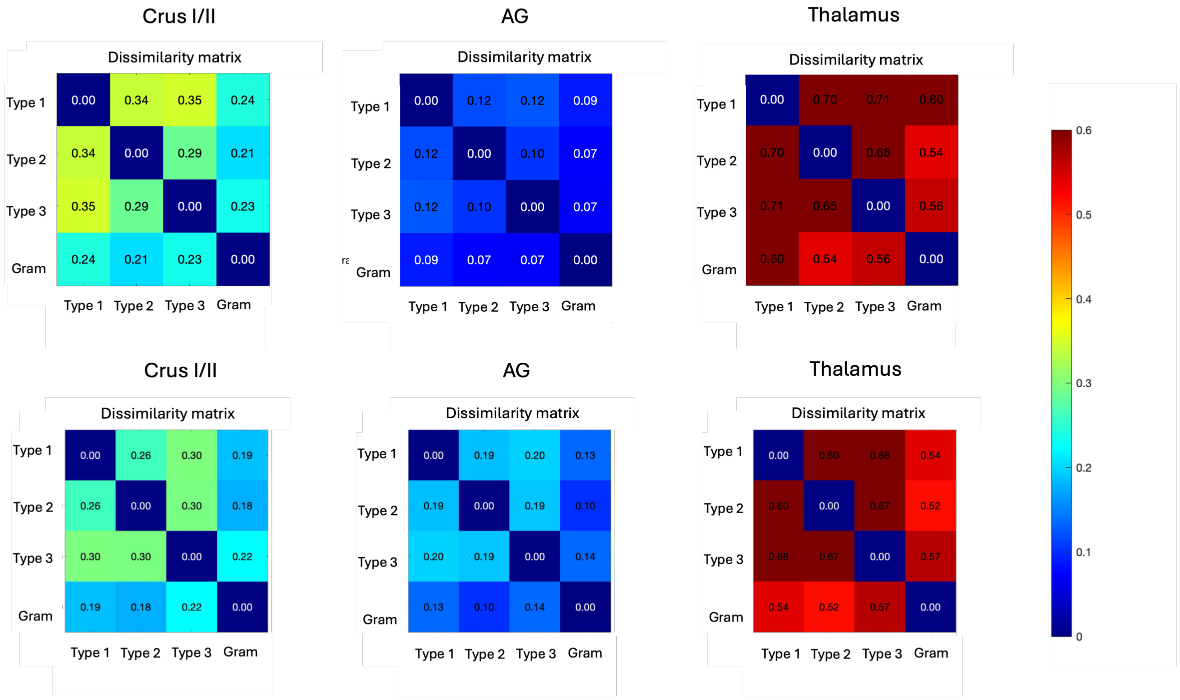


Figure 4.16: RDM comparison for GJ. We chose the thalamus as the representative of the subcortical regions. The dissimilarity scores of AG RDMs were significantly lower than those of Crus I/II. The dissimilarity scores of subcortical regions RDMs were significantly higher than those of Crus I/II. Gram = grammatical sentences.

4.18, the BMC analysis revealed that automatic commonalities models outperformed controlled commonalities models in Pre-GJ and Post-GJ. Moreover, the automatic model with d-prime as the individual difference factor outperformed the controlled d-prime model in Post-GJ. In fact, the posterior probabilities of four d-prime automatic models were higher than those of controlled models, but the evidence for AJ model comparisons was not strong. For AJ commonalities models, the posterior probabilities of controlled models were higher than automatic models, but the posterior probability was not higher than 95%.

Thirdly, based on the BMC results, we extracted modulatory effects from GJ PEB models. In the Pre-GJ automatic commonalities models, grammatical sentence judgment inhibited the connection from right Crus II to left IFG. It also inhibited the intrinsic connection of the right Crus II. Moreover, ungrammatical sentence judgment strengthened the connection from left IFG to right Crus I, inhibited the connection from left thalamus to right Crus I, and inhibited the intrinsic left IFG connection. In the Post-GJ automatic commonalities models, these effects changed, with grammatical sentence judgment less inhibiting the right Crus II to left IFG connection. Ungrammatical sentence judgment strengthened the left IFG to right Crus II connection and the left thalamus to right Crus I connection. It

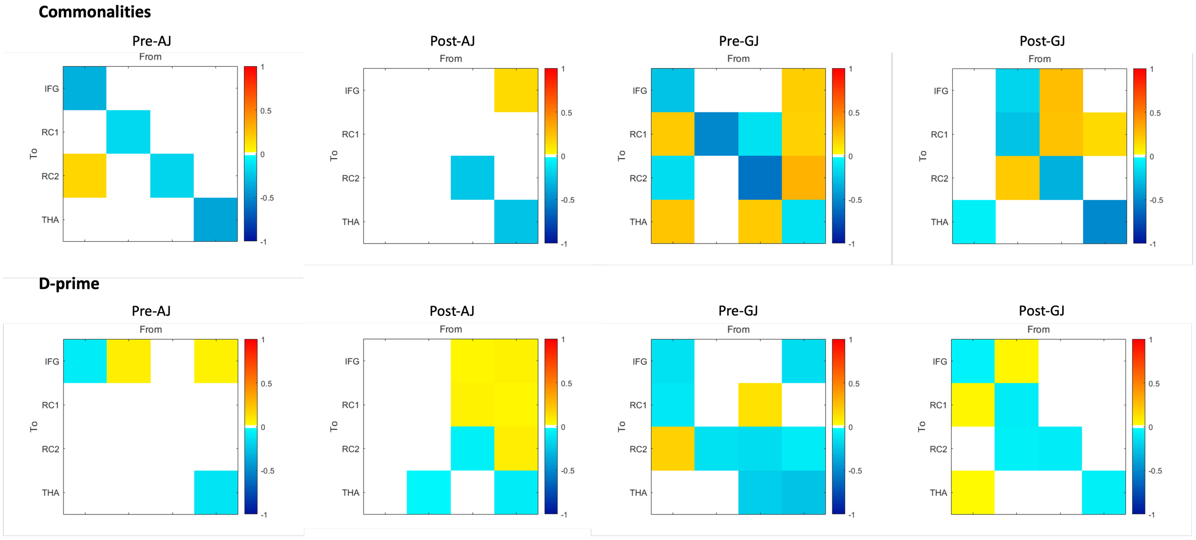


Figure 4.17: Averaged fixed connections with or without covariates for artificial language learning. Commonalities: models without individual difference factors; d-prime = models with task d-prime scores as the individual difference factor; Pre = fMRI session before training; Post = fMRI session after training; AJ = associative judgment; GJ = grammar judgment; IFG = left inferior frontal gyrus; THA = left thalamus; RC1 = right Crus I; RC2 = right Crus II.

also further inhibited the intrinsic left IFG connection.

In the Pre-GJ model with d-prime as an individual difference factor, grammatical sentence judgment showed a contrary pattern, enhancing the connection from right Crus II to left IFG. In addition, it inhibited the intrinsic connection of right Crus I. Grammatical sentence judgment enhanced the left thalamus-to-right Crus I connection but inhibited the left IFG-to-right Crus I connection. In the Post-GJ d-prime model, grammatical sentence judgment strengthened the right Crus II-to-left thalamus connection. In contrast, ungrammatical sentence judgment inhibited two downward connections, including left IFG-to-right Crus II and left thalamus-to-right Crus I connections. Interestingly, no significant modulatory effect was observed in the connection between left IFG and left thalamus during GJ.

4.3.1.5 Summary

Using activation analysis, we investigated cortical and subcortical engagement and change in automatic and controlled processing. Similar to the cerebellar findings, language-related regions, particularly the bilateral IFG and left MTG, were more involved in controlled processing. SFG, thalamus, and BG were involved in both processing. These results were consistent with previous studies (Friederici et al., 2006; Forkstam et al., 2006; Petersson et al.,

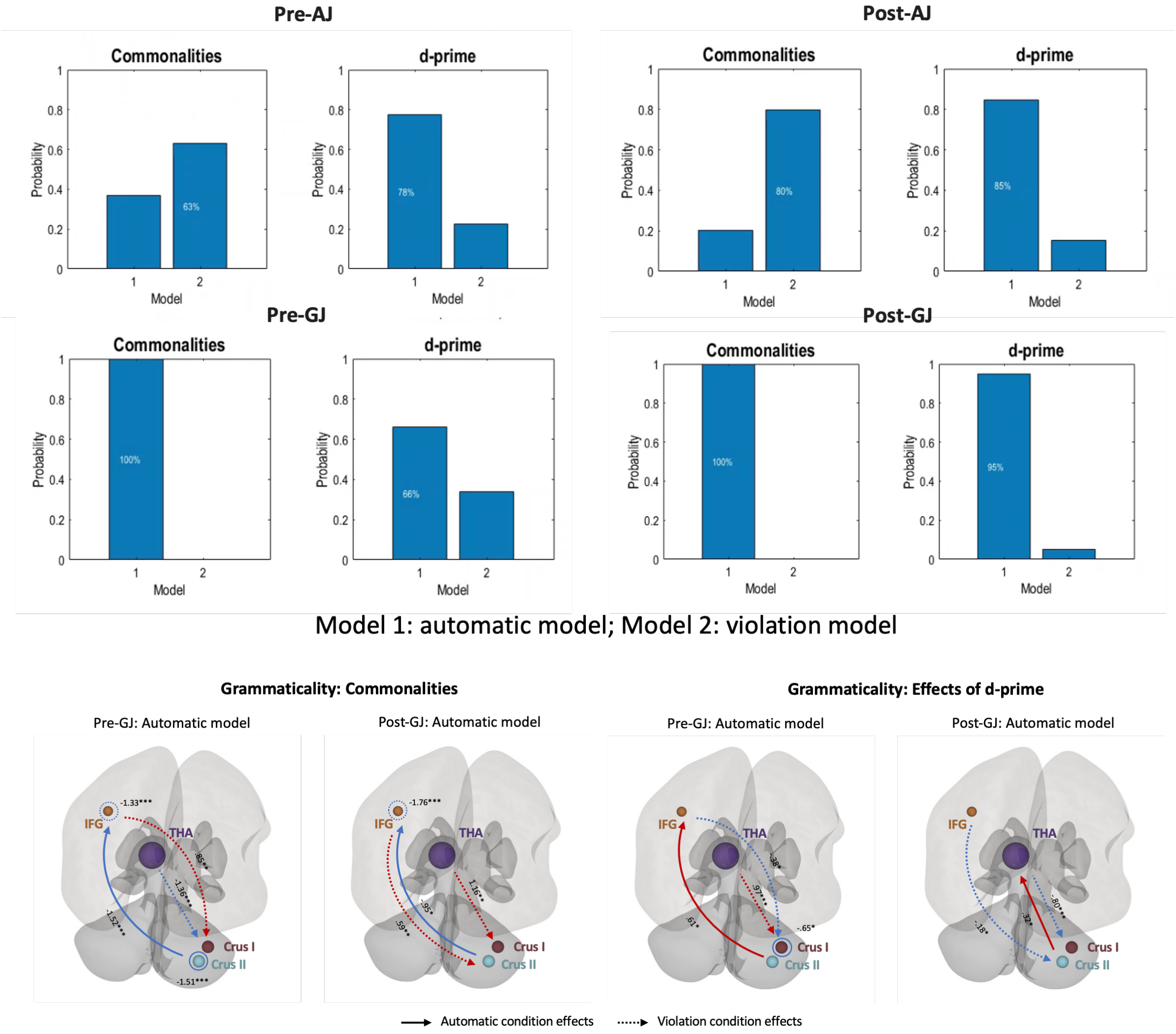


Figure 4.18: Averaged modulatory connections with or without covariates for artificial language learning. The arrowed lines display the information flow among the left IFG, left thalamus, and right Crus I/II. The solid and dashed lines indicate automatic and controlled condition effects, respectively. The mean modulatory parameter estimates (in hz) are presented alongside the arrowed lines. Red lines indicate that the input strengthens the connection, while blue lines indicate that the input weakens or inhibits it. Pre = fMRI session before training; Post = fMRI session after training; GJ = grammar judgment. IFG = inferior frontal gyrus; THA = thalamus. $^{***}P = 1.0$;$^{**}P > .99$;$^{*}P > .95$.

2012). Furthermore, the left caudate and left MFG demonstrated change during GJ, which mirrors the pattern of the left Crus I. However, the left IPL and right MFG demonstrated an opposite interaction effect between processing type and stage with the right Crus I during AJ.

We further examined the proficiency effects on these differences using task d-primes and reaction times. Regarding the effects of d-primes, we found that, similar to the cerebellum's language-related areas, activations in the right IFG and left MTG decreased during AJ acquisition among participants with greater d-prime improvement, whereas activations in the left parahippocampus increased. We also found an activation increase in the left parahippocampus during GJ acquisition, as well as in the left putamen and left cingulate gyrus. However, we observed no interaction effect in AJ and GJ. Among the participants with shorter reaction times, we found that the left MFG and left IFG showed increased engagement in controlled processing during the late stage of AJ acquisition, consistent with cerebellar patterns. However, multiple regions in the cortical and subcortical areas were more engaged in controlled processing and demonstrated interaction effects, which were not observed in the cerebellum. Interestingly, it seems that the left IFG closely mirrors the cerebellar activation patterns.

As for RSA, while ROIs exhibited similar neural patterns in distinguishing sentence types, cerebellar Crus I/II contributed uniquely to processing different sentence types compared to cortical and subcortical regions, particularly the AG and subcortical ROIs. However, they showed less pronounced differences in the later stage. From the analysis for RQ1, we found that Crus I/II demonstrated decreased activity over time, indicating more integrated and efficient neural processing. It is possible that, over time, Crus I/II worked more cohesively with language-related regions, supporting the fine-tuning and optimisation of learned grammar rules. This increased integration results in a reduction in the difference between the neural patterns of these regions during the later stages of learning. Moreover, the greater difference in terms of the ungrammatical sentence types suggests that Crus I/II are not only involved in distinguishing automatic and controlled conditions but also different types of syntactic violations. The changing difference in grammaticality sensitivity suggests the update of the internal model in the cerebellum.

Our initial prediction is that only cerebrum regions without strong structural connections to Crus I/II would exhibit dissimilar functional patterns. The AG findings align with this prediction, as one prior study confirmed that cerebro-cerebellar tracts projecting to the IFG are more robust than those terminating in the AG (Jobson et al., 2024). However, the case of the thalamus presents a more complex picture. As a critical hub in the cerebro-cerebellar loop, its different pattern from Crus I/II suggests that structural connectivity does not necessitate functional homogeneity. We propose that even within a coordinated network subserving a shared internal model, distinct nodes can perform complementary computations. This interpretation is consistent with Ito's foundational framework, yet it extends it by highlighting the specific and underexplored contribution of subcortical regions. Consequently, we observed that subcortical regions, particularly the thalamus, demonstrated distinct functional patterns from Crus I/II across both language tasks. This finding suggests a specialised division of labor within the circuit, a specific mechanism that warrants targeted investigation in future research.

Regarding effective connectivity, we identified closed loops in fixed connections, which aligns with previous findings in social sequence and controlled processing (Pu et al., 2022). In terms of modulatory effects, we found that GJ automatic models outperformed controlled models, while no specific pattern was observed for AJ. Overall, in GJ automatic commonalities models, most downward connections were positive and upward connections were negative, especially between the left IFG and right Crus I/II. This pattern is similar to that found in Van Overwalle et al. (2019) and Van Overwalle et al. (2020), which assessed effective connectivity between bilateral posterior cerebellum and bilateral temporo-parietal junction during social processing. However, in GJ automatic models with d-prime as the factor, an opposite pattern was observed. This finding reflects that the cerebellum of the highly proficient participants drives the cerebrum through positive connections, supporting automatic processing, while the cerebrum inhibits the cerebellum during controlled processing. However, in a study assessing how fronto-cerebellar effective connectivity mediates cognitive processing speed, negative left lobule VI → left THA and higher positive left inferior frontal junction → right lobule VI were found to predict faster speed significantly (C. H. Y. Wong et al., 2021). These inconsistencies may be due to the examination of different cognitive processes. Considering the sample size of the current study is rather small, the results should be interpreted cautiously. These findings suggest that the automatization mechanism may play a prominent role during GJ, and the specific effective connectivity can be significantly modulated by d-prime scores.

4.3.2 Correct-Related and Error-Related Processing

4.3.2.1 Engagement in correct-related and error-related processing

Figure 4.19 shows the whole-brain activations during correct-related and error-related processing. Except for the Sentence_inc > Sentence_cor contrast in Pre-GJ, we observed a wide range of cortical and subcortical activations. Overall, the SFG and basal ganglia were consistently activated across contrasts during both judgment and feedback processing, without specific involvement in particular processes. The insula was engaged in both positive and negative feedback processing. Additionally, regional differences were observed based on processing type. The left IFG and left superior parietal lobe showed greater activation during correct judgments in Post-GJ. The left hippocampus was more engaged during positive feedback processing, while the left STG and left thalamus were more active during negative feedback processing in Post-GJ.

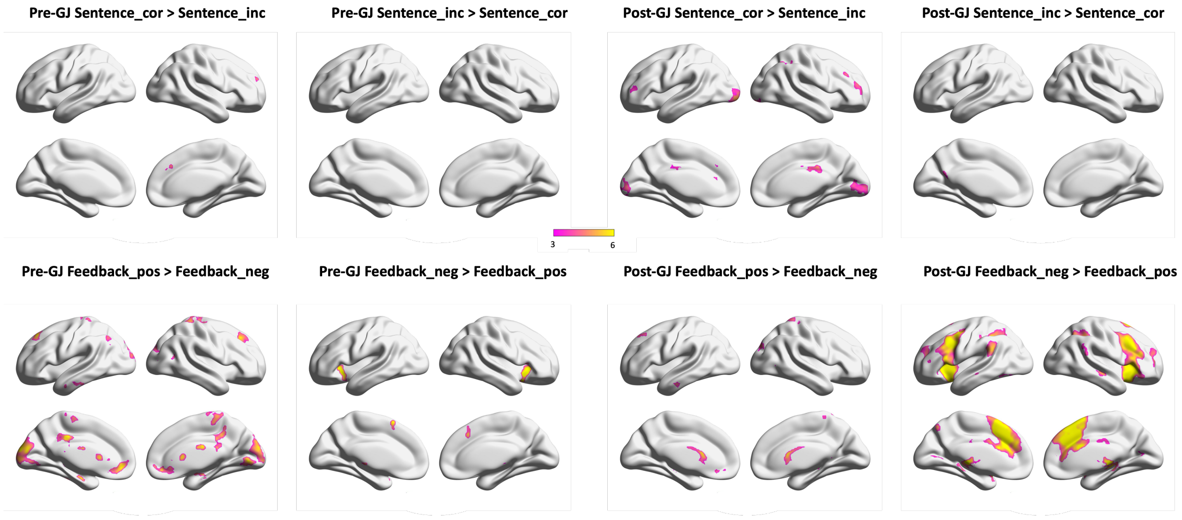


Figure 4.19: Whole-brain correct-related and error-related processing activations. Pre = fMRI session before training; Post = fMRI session after training; AJ = associative judgment; GJ = grammar judgment; Sentence_cor/inc = correct or incorrect sentence judgment; Feedback_pos/neg = positive or negative feedback.

Effects of d-prime. No significant result was found for task d-primes effects regarding the correct and incorrect judgment comparison. However, in Pre-GJ, the right caudate and left SFG were more involved in negative than positive feedback processing. In Post-GJ, bilateral IFG, right parahippocampus, right inferior parietal lobe, right cingulate gyrus, left insula, and left MFG were also more involved in negative feedback processing.

Effects of reaction time. No significant reaction time effect was found for judgment and feedback in both Pre-GJ and Post-GJ.

4.3.2.2 Change in correct-related and error-related processing

In terms of the cerebrum's change in correct- and error-related processing, we observed opposite patterns in GJ judgment and feedthat the cerebrum is more involved in positive feedback processing during the early stage, whereas in negative feedback processing, it is more involved during the late stage, which aligns with the pattern observed in the cerebellumt. Furthermore, the right IFG showed an interaction effect for the contrast (Post-GJ Sentence_cor >Sentence_inc) >(Pre-GJ Sentence_cor >Sentence_inc). For feedback, there was no significant change in positive feedback processing. However, a wide range of cerebrum regions showed an increase in activity from Pre-GJ to Post-GJ, including bilateral IPL, right IFG, right MTG, right cingulated gyrus, precuneus, left caudate, and right MFG. Moreover, right MFG, bilateral caudate, left putamen, left insula, right fusiform gyrus, left thalamus, right IPL, right precuneus, right MTG, and right cingulate gyrus demonstrated an interaction effect for the contrast (Pre-GJ Feedback_pos >Feedback_neg) > (Post-GJ Feedback_pos >Feedback_neg).

Effects of d-prime. Similar to the engagement exploration, we did not observe effects of d-prime on judgment. As for feedback, among participants with greater d-prime improvement, activity in right MFG decreased during positive feedback processing from Pre-GJ to Post-GJ, whereas activity in right precuneus and left MTG decreased during negative feedback processing.

Effects of reaction time. No significant reaction time effect was found for judgment and feedback in both Pre-GJ and Post-GJ.

4.3.2.3 Summary

For the engagement in correct-related and error-related processing, similar to the cerebellar Crus I/II, the left IFG and left superior parietal lobe exhibited increased activation during correct judgments. Moreover, in terms of feedback processing, we found that the cerebrum is more involved in positive feedback processing during the early stage, whereas in negative feedback processing, it is more involved during the late stage, which aligns with the pattern observed in the cerebellum. In contrast, although no cerebellar language-related region was more involved in incorrect sentence judgment, this effect was found in the right caudate during Post-GJ. Moreover, a group of cortical and subcortical regions contributes to feedback processing differently from cerebellar language-related regions. In Pre-GJ, the left thalamus and left SFG were more active during negative feedback processing, and in Post-GJ, the left caudate, left hippocampus, left MTG, and left SFG were more active during positive feedback processing.

We only observed d-prime effects on feedback processing, specifically, the contrast Feedback_neg > Feedback_pos, which is in line with the cerebellum findings. Many language-related regions demonstrated a similar pattern in positive and negative feedback processing, including bilateral IFG, right parahippocampus, and left MFG.

For change, similar to left Crus I, the right SFG and right IFG showed decreased activations during correct judgment. However, we found an interaction effect in the right parahippocampus during judgment, which was not observed in the cerebellum. Further analysis revealed that, compared with correct sentence judgment, the activity associated with correct sentence judgment decreased more significantly from the early to the late stage. The proficiency effects did not influence the change of the cerebrum and cerebellum.

Regarding feedback, multiple cortical and subcortical regions exhibited an increase in activity over time during negative but not positive feedback processing. Many of these regions also demonstrated interaction effects, including MFG, IPL, MTG, caudate, cingulate gyrus, and prenueus. This suggests that the cerebrum activity related to processing negative feedback increased more significantly than its activity related to processing positive feedback, which aligns with the pattern found in the cerebellum. When considering d-prime effects on feedback processing, we found a significant decrease in cerebrum activity in both feedback types for those with greater improvement; however, the cerebellum only showed reduced activations in positive feedback.

4.4 INDIVIDUAL DIFFERENCE INFLUENCE

Our third RQ is: What are the individual differences that influence the internal model of language learning? We investigated this question by comparing the effects of individual difference factors on automatic versus controlled processing and correct-related versus error-related processing. To measure the cognitive and language individual difference effect on cerebellar activations, we used Cognitive PC1 and Language PC1 to correlate activation and functional connectivity contrast results. The selection and summary of individual difference factors is described in Section 4.1.2. The analysis of whole-cerebellum activation and gPPI ROI functional connectivity was conducted based on the previously described contrasts and procedures.

Furthermore, we explored whether the individual difference factors can moderate the relationship between individual differences and successful language learning. We compared three models of artificial language learning performance, indexed by d-prime, reaction time, and their improvement over time. The first baseline model included only Cognitive PC1 and Language PC1. The second model included the additive effects of individual difference factors and cerebellar patterns. The third model tested how individual difference factors and cerebellar patterns interacted to influence artificial language learning performance. We predicted that the third model would outperform the first two models, which reflects the moderating effect of cerebellar patterns.

4.4.1 Automatic and Controlled processing

4.4.1.1 Engagement in automatic and controlled processing

Activation. As shown in Table 4.2, higher Language PC1 was associated with stronger right lobule VI activations in mismatched association judgment compared with matched association judgment in Post-AJ.

Region	Side	Size	Peak-level statistics			
			T value	MNI coordinates		
				x	y	z
Pre-AJ:						
-	-	-	-	-	-	-
Pre-GJ:						
-	-	-	-	-	-	-
Post-AJ:						
Language PC1						
Lobule VI	R	42	-4.05	22	-62	-20
Post-GJ:						
-	-	-	-	-	-	-

Table 4.2: Individual difference effects on automatic and controlled processing. The contrasts are automatic > controlled processing. Pre = fMRI session before training; Post = fMRI session after training; AJ = associative judgment; GJ = grammar judgment.

Functional connectivity. In Pre-AJ, for the contrast Word_mat > Word_mis, Cognitive PC1 modulated the functional connectivity between the left Crus I and left thalamus (β = .19, $T(16)$ = 4.02), and between the right Crus II and right MFG (β = .39, $T(16)$ = 4.18), right IFG (β = .51, $T(16)$ = 3.70), right putamen (β = .46, $T(16)$ = 3.53), left putamen (β = .51, $T(16)$ = 3.48), or left thalamus (β = .38, $T(16)$ = 3.37).

4.4.1.2 Change in automatic and controlled processing

Activation. We also found individual difference effects on cerebellar change in automatic and controlled processing during AJ and GJ (Table **??**). Higher Cognitive PC1 was associated with decreased left Crus II activations from Pre-AJ to Post-AJ during both types of processing. In contrast, higher Language PC1 was associated with decreased vermis IX activations from Pre-GJ to Post-GJ during both types of processing.

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
Pre-AJ >Post-AJ Word_mat:						
Cognitive PC1						
Crus II	L	26	5.54	-30	-80	-36
Pre-AJ >Post-AJ Word_mis:						
Cognitive PC1						
Crus II	L	73	7.00	-28	-76	-38
Pre-GJ >Post-GJ Sentence_gra:						
Language PC1						
Vermis IX	R	43	7.37	4	-44	-32
Pre-GJ >Post-GJ Sentence_ung:						
Language PC1						
Vermis IX	R	30	6.29	6	-44	-34

Table 4.3: Individual difference effects on cerebellar change in automatic and controlled processing. Pre = fMRI session before training; Post = fMRI session after training; AJ = associative judgment; GJ = grammar judgment; Word_mat/mis = judgment of matched or mismatched associations. Sentence_gra/ung = judgment of grammatical or ungrammatical sentences.

Functional connectivity. In terms of functional connectivity, for the contrast Pre-AJ > Post-AJ Word_mat, higher Cognitive PC1 was associated with decreased functional connectivity between the right Crus II and right Crus I. However, for the contrast Pre-AJ > Post-AJ Word_mis, higher Cognitive PC1 was associated with increased functional connectivity between the right Crus II and left MFG ($\beta = -.72$, $T(16) = -3.68$), right IFG ($\beta = -.73$, $T(16) = -3.18$), right putamen ($\beta = -.50$, $T(16) = -3.15$), or right MFG ($\beta = -.51$, $T(16) = -3.11$).

For the contrast Pre-GJ > Post-GJ Sentence_gra, higher Cognitive PC1 was associated with decreased functional connectivity between the right Crus I and right putamen ($\beta = 1.74$, $T(16) = 3.60$) or left STG ($\beta = 3.00$, $T(16) = 3.35$). In addition, for the contrast Pre-GJ > Post-GJ Sentence_ung, higher Cognitive PC1 was associated with decreased functional connectivity between the right Crus I and right putamen ($\beta = 1.68$, $T(16) = 3.34$), left STG ($\beta = 2.89$, $T(16) = 3.32$), or right parahippocampus ($\beta = 3.09$, $T(16) = 3.19$).

4.4.1.3 Moderating effects

For the moderating effect models, the linear models were fitted using the formula: $Outcome \sim Cognitive\_PC1 * (Word\_mat - Word\_mis) + Language\_PC1 * (Word\_mat - Word\_mis)$ or $Outcome \sim Cognitive\_PC1 * (Sentence\_gra - Sentence\_ung) + Language\_PC1 * (Sentence\_gra - Sentence\_ung)$. As shown in Figure 4.20, likelihood ratio tests (LRTs) revealed that the moderating effect model outperformed the baseline model in predicting Pre-AJ reaction time. In addition, the moderating effect model outperformed the baseline model and additive effect model in predicting Pre-GJ d-prime. However, these two models did not reveal interaction effects between individual differences and cerebellar patterns.

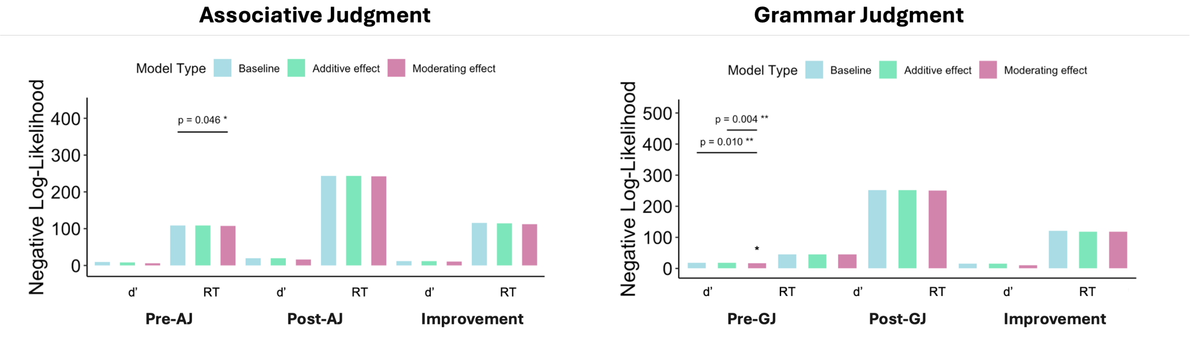


Figure 4.20: The moderating effects of cerebellar patterns in automatic and controlled processing. Negative log-likelihood ratios for the models. Significance bars indicate model comparisons (LRTs); only significant differences are shown. Asterisks above bars indicate models with a significant overall fit. d' = d-prime. RT = reaction time. $^*p < .05$, $^{**}p < .01$.

4.4.1.4 Summary

While both cognitive and language individual differences influenced cerebellar engagement and change in automatic versus controlled processing in terms of local activation, functional connectivity was modulated only by cognitive individual differences. Higher Language PC1 was correlated with stronger cerebellar activations during mismatched association judgment in Post-AJ. In contrast, higher Cognitive PC1 was linked to stronger cerebellocerebral connectivity during matched association judgment in Pre-AJ.

Notably, higher Cognitive and Language PC1 were associated with decreased cerebellar activations during associative and grammar judgment, respectively. Furthermore, regarding functional connectivity, Cognitive PC1 affected cerebellar change differently in matched and mismatched associations. In contrast, higher Cognitive PC1 was associated with decreased cerebellum-cerebrum connectivity in GJ, regardless of processing type.

Moreover, we tested moderating effect models to examine whether individual differences in cognitive and language abilities influenced the relationship between language processing conditions and behavioural outcomes. Model comparisons using likelihood ratio tests revealed that the moderating effect model provided a superior fit for predicting Pre-AJ reaction time and Pre-GJ d-prime compared to baseline and additive models. However, despite this overall improvement in model performance, the analysis did not identify any statistically significant interaction effects between the individual difference measures and the cerebellar activation patterns in automatic and controlled processing, indicating that the source of the improved fit was not a clear, specific moderating influence as initially hypothesised.

4.4.2 Correct-Related and Error-Related Processing

4.4.2.1 Engagement in correct-related and error-related processing

Activation. As shown in the Table 4.5, in Post-GJ, increased Cognitive PC1 was associated with greater right lobule VI and Crus I activations during incorrect judgment compared to correct judgment.

Functional connectivity. Pre-GJ analyses revealed negative associations between the Cognitive PC1 and functional connectivity from right Crus I to left STG during correct versus incorrect judgment ($\beta = -.31, T(16) = -3.33$), as well as between the Language PC1 and the same connection ($\beta = -.27, T(16) = -3.65$). A negative association was also observed between Language PC1 and functional connectivity from left Crus I to left IFG during positive versus negative feedback ($\beta = -.54, T(16) = -3.68$).

4.4.2.2 Change in correct-related and error-related processing

Activation. As shown in Table 4.5, higher Language PC1 was linked to decreased left lobule VIIb activities from Pre-GJ to Post-GJ during incorrect judgment. In contrast, higher Language PC1 was associated with increased bilateral lobule VI and right lobule VIII activities during positive feedback.

Functional connectivity. Longitudinal comparisons for change investigation indicated that higher Cognitive PC1 was correlated to increased functional connectivity from pre- to post-training between right Crus I and right putamen ($\beta = -1.86, T(16) = -3.55$) and be-

Region	Side	Size	Peak-level statistics			
			T value	MNI coordinates		
				x	y	z
Pre-GJ Judgment:						
-	-	-	-	-	-	-
Pre-GJ Feedback:						
-	-	-	-	-	-	-
Pre-GJ Judgment:						
Cognitive PC1+						
Lobule VI	R	58	-5.67	18	-52	-24
Right Crus I	R	24	-4.55	38	-52	-34
Post-GJ Feedback:						
-	-	-	-	-	-	-

Table 4.4: Individual difference effects on correct-related and error-related processing. The contrasts are correct-related > error-related processing. Pre = fMRI session before training; Post = fMRI session after training; AJ = associative judgment; GJ = grammar judgment.

tween right Crus I and left STG ($\beta = -3.00$, $T(16) = -3.51$) during correct judgment. A similar pattern was observed between right Crus I and right putamen during incorrect judgment ($\beta = -1.82$, $T(16) = -3.59$). Conversely, higher Cognitive PC1 was associated with decreased functional connectivity between left Crus II and left MTG ($\beta = 5.86$, $T(16) = 4.21$) and between left Crus II and left parahippocampus ($\beta = 6.56$, $T(16) = 3.59$) during positive feedback. Similar decreases were found during negative feedback for the same connections (Left Crus II-Left MTG: $\beta = 5.40$, $T(16) = 3.91$, Left Crus II-Left Parahippocampus: $\beta = 5.92$, $T(16) = 3.74$).

4.4.2.3 Moderating effects

For the moderating effect models, the linear models were fitted using the formula: $Outcome \sim Cognitive\_PC1 * (Sentence\_cor - Sentence\_inc) + Cognitive\_PC1 * (Feedback\_pos - Feedback\_neg) + Language\_PC1 * (Sentence\_cor - Sentence\_inc) + Language\_PC1 * (Feedback\_pos - Feedback\_neg)$. LRTs revealed that the moderating effect model outperformed both the baseline and additive effect models in predicting Pre-/Post-GJ d-prime

			Peak-level statistics			
Region	**Side**	**Size**	**T value**	**MNI coordinates**		
				x	**y**	**z**
Incorrect Judgment:						
Language PC1						
Lobule VIIb	L	22	4.80	-14	-66	-42
Positive Feedback:						
Language PC1						
Lobule VIII	R	20	-5.80	26	-52	-50
Lobule VI	L	45	-5.74	-32	-44	-28
Lobule VI	R	92	-5.12	12	-66	-20

Table 4.5: Individual difference effects on change in correct-related and error-related processing. The contrasts are Pre-GJ > Post-GJ. Pre = fMRI session before training; Post = fMRI session after training; AJ = associative judgment; GJ = grammar judgment.

(Figure 4.21). Notably, these two moderating effect models were the only ones to achieve a statistically significant fit. This finding indicates that AGL d-prime is best accounted for by the interaction between IDs and cerebellar patterns.

Specifically, the moderating effect analysis for Pre-GJ d-prime revealed a statistically significant model that accounted for a substantial proportion of variance ($F(8, 9) = 3.24$, $p = .048$, Rš = .739). This model identified one significant moderating effect: the interaction between Cognitive PC1 and Crus I/II patterns for judgment correctness ($\beta = -1.033$, $p = .012$). Cognitive PC1 ($\beta = .580$, $p = .007$) and cerebellar response for Correct > Incorrect Judgment ($\beta = .812$, $p = .030$) are also significant predictors. For Post-GJ d-prime ($F(8, 29) = 2.63$, $p = .027$, Rš = .420), the model also revealed one significant moderating effect: Language PC1 and Crus I/II patterns for feedback type ($\beta = -.196$, $p = .016$). This is the only significant factor of the model. Figure 4.21 shows the interaction effects between individual differences and cerebellar pattern factors. These findings imply that, in Pre-GJ, as the involvement of cerebellar Crus I/II in incorrect judgment increases, the positive predictive effect of Cognitive PC1 on d-prime increases. In Post-GJ, when the Crus I/II response to negative feedback is stronger, higher Language PC1 is more associated with higher d-prime.

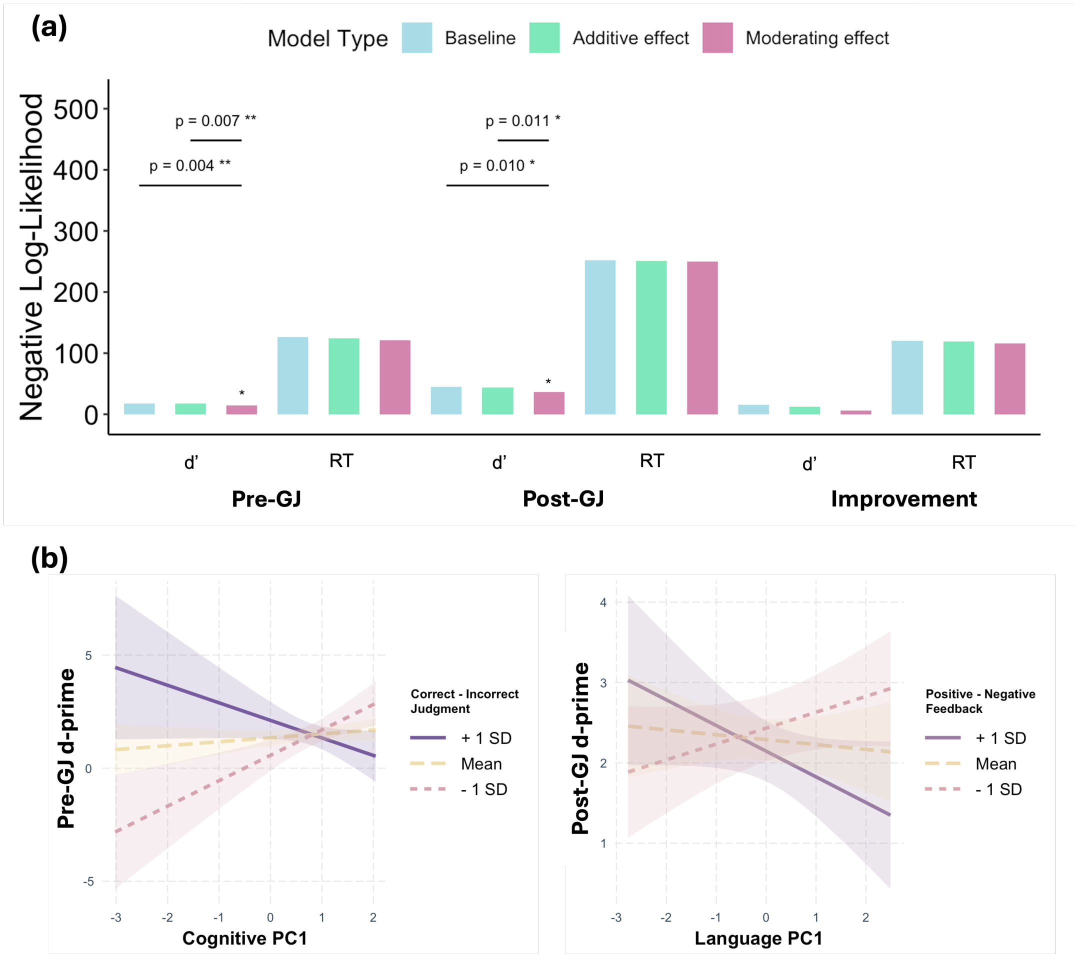


Figure 4.21: The moderating effects of cerebellar patterns in correct- and error-related processing. (a) Negative log-likelihood ratios for the models. Significance bars indicate model comparisons (LRTs); only significant differences are shown. Asterisks above bars indicate models with a significant overall fit. d' = d-prime. RT = reaction time. *$p < .05$, **$p < .01$. (b) Interaction plots for individual differences and cerebellar pattern factors.

4.4.2.4 Summary

For the cerebellar activations, Cognitive PC1 modulated post-training fMRI activations during judgment, with higher values associated with stronger activations in incorrect judgment. Language PC1 influenced cerebellar change, with opposing effects on judgment and feedback processing, such that higher values were associated with reduced cerebellar activations during incorrect judgments but increased activations during positive feedback.

Regarding cerebellum-cerebrum functional connectivity, Cognitive PC1 influenced both cerebellar engagement and change, whereas Language PC1 affected engagement only. In the pre-training session, higher Cognitive PC1 or Language PC1 scores correlated with stronger cerebellum-cerebrum functional connectivity during error-related processing. Longitudinally, Cognitive PC1 demonstrated contrasting longitudinal effects on functional connectivity, with increased judgment-related functional connectivity but decreased feedback-related functional connectivity from pre- to post-training sessions.

Furthermore, we found that Crus I/II activation patterns moderated the influence of individual differences on AGL d-prime. Before training, the positive effect of Cognitive PC1 on d-prime was stronger when cerebellar Crus I/II was more active during incorrect judgments. After training, the relationship between Language PC1 and d-prime was stronger when the Crus I/II was more active during negative feedback.

Integrating the results from the comparison of automatic and controlled processing reveals a key distinction in cognitive and linguistic individual differences: cerebellar activation is influenced by both Cognitive PC1 and Language PC1, whereas cerebellum-cerebrum functional connectivity is primarily affected by Cognitive PC1 alone. This pattern suggests a modular cerebellar architecture, whereby local activations subserve precise sequence learning for language, and functional connectivity facilitates integration with cerebral hubs supporting general cognition. Our findings challenge a strict dichotomy, favouring an integrated perspective in which cerebellar support for language combines general cognitive mechanisms with specialised linguistic adaptations.

Indeed, the cerebellum contributes to domain-general operations, such as prediction and timing (K. Friston, 2010; Keller & Mrsic-Flogel, 2018), whilst also exhibiting specificity in performing highly specialised tasks. This dual role is enabled by the topographic organisation of cerebro-cerebellar loops; despite sharing a common underlying mechanism, these loops are functionally distinct. For example, posterolateral cerebellar regions, such as Crus I/II, are preferentially connected with inferior frontal and posterior temporal language areas (Buckner et al., 2011; Buckner, 2013), establishing a neural substrate for language-specific computations. Further corroborating this dual role, King et al. (2019) mapped cerebellar topography and observed partially overlapping activations in Crus I/II during both cognitive tasks (e.g., maths) and language tasks (e.g., verb generation). These findings indicate broadly similar processing capabilities within these regions, with nuanced differences contingent on task demands. Building on this, a recent synthesis of data from multiple experiments identified two distinct categories of cerebellar regions: one that responds selectively to language and processes sentence-level meaning, and another that exhibits mixed-selectivity profiles (Casto et al., 2025).

CHAPTER

5

DISCUSSIONS

The cerebellum, traditionally associated with motor functions, has been increasingly recognised for its role in higher cognitive processes, such as language learning. The internal model of cognitive control hypothesis suggests that the cerebellum may regulate cognitive functions similarly to motor processes (Ito, 2008, 2012), though the neuronal representation of abstract mental models remains unclear. To gain a comprehensive understanding of cerebellar function, we should examine cerebellar activity in conjunction with cerebrum patterns, as isolated studies provide limited insights. Moreover, individual differences, such as cognitive abilities and language competencies, influence the development of internal models, offering insights for improving language learning approaches.

In this chapter, we summarised the results for the three research questions. Then, we discussed findings from the perspective of the internal model hypothesis. Finally, we revisited the internal model hypothesis, providing explanations for the emergence of the specificity of cerebellar function and suggestions for elaborating this hypothesis. We proposed that evaluating the domain-general internal model hypothesis requires a clearer mechanism description of modules and accounting for individual differences.

5.1 SUMMARY OF RESULTS

We conducted analyses to answer three RQs: 1) What is the role of the cerebellum in the internal model of language learning? (2) How does the cerebellar internal model contribute to language learning differently from cortical and subcortical areas? (3) What are the individual differences that influence the internal model of language learning? To investigate those RQs, we examined three key aspects of the internal model: (A) the cerebro-subcortical-cerebellar network, which examines different functions within the proposed internal model control system; (B) the cerebellums distinct roles in automatic processing versus controlled controlled processing, which explores the associativity and grammaticality of artificial language to address explicit and implicit processing; and (C) The cerebellums distinct roles in correct-related versus error-related processing, focusing on the execution (i.e., correct and incorrect judgment) and updating (i.e., positive and negative feedback) of the internal model. The first RQ examined three aspects, while the second and third RQs focused on the latter two aspects.

5.1.1 The Cerebellum's Role in Language Learning

The cerebro-subcortical-cerebellar network. Crus I and Crus II are most consistently implicated in previous language studies. In this research, these regions were also found to be co-activated with cortical and subcortical language-related regions during artificial language learning (i.e., judgment and feedback processing). Moreover, they demonstrated functional connectivity with these regions. As for the task difference, bilateral Crus I/II and cerebrum language-related regions were more active in association than in grammar judgment. In contrast, grammar feedback processing engaged more regions than association feedback. These findings indicate that Crus I and Crus II facilitate artificial association and grammar learning in collaboration with cortical and subcortical regions, albeit through distinct mechanisms.

Automatic processing versus controlled processing. The cerebellum showed different engagement and change in automatic and controlled processing. The activation analysis revealed distinct cerebellar engagement patterns in automatic and controlled processing. The right Crus I was more active in controlled processing during Pre-AJ, with dynamic activity trends based on processing type. In GJ, right Crus I/II were more active in controlled processing during Pre-GJ, and left Crus II activity decreased over time. Higher proficiency enhanced cerebellar involvement in controlled processing in AJ, but cerebellar regions (i.e., Crus I/II and lobule VI) showed different engagements in GJ. Greater proficiency improvement was associated with a decrease in cerebellar activity in AJ but not GJ. Functional connectivity between Crus I/II and cortical/subcortical areas varied by proficiency and stage, shifting from more automatic-related to more controlled-related over time. Cerebellar change was evident in participants with greater improvement, indicating adaptive cerebellar-cerebrum interactions.

Correct-related versus error-related processing. Furthermore, distinct cerebellar engagement and change patterns emerged for correct-related and error-related processes. The cerebellum, particularly bilateral Crus I/II, was more active in correct than incorrect sentence judgment during grammar learning, with left Crus I/II and right Crus I activities decreasing over time for correct judgments but not tied to proficiency. No significant change or interaction effects were found for incorrect judgments. Crus I, Crus II, and lobule VI showed higher activation for positive feedback early and negative feedback later, with interaction effects showing decreasing positive and increasing negative feedback activity over time. The connectivity between Crus I/II and cerebrum regions was modulated by processing type, stage, and their interaction. These engagement and change patterns were highly influenced by proficiency, especially task d-prime.

5.1.2 Cortical, Subcortical, and Cerebellar Contribution Difference

Automatic processing versus controlled processing. For automatic and controlled processing, language-related cerebrum regions, especially bilateral IFG and left MTG, were more engaged in controlled processing, similar to cerebellar findings. Left caudate and MFG exhibited change in GJ, mirroring left Crus I. However, left IPL and right MFG showed an opposite interaction effect with right Crus I in AJ. When examining the effect of proficiency, the left IFG closely mirrored the cerebellar activation patterns. The effective connectivity analysis revealed that GJ automatic models outperformed controlled models, while no specific pattern was observed for AJ. In terms of the multivariate patterns of POS and sentence type processing, Crus I/II showed different patterns from cortical/subcortical regions (e.g., AG and thalamus), with greater sensitivity to violation types than to the difference between automatic and violation conditions.

Correct-related versus error-related processing. The cerebrum and cerebellum also show both similarities and differences in their engagement and change during correct-related and error-related processing. Both cerebellar Crus I/II and cerebral regions like the left IFG and superior parietal lobe exhibited increased activation for correct sentence judgments, and both displayed wider involvement in positive feedback processing early and negative feedback later. However, unlike the cerebellum, which showed no increased activity in language-related regions for incorrect judgments, the right caudate was more active in Post-GJ. D-prime effects highlighted stronger neural responses to negative versus positive feedback, aligning with cerebellar patterns, with language-related regions showing comparable feedback processing dynamics. Change analysis revealed reduced activation in specific cortical areas and the cerebellum during correct judgments, with a unique interaction effect in the parahippocampus. Proficiency did not modulate cerebral and cerebellar change. Negative feedback processing showed increased cortical/subcortical engagement over time, consistent with the cerebellum. However, greater proficiency led to decreased cerebral activity for both feedback types, contrasting with the cerebellums selective reduction for positive feedback.

5.1.3 Individual Difference Influence

Automatic processing versus controlled processing. Both cognitive and language abilities influenced cerebellar patterns at the level of local activation, but only cognitive abilities modulated functional connectivity. Specifically, higher language ability was linked to stronger cerebellar activation during mismatched association judgments in the late stage, whereas higher cognitive ability predicted stronger cerebellumcerebrum connectivity during matched association judgments in the early stage. Conversely, higher cognitive and language abilities were associated with reduced cerebellar activation during associative and grammar judgments, respectively. For functional connectivity, cognitive ability differentially impacted change for matched versus mismatched associations and was associated with decreased cerebellumcerebrum connectivity during grammar judgments regardless of processing type.

Correct-related versus error-related processing. We found that both cognitive and language individual differences influence cerebellar engagement and change in correct-related and error-related processing. Individuals with higher cognitive or language abilities showed stronger cerebellar activations and cerebellum-cerebrum functional connectivity during error-related processing. Furthermore, cognitive and language individual differences have different effects on changing patterns of judgment and feedback. Higher language measures were associated with reduced activation during incorrect judgment and increased activation during positive feedback from the early to the late stages. Higher cognitive measures were associated with decreased cerebellum-cerebrum functional connectivity during both correct and incorrect judgment, while functional connectivity increased during both positive and negative feedback. Moreover, we found that activation in cerebellar Crus I/II moderated the influence of individual differences on AGL performance, and this moderating effect was associated with error-related processing.

5.2 THE CEREBELLUM'S ROLE IN LANGUAGE LEARNING

In this research, we explored the cerebellum's role in language learning from the perspective of the internal model. Building on prior research, we investigated both cerebro-cerebellar interactions and the distinct contributions of the cerebellum to various processing types (i.e., automatic versus controlled and correct-related versus error-related processing). Consistent with previous studies, we observed coordinated activity across cerebrosubcortical-cerebellar circuits during artificial language learning. Furthermore, we identified multiple, dissociable patterns associated with artificial language learning that varied substantially with proficiency. Below, we discuss these results within the framework of the internal model hypothesis.

5.2.1 The Cerebro-Subcortical-Cerebellar Network

5.2.1.1 Cooperation

The internal model hypothesis suggests that, during cognitive activity, the cerebellum constructs internal models that mirror cerebral computations, co-activating with prefrontal and temporo-parietal cortices (Ito, 2008). In line with previous studies, bilateral Crus I/II were co-activated and functionally connected with cerebrum ROIs during judgement and feedback phases.

We do not claim that the cerebellum is the sole driver of language; rather, it operates in concert with cortical and subcortical systems. The internal model is now regarded as a predictive forward model in terms of cognitive processing. In cognitive domains, the cerebellar internal model is typically construed as a predictive forward model. However, predictive processing is not unique to the cerebellum. During language tasks, both cerebellar and widespread corticalsubcortical networks are sensitive to the predictability of linguistic context. (Moberget et al., 2014).Furthermore, recent work on cerebello-cerebral dynamics indicates that the cerebrum plays a predominant role in reading (Tao et al., 2024).

Notably, we did not observe the commonly reported right-lateralised pattern in the cerebellum. Instead, most significant connections originated from the left Crus I/II. This may reflect the process of bilingual language control (i.e., artificial language and Chinese), as the bilateral lobule VI and VIII were found to be involved in the bilingual picture naming task (Yuan et al., 2022). However, this study also suggested that the right cerebellum is more involved in language control. In contrast, its left counterpart undertakes a computational role in cognitive control function by connecting with more prefrontal, parietal, and subcortical areas, which should be further examined.

5.2.1.2 Task difference

The cerebellum showed functional heterogeneity in associative and grammar learning tasks. While the lateral Crus I and medial Crus I/II were engaged in association judgment, only medial Crus I/II contributed to grammar judgment, and this difference was stronger in the late stage. This is a surprising finding, as the lateral Crus I was related to working memory, which is more required for grammar learning. In addition, Nakatani et al. (2022) reported respective involvement of the right Crus I and II in syntactic and semantic processing during sentence comprehension.

It is important to note that functional boundaries of the cerebellum do not correspond to macro-anatomical landmarks. In fact, many lobular borders do not demarcate functional changes greater than the variability observed within lobules (Diedrichsen et al., 2019). Functional specialisation within the hemispheric portion of lobule VII has been shown to shift multiple times from paravermal to lateral regions (Marek et al., 2018). Consequently, functionally defined atlases are required to investigate cerebellar organisation and function (Nettekoven et al., 2024).

We also observed task-dependent differences in cerebral and subcortical regions. Given the cerebellums relative structural homogeneity, its functional heterogeneity likely reflects variation in inputs from the cerebrum. In a key study, Buckner et al. (2011) analysed resting-state fMRI data from 1000 participants to produce a detailed map of cerebellar organisation, confirming connectivity between lobule VII and prefrontal and parietal association cortices. Additionally, subcortical regions serve as relays between the cerebral cortex and the cerebellum. In this research, stronger cerebellar activations were accompanied by stronger cerebral activations, further supporting a cerebrosubcorticalcerebellar network in artificial language learning. However, further analyses are needed to establish the specific mappings involved.

5.2.2 Universal Transform or Multiple Functionality

At the algorithmic level of cerebellar computation, the universal transform hypothesis suggests that cerebellar circuits contribute to diverse functions through a general computational process. Conversely, the multiple functionality model proposes that different tasks depend on varying contributions from distinct cerebellar functional modules, each requiring a unique algorithmic description (Diedrichsen et al., 2019).

The internal model hypothesis offers a compelling account of both motor and cognitive functions. The generation of predictions and the processing of prediction-error signals exemplify a putative universal transform. For example, McDougle et al. (2022) proposed that the cerebellum supports dynamic, continuously evolving transformations of mental representations. However, how such continuity should be instantiated at the level of higher cognition remains unclear. At present, there is no direct, established evidence for continuous, dynamic processes in higher cognition. In fact, prior studies have examined heterogeneous tasks and produced mixed findings in support of a cognitive internal model. For example, the same group found no support for semantic prediction deficits in individuals with cerebellar degeneration (King et al., 2024). In contrast, Daniel et al. (2025) reported that the cerebellum is critical for violation of expectations across symbolic subtraction, alphabet letter transformation, and novel artificial grammar learning. Therefore, we ask whether artificial and grammar learning are underpinned by uniform or differentiated cerebellar patterns. We also examine whether the cerebellum employs the same mechanism across time.

5.2.2.1 Multiple patterns

In this research, we explored the cerebellum's role in language learning by comparing its contributions to automatic and controlled processing, as well as correct-related and error-related processing. As a result, we found that the cerebellar regions contributed to artificial and grammar learning using different mechanisms over time (see the summary of each analysis). Even within the same task, the cerebellar regions demonstrated varying engagement and change in the examined processing types over time. These results suggest that artificial language learning is supported by multiple cerebellar internal model modules (located in the same or different regions), each of which may serve a distinct function.

Although we observed patterns of engagement and change consistent with prior work (as summarised in each analysis), earlier studies typically examined only a single processing condition. For example, Balsters and Ramnani (2011) focused on correct-related activity while neglecting error-related processing. Moreover, conclusions were often drawn from a single language task. For instance, Lesage et al. (2017) concluded that right Crus II supports phonological but not semantic or orthographic processingan important constraint rarely emphasised in subsequent literature. By contrast, our study systematically compared these dimensions.

Indeed, we must acknowledge that these relevant studies have identified certain aspects of internal model updating, thereby advancing our understanding of the underlying mechanisms. However, we propose that linking these updates to specific neural patterns, particularly cerebellar engagement in one particular processing type, is an incomplete description of the cognitive internal model. These patterns require cautious examination, especially given the varying proficiency levels of participants, because we found that proficiency factors can significantly modulate activation and connectivity patterns. Moreover, we found a dissociation between cerebellar activity and cerebellum-cerebrum connectivity. For example, while the bilateral Crus I were more active during negative feedback in Post-GJ, their connectivity with MFG was stronger during positive feedback. This finding highlights the cerebellum's multifaceted role in coordination with the cerebrum's regions for various aspects of processing. Therefore, updating the internal model should be investigated in a broad context.

Moreover, as shown in Figure 4.6 and Figure 4.8, engagement and change during judgement and feedback differed markedly across tasks, particularly when accounting for d-prime. Cerebellar regions also demonstrated interaction effects between processing types and stages. The traditional idea is that cerebellar activity is significantly higher during early learning phases if it drives initial acquisition, and notably increased in later phases if it supports the performance of automatised behaviours (Diedrichsen et al., 2019). However, our findings indicate that this is not consistently true. Indeed, Balsters and Ramnani (2011) also reported that the more automatic group exhibited greater reductions in posterior cerebellar activation during rule acquisition.

Finally, comparing our findings with those from motor tasks reveals divergent patterns in language processing. In motor tasks, error-related activity (i.e., incorrect mouse movement with negative feedback) decreased more sharply than correct-related activity. However, while the cerebellum showed decreased activity during GJ correct judgment over time, no significant change effects in activation were observed for GJ incorrect judgment, nor was there a significant interaction between stage and processing type. For GJ feedback, the trend reversed: activity to positive feedback decreased over time, whereas activity to negative feedback increased. These results suggest that mechanisms supporting motor function may not directly generalise to cognitive processing.

5.2.2.2 Universal patterns

Nevertheless, several general patterns emerged. First, during grammar judgment, Crus I/II exhibited a decreasing trend in activation across all processing types, although with varying degrees of change depending on the processing type. This reflects the change of the cerebellum in artificial grammar learning, demonstrating a more integrated and efficient neural processing. Such efficiency may reflect reduced spiking or related synaptic events (Cheron et al., 2016), although this interpretation requires confirmation in larger samples.

Second, Crus I/II showed greater engagement in controlled processing during association and grammar judgment in Pre-fMRI, aligning with Lesage et al. (2017) and Moberget et al. (2014). When accounting for proficiency factors, the Crus I/II were also more active in controlled processing during Post-AJ. The controlled conditions introduced semantic or syntactic violations, creating a mismatch between expected and encountered linguistic input. These mismatch signals can drive updates to the internal model (Peterburs & Desmond, 2016). Accordingly, Crus I/II may rely more heavily on an error-tuning mechanism during artificial language learning.

Third, correct judgments elicited greater Crus I/II activation than incorrect judgments during grammar judgment. Therefore, correct execution of the internal model is associated with greater Crus I/II engagement, reflecting their role in supporting accurate syntactic processing, predictive coding, and efficient cognitive integration, which are less engaged or disrupted during incorrect judgment. This pattern suggests a correct-related contribution of the cerebellum to grammar judgement, although differences in cognitive load between correct and incorrect trials may also account for the effect.

Lastly, Crus I/II were more involved in negative feedback processing compared with positive feedback in Post-GJ, even when accounting for d-prime effects. This result is consistent with previous findings in associative learning (Peterburs et al., 2018). Negative feedback represents the error signals for updating the internal model, as it indicates a discrepancy between the predicted judgment outcome and the actual judgment outcome. However, we observed an opposite pattern in Pre-GJ, suggesting a shift in the mechanism during feedback processing over time.

Notably, two predictive processes were engaged during the language judgement task. First, participants predicted upcoming input by comparing stimuli with their knowledge of the artificial language. Second, they predicted their own response accuracy, which was either confirmed by positive feedback or contradicted by negative feedback. As discussed in Section 2.1, two distinct classes of violations or error signals can arise from these processes, and they must be carefully distinguished.

5.3 CORTICAL, SUBCORTICAL, AND CEREBELLAR CONTRIBUTION DIFFERENCE

The cerebellum plays a supportive, modulatory role in collaboration with cortical and subcortical regions during language processing. If the cerebellar internal model consistently mirrored the dominant cerebral regions, its neural patterns would closely resemble those of the corresponding regions. However, evidence also indicates functional segregation between the cerebrum and cerebellum (Ramnani, 2014; Tao et al., 2024; Turker, Kuhnke, Eickhoff, et al., 2023). Therefore, in this research, we examined the extent to which the cerebellum contributes to language learning in ways that are similar to, or distinct from, cortical and subcortical regions, with a particular focus on the latter. Specifically, we compared their contributions to automatic versus controlled processing and to correct-related versus error-related processing.

5.3.1 Automatic and Controlled Processing

While Ramnani (2014) proposed that System 2 is mainly supported by the cerebrum, especially by the prefrontal cortex, whereas the cerebellum may make important contributions to System 1, we found that there are no salient preferences for the engagement of cerebrum and cerebellum in automatic and controlled processing. The local cerebellar activation and cerebellum-cerebrum connectivity patterns, therefore, appear flexible and dynamic. Notably, in grammar processing, neural differences between types of grammatical violations exceeded those between automatic and controlled conditions.

Across automatic versus controlled and correct-related versus error-related processing, the IFG consistently exhibited patterns similar to the cerebellum. Previous studies have reported that there are intrinsic connections between the posterior cerebellum and prefrontal cortex, such as the left IFG (Buckner et al., 2011; Nakatani et al., 2022). Consistent with this, we found that crus I/II co-activated with, and showed positive connectivity to, the IFG during artificial language judgement and feedback. The IFG, especially the left IFG, is critical for unifying linguistic information, which aligns closely with the cerebellar, especially Crus I/II's, function in refining internal models for language learning. This functional overlap may result in similar neural patterns. Moreover, the prefrontal cortex acts as a controller in the internal model (Ito, 2008). In the forward-model control system, the controller is connected with the cerebellar model in closed loops. This closed-loop circuit represents a fundamental architectural feature of cerebro-cerebellar interactions. For example, Kelly and Strick (2003) reported that the region of the cerebellum that receives projections from area 46 sends projections back to prefrontal area 46. This closed-loop circuit was also observed in our DCM analysis of fixed connections–the right Crus I/II showed closed-loop connections with the left IFG in the Post-GJ d-prime model.

Furthermore, several regions demonstrated distinct neural patterns in relation to the cerebellum, including the IPL, MFG, and parahippocampus; however, no region consistently displayed an opposing pattern. In the RSA analysis, hierarchical clustering revealed that Crus I/II exhibited distinct patterns from other cortical and subcortical ROIs in sentence type processing, particularly differing from the left MTG and thalamus. However, these regions were also positively connected with Crus I/II. In the DCM analysis, the left thalamus even demonstrated closed-loop circuits and modulated effective connectivity with right Crus I/II. This suggests that, while the cerebellum collaborates closely with these regions in automatic and controlled processing, their functional roles differ. In internal model control systems, the temporoparietal lobe contains the mental model, which acts as a controlled object manipulated by the prefrontal cortex. Unfortunately, the role of subcortical regions, such as the thalamus, is underexplored in discussions of the internal model.

Finally, although when accounting for the task proficiency, the right Crus I/II were more engaged in controlled processing, there was an opposite effective connectivity pattern for grammar judgment. The higher posterior probability of automatic versus controlled DCM models suggests that information flow among the left IFG, left thalamus, and right Crus I/II aligns more closely with the automatic pattern. This further highlights the dissociation between intra-cerebellar activity and cerebro-cerebellar connectivity patterns. Notably, this dissociation did not appear in association judgement, indicating task-specific differences.

5.3.2 Correct-Related and Error-Related Processing

Similar to the cerebellum, the cerebrum regions also showed different patterns regarding correct-related and error-related processing. In artificial grammar learning, repeated novel syntactic structures have been found to trigger repetition enhancement in the IFG, whereas repeated familiar structures lead to repetition suppression (Weber et al., 2016). However, in the current research, the IFG showed decreased activation from the early to late stages during correct sentence judgment. Interestingly, the parahippocampus exhibited interaction effects, demonstrating a decreasing trend in activity during correct sentence judgment and an increasing trend during incorrect sentence judgment. Although this interaction effect between judgment types and stages was observed in the cerebellum, a wide range of cerebellar regions demonstrated an interaction effect between feedback types and stages. This suggests the error-tuning nature of the cerebellum. During early learning stages, positive feedback reinforces correct responses, engaging the cerebellum to consolidate successful patterns, as evidenced by the initial increase in activation. As learning progresses and performance improves, reliance on positive feedback decreases, resulting in reduced related cerebellar activity, as the behaviour becomes more automated. Conversely, negative feedback signals errors, prompting the cerebellum to update its internal models to correct mistakes. Interestingly, this pattern was also found in the cortical and subcortical areas.

In contrast to the cerebellum, the caudate was more active during incorrect grammar judgment compared to correct grammar judgment. Moreover, the connectivity between

Crus I and the right caudate was stronger during incorrect grammar judgment. These findings highlight the caudate's role in detecting errors. Previous neuroimaging studies have provided evidence for the involvement of the caudate nucleus in goal-directed action, which emphasises the expectation of an outcome prior to, or during, choice behaviour. Specifically, tasks engaging the caudate nucleus often involve outcomes dependent on behaviour, awareness of those outcomes, and an incentive that makes the goal appealing (Grahn et al., 2008). Combining the results that the thalamus contributes to automatic and controlled processing differently from the right Crus I/II, we propose that it is essential to consider the role of the subcortical region in the internal model system.

In summary, while the cerebellum collaborates with cortical and subcortical regions in language processing, its circuitry makes distinct contributions that can be distinguished from those of other brain areas. This underscores a complex braincognition relationship that resists simplistic one-areaone-function mappings. Variability in neural patterns across tasks and processing dimensions cannot be fully captured by invoking a single language network, nor should such a network be considered exclusive to language.

5.4 INDIVIDUAL DIFFERENCE INFLUENCE

Individual variability is not noise but an informative dimension that reveals multiple routes to successful language learning. While rarely addressed in previous studies, we identified the impact of individual differences on the internal model of language learning. This effect can be attributed to two key factors. First, individual differences are linked to structural and functional variations in the cerebellum and its connectivity with other brain regions. Second, greater individual differences may enhance neuroplasticity, allowing for the development of more accurate and adaptable internal models.

More importantly, we investigated how domain-general cognitive individual differences and domain-specific language individual differences modulate cerebellar patterns during artificial language learning. Our goal was to explore whether cerebellar support for language is domain-general, language-specific, or a hybrid of both. Our findings are consistent with a hybrid account in which the cerebellum contributes to language learning via both domain-general cognitive mechanisms and domain-specific language adaptations.

5.4.1 Mechanisms Underlying Individual Difference Influence

5.4.1.1 Structural and functional differences

Structural differences in the cerebellum include variations in its size, volume, surface area, and microstructure, which can influence its capacity to support motor and cognitive functions. Cerebellar morphology is frequently as good as–or even better–at predicting performance than the prefrontal cortex (Bernard & Seidler, 2014). For instance, gray matter volume in the cerebellum can predict general cognitive ability in older adults, even when total intracranial volume and gray matter and white matter volumes in frontal lobes are statistically controlled (Hogan et al., 2011). Moreover, increased gray matter volume in the posterior cerebellum of a younger group aged 817 was correlated with higher scores on vocabulary, reading, working memory, and set-shifting (Moore et al., 2017). The posterior lobules are more engaged in cognitive functions compared with the anterior lobules. In addition, differences in gray matter density in the cerebellar cortex have been linked to intelligence (Frangou et al., 2004). These results suggest that increased grey matter may enhance cognitive function by increasing synapses or dendritic branching, potentially facilitating more complex neural circuits.

Functional differences in the cerebellum refer to how it interacts with other brain regions, processes information, and contributes to motor and cognitive tasks. The cerebellum is one of the most globally connected regions in the brain–connected to almost every other brain region and outranking several neocortical regions (B. Wang et al., 2025). These intrinsic connections can contribute to various cognitive functions (Habas et al., 2009). Moreover, the resting-state connectivity can be modulated by individual differences, such as verbal working memory performance (Y. Li et al., 2022).

Individual differences are likely reflected in the efficiency of these cerebellar mechanisms. As reviewed in Section 2.6, individuals with higher cognitive or language capacities may exhibit more precise cerebellar predictions, thereby enhancing their ability to handle complex cognitive demands. Moreover, individual differences such as intelligence and cognitive flexibility are often associated with error detection and correction abilities, which are central to the cerebellums function. In individuals with better cognitive and language abilities, we expected more effective cerebellar-cortical loops, which support more efficient learning. As the cerebellums internal model relies on prediction and error correction mechanisms, supported by its functional connectivity with cortical and subcortical regions, individual differences in the strength of these circuits can lead to variations in its formation and updating.

5.4.1.2 Neuroplasticity

Experience can shape cerebellar plasticity. In a study that examined cerebellar change in the young participants between 12 and 21 years old, researchers found that functional networks of Crus I/II showed significant connectivity decreases over one year, though there were no differences in lobule V. Furthermore, these changes in functional connectivity were associated with enhanced structural integrity of white matter in the corresponding cerebello-thalamo-cortical tract. (Bernard et al., 2016). Moreover, learning a foreign language in older adults can modulate the functional connectivity of distinct cerebellar subregions with cortical areas (Bubbico et al., 2025). These findings represent a refining of the cognitive cerebellar network due to both synaptic pruning and increases in structural connectivity.

Additionally, the dopaminergic systems have been shown to significantly modulate and shape neuroplasticity. For instance, the inverted U-shaped function of dopamine signalling, where optimal levels enhance neuronal function while too little or too much dopamine reduces it (Voss et al., 2017). The dopamine systems interaction with the cerebellum is a relatively underexplored area, but emerging evidence suggests that dopamine signalling directly affects cerebellar physiology and that the cerebellum, in turn, can influence dopamine release in other brain regions, such as the basal ganglia and prefrontal cortex (Ramnani, 2014).

In summary, individual differences can influence how efficiently the cerebellum integrates sensory and cognitive information to build and refine internal models for language learning.

5.4.2 A Hybrid Domain-General and Domain-Specific Account

The cerebellums canonical computation is commonly described as prediction and error-driven updating of internal models via long-term synaptic modifications operating over a largely uniform microcircuitry (Kawato et al., 2021; Marr, 1982). This architecture generalises beyond motor control to encompass cognitive processing (Ito, 2008; Popa & Ebner, 2018). In addition, the cerebellum forms closed-loop circuits with the prefrontal and parietal cortices, which support executive functions, attention, and working memory (Buckner et al., 2011; Stoodley et al., 2010). To illustrate, the reconfiguration of functional connectivity during learningrelated and errorrelated processing–reduced cerebellocerebral coupling during judgement but increased coupling during feedback over time as a function of cognitive individual differences–suggests dynamic control of model selection, hypothesis testing, and credit assignment, all hallmarks of domaingeneral learning (Doya, 1999; Kelly

& Strick, 2003). Early in learning, individuals with stronger cognitive abilities may rely on broader cerebellofrontoparietal coordination. As rules consolidate, coupling during judgement can be pruned, whereas feedback periods recruit stronger crossnetwork integration for error attribution and policy updating. These results, therefore, place cerebellar contributions within a general predictivecontrol architecture that orchestrates learning irrespective of domain while flexibly coordinating with cortical control networks as training progresses.

Concomitantly, our findings reveal languagespecific adaptations that implicate specialised cerebellar contributions to the construction of linguistic structure. This pattern suggests representational tuning of cerebellar computations to linguistic information: greater efficiency in signalling prediction violations once internalised, coupled with heightened reinforcement of correct rule mappings when predictions are confirmed (Sokolov et al., 2017). Such tuning accords with the topographic organisation of corticocerebellar loops linking posterolateral cerebellar territories, especially Crus I/II, to inferior frontal and temporotemporoparietal language regions, providing an anatomical substrate for languageselective plasticity within otherwise generalpurpose circuitry (Guell et al., 2018). Converging clinical and developmental evidencelanguage deficits following cerebellar lesions, developmental language delays associated with cerebellar dysfunction, and modulation of linguistic performance via cerebellar stimulationfurther supports experiencedependent specialisation of cerebellar processes for linguistic operations (Mariën & Manto, 2015; Mariën & Borgatti, 2018).

Integrating these strands, a hybrid account emerges in which the cerebellum applies a common predictionanderror algorithm to domainspecific representational content. On this view, the basic mechanism is domain-general (K. Friston, 2010; Keller & Mrsic-Flogel, 2018), but the internal models being updated are shaped by the statistics and priors of the linguistic input, yielding language-dependent response profiles within language-preferring cerebro-cerebellar loops. In summary, the present results indicate that domain-general and domain-specific accounts are complementary rather than competing: the cerebellum employs generic predictive computations while fine-tuning its representational and reinforcement dynamics to the linguistic structures being learned.

5.5 REVISITING THE INTERNAL MODEL HYPOTHESIS

5.5.1 The Emergence of Specificity

5.5.1.1 Mosaic theory

Language is proposed to be a modular or a mosaic system. The modularity of mind proposed that the human mind's core infrastructure comprises several independent, relatively automatic computational systems, each linked to specific neural structures (Fodor, 1983). However, biological mechanisms supporting language are not exclusively dedicated to language processing. The same neural equipment supports other cognitive functions, such as memory and perception, which likely evolved before language. To be more specific, W. S.-Y. Wang (1982) proposed the Mosaic theory, suggesting that the biological basis of language does not imply that it relies on modular, task-specific components. The same neural "equipment" used for language is likely also engaged in more generaland evolutionarily earlierfunctions like cognition, memory, and perception. It is important to clarify how these general-purpose systems interact with the unique demands of learning and using language. To postulate mechanisms that are exclusively dedicated to language, serving no other function, currently seems unwarranted.

In line with the Mosaic theory, this research demonstrates that the cerebellum, traditionally considered a motor region, contributes to language processing and supports different processing in diverse ways. Therefore, it is essential to recognise that language processing in the brain involves interconnected networks, rather than isolated regions–both across the frontal, temporal, and parietal cortex, as well as the subcortical and cerebellar cortex. This aligns with Mesulam (1990)'s view that no single "centres" exist for specific language functions; instead, specialised nodes within a distributed network collaborate to process linguistic information. The internal model hypothesis offers a comprehensive framework for understanding the cerebellums role in language processing, positing a general predictive function. However, our findings suggest that while the cerebellum engages in multiple language processes, no universal pattern fully describes its role or its interactions with the cerebrum.

This research also highlights a distinction between the cerebellar and cerebral contributions to language. While core language regions in the cerebrum–such as the left inferior frontal cortex, temporal cortex, and parietal cortex–are primarily responsible for processing elementary linguistic units, the cerebellum supports language through different mechanisms. Along with subcortical structures like the thalamus and basal ganglia, the cerebellum fine-tunes the timing and sequencing operations essential for language processing (Andersen & Dalal, 2024; Imamizu & Kawato, 2009). Effective language function thus emerges from the dynamic interaction between these systems: the retrieval of lexical information from memory and the unification of these elements into a coherent structure (Hagoort, 2019). Although the integration of these multiple networks is essential for language, the constituent networks themselves are not language-specific and are likely recruited for other cognitive functions.

From an evolutionary perspective, language likely emerged through the modification, recombination, and exaptation of ancestral neural infrastructures (Arnon et al., 2025). One influential proposal posits that humans uniquely evolved a cognitive module for recursion, potentially arising from the interaction between sequential manipulation faculties and working memory (Bolhuis et al., 2010). The FOXP2 gene provides a compelling case study for this process. Researchers discovered that a rare mutation in FOXP2 would disrupt the coordinated sequencing of orofacial movements (Lai et al., 2001). Crucially, FOXP2 is expressed in conserved neural circuits for motor-skill learning, including the cortex, basal ganglia, thalamus, and cerebellum (Barbas et al., 2013). This suggests that its role in human speech is built upon ancient evolutionary pathways for motor coordination. Therefore, the principle of Mosaic theory can be extended to the cerebellum. The lateral cerebellum has undergone significant expansion in human evolution (Schoenemann, 2009). Its contribution to language, potentially through fine-tuning the timing and sequencing of cognitive processes, may represent a similar exaptation, illustrating how established brain networks can be specialised for new, complex functions like language.

Language evolution is driven not only by biological factors but also by cultural ones. Children construct their unique "linguistic fingerprint" by sampling from their environmental input, building upon their genetic blueprint. Our research reveals that individual differencesboth general cognitive and language-specific abilitiesdistinctly influence cerebellar activation patterns. Although the boundary between cognitive and language functions is inherently blurry, our findings at least provide some hints that the cerebellum does, in fact, exhibit mechanisms that can be tuned to language. This specialisation, however, is observable at the level of individual differences. To invoke Jacob's famous metaphor, evolution is a "tinkerer," repurposing existing components for new functions (Jacob, 1977). The individual differences we observe may represent the incremental steps through which such tinkering embeds new capacities into the brain's circuitry for sophisticated language use. Ultimately, this process of external cultural influence shaping internal brain function may, over time, become crystallised in our biologymuch like the classic Sapir-Whorf hypothesis suggests that language shapes thought. What begins as an individual influence may ultimately be selected for and woven into the genetic fabric of our species through the tinkerer's slow hand.

5.5.1.2 Multiple functionality of the cerebellum

The difference between uniform transform and multiple functionality reflects the longstanding debate in neurobiology about language, specifically the views on domain-general and domain-specific functional organisation of the brain. However, Hagoort (2025) thought these are not opposing views: "Specificity is an emergent property of the interaction between domain-general operations and domain-specific knowledge representations".

In our context, domain-general operations are flexible, broadly applicable functions, such as working memory and prediction, that operate across multiple tasks. Domain-specific knowledge representations are specialised knowledge structures tailored to particular tasks or domains, such as grammatical rules. The cerebellum (e.g., Crus I/II) contributes to domain-general operations, such as predictive coding and error detection, but it also demonstrates specificity when performing highly specialised tasks. This specificity may emerge not from tasks being directly encoded in a single region or process but from the interaction of multiple components. Here we listed two possible explanations:

On the one hand, the diversity of the nature of input and output signals in the cerebellum suggests a diversity of function. For instance, mossy fibre input often conveys motor command copies but can also transmit sensory stimuli or contextual information. Climbing fibre input typically serves as an error signal but may also encode expected stimuli or reward signals (Orban de Xivry & Diedrichsen, 2024). This function distinction was also observed in single neurons in the temporal cortex of macaque monkeys during cognitive processing (Sugase et al., 1999). Therefore, the activity of a single neuron can involve more than one task or function. Furthermore, the cerebellar cytoarchitecture is more complex and less uniform than previously assumed (Beckinghausen & Sillitoe, 2019).

On the other hand, complex cognitive processes, including language, visual perception, arithmetic, and emotion, rely on interconnected brain networks, often involving multiple networks, such as the one in the cerebellum. Additionally, individual cerebrum regions or cerebellar lobules typically support several functions (King et al., 2019; Nettekoven et al., 2024). For example, Crus I/II are engaged not only in language processing but also in working memory and social and emotional processing. Moreover, cerebellar lobules demonstrated different connections with the cerebrum–the anterior lobe and lobule VIII connect to cortical motor and premotor areas, while lobule VII and IX connect to prefrontal and parietal association areas (Buckner et al., 2011).

Therefore, in summary, the variations of language cannot be fully explained by attributing them to a single language network, nor can such a network be considered exclusive to language. Investigating cerebellar function within specific task domains will clarify its functional diversity. Through specific descriptions of dynamics within neuronal networks, we can form a better understanding of the internal model hypothesis.

5.5.2 Elaborating the Internal Model Hypothesis

Based on our results and discussions, we proposed three points to elaborate on the internal model hypothesis.

First, given the functional heterogeneity of the cerebellum, the aspects under investigation must be clearly defined. It is important to recognise that the cerebellum contributes to language learning through multiple computations. However, many unresolved questions remain: What constitutes the automatic stage of learning, and is it primarily associated with task accuracy, reaction time, or both? Which error signals drive updates to the internal model? Do they reflect violations of predicted context, incorrect execution of the internal model, or bothand if both, which is more critical? Additionally, does the cerebellums varying involvement in cognitive tasks stem from differences in cognitive load?

Second, it is essential to incorporate subcortical regions into the internal model system. From the perspective of sequence, subcortical structures work with the cerebellum to ensure the precise timing and coordination of sensory consequences, helping to synchronise movements and maintain fluidity. Moreover, subcortical structures, such as the thalamus, act as critical relays between the cerebellum and other parts of the brain. In addition, brainstem nuclei, such as the pontine nuclei, provide the cerebellum with sensory information essential for creating predictive models.

Third, the internal model is shaped by individual differences, which modulate the cerebellums efficiency in integrating sensory and cognitive information to develop and refine internal models for non-motor functions, such as language learning. On the other hand, by leveraging variations in cerebellar neural efficiency during learning, we can design more tailored learning strategies.

The cerebellum implements internal models, which are neural representations of context-specific, dynamic interactions between the agent and the environment. While examining the extent to which the internal model hypothesis can explain findings in cognitive processing, we should also enhance the comprehensiveness of the internal model by exploring its heterogeneous applications.

CHAPTER 6

SIGNIFICANCE AND LIMITATION

This chapter highlights the significance of this dissertation, acknowledges its limitations, and outlines future directions to advance understanding of cerebellar contributions to language learning.

6.1 SIGNIFICANCE

For decades, the cerebellum has been largely overlooked or deliberately excluded from neuroimaging studies. In fact, over 60% of these neuroimaging studies ignored the cerebellum despite claiming to investigate the "whole brain" (B. Wang et al., 2025). However, excluding the cerebellum risks an incomplete or misleading knowledge of brain function. It is therefore argued that including the cerebellum is an essential step toward a comprehensive understanding of the brain and its diverse functions.

This research challenges three traditional views: (1) the cerebellum's role, (2) universal cerebellar transform, and (3) the localisation of neural infrastructure for language. It aims to enhance our understanding of the neurobiology of language. First, Leiner et al. (1986) initiated the cerebellar cognitive revolution with their groundbreaking paper, proposing that the cerebellum plays a role in cognitive functions beyond motor skills. Their foresight proved accurate, as they predicted at the onset of the neuroimaging era that cerebellar activation would be linked to numerous cognitive processes. This prediction has been validated by numerous studies, which have shown cerebellar activation in a diverse array of non-motor tasks, even when controlling for overt motor demands (LeBel & DMello, 2023;

Mariën & Borgatti, 2018; Sokolov et al., 2017). In addition, the majority of the cerebellum was connected to cerebral networks associated with cognitive functions, including language (Moberget & Ivry, 2016; Buckner et al., 2011). This research provided further empirical evidence to support the cerebellar contribution to cognition.

Second, the hypothesis of universal cerebellar transform holds that the same neurological process subserves cerebellar modulation of movement, cognition, and emotion (Guell et al., 2018). In the neocortex, distinct regions are characterised by unique cytoarchitecture, myelination patterns, and gene expression, indicating a highly specialised organisation with processing modules dedicated to specific functions supported by local circuitry (Toga et al., 2006). In contrast, the cerebellum exhibits highly uniform circuitry across its cortex. While we agree that the internal-model frameworkprimarily the predictive forward modelapplies to both motor and cognitive domains, its mechanisms likely operate more dynamically than often assumed. Our findings indicate that different cerebellar regions may engage distinct mechanisms within the same task. It is therefore plausible that complex cognitive activities, such as language, are supported by multiple cerebellar internal model modules, each performing a distinct function. This raises a key question: Does a single structure consistently predict a specific mechanism? Addressing this will require more fine-grained analyses, potentially at the microcircuit or cellular level. These insights complicate the internal-model hypothesis and pose new challenges. Yet, as Chao and Dil (1976) observed, Thus in matters linguistic, as in matters any other scientific, we try to make things simple, but things are never as simple as we make them (p. 305).

Third, traditional accounts of the neurobiology of language posit specialised systems for specific cognitive functions. Although often neglected in neurolinguistics, the cerebellum plays a substantial role in both language comprehension and production (LeBel & DMello, 2023). Most, if not all, language functions represented in the cerebral cortex also appear in the cerebellum, with differences that may render it particularly important for higher-order semantic processing, language development, and related disorders. Our findings reveal cerebellar contributions to associative and grammar learning with diverse patterns. Consequently, the question of where language resides neurally cannot be answered by assigning it a fixed address in the brain. According to the Mosaic theory, the highly complex language function should be supported by interconnected networks in the brain. In this research, we provided evidence that the cerebellar network is one of them.

Besides the challenge of traditional views, this research also highlights the critical role of subcortical areas in the development of the internal model. Subcortical areas have long been recognised for their important contributions to a variety of cognitive functions, including but not limited to basal ganglia-mediated reinforcement learning. These areas engage in intricate, recurrent loops with the cerebral cortex and cerebellum, facilitating robust bidirectional information flow. Moreover, these interactions are crucial for the dynamic integration of context-specific information into internal models.

To the best of our knowledge, this research is among the few to examine the effects of individual differences on the cerebellum's contribution to language, comparing cognitive abilities (e.g., interference control) and language abilities (e.g., language analytical ability). These factors influence not only cerebellar engagement and plasticity but also cerebrum-cerebellum connections. However, since our participants were young, future research is needed to explore these effects in older populations.

Regarding social impacts, our findings revealed that more successful language learners exhibit distinct cerebellar activity patterns, which may have significant implications for education. For example, individuals with varying cognitive and language abilities may respond differently to errorful and errorless learning approaches. Furthermore, this research highlights that neuroplasticity can be influenced through language learning, even in adulthood, underscoring the potential for lifelong learning and cognitive development.

6.2 LIMITATIONS AND OUTSTANDING QUESTIONS

The findings of this research should be interpreted cautiously for several reasons. Firstly, due to the practical issues, one cohort underwent only a single fMRI session, yet we combined data from two cohorts for the Post-fMRI evaluation. Despite efforts to ensure comparable exposure to the artificial language of the two cohorts, and the training and fMRI sessions are largely the same, unavoidable differences in the learning environments (lab room versus scanner) persisted. This approach also led to a limited sample size for analysing changes between Pre-fMRI and Post-fMRI, particularly for examining individual differences, which constrains the robustness of these findings.

Additionally, the lack of control over task complexity led to participants quickly reaching a ceiling effect in associative learning, but not in grammar learning. This difference may confound interpretations of task differences, as the two tasks likely impose distinct cognitive demands. Furthermore, the limited data prevented us from distinguishing between learning-related and error-related processing in associative learning. However, word learning is inherently simpler than grammar learning in natural language contexts. If participants fail to grasp word meanings, it raises significant doubts about their ability to process grammar during the task.

Moreover, we did not control the hand used for button presses during fMRI sessions, resulting in prominent neural differences between automatic and control conditions, primarily in motor-related regions. However, significant effects were observed in cognitive-related regions. Additionally, correlating these findings with task proficiency helped mitigate this confound.

Finally, the exploration of the cerebellum in language learning has emphasised sequence processing, yet timing control remains a core, albeit temporally unresolved, mechanism. The limited temporal resolution of fMRI has constrained this inquiry. Thus, future work should use Magnetoencephalography (MEG) to capture the millisecond-scale dynamics underlying cerebellar function.

Although this research supports and expands the internal model hypothesis from multiple perspectives, several questions remain unresolved. First, how does the cerebellum support diverse activities through distinct computations? Could this stem from varied error signal inputs? Second, the cerebellum both mirrors and diverges from the functions of cerebral cortical and subcortical regions, even within the same areas. How does its uniform circuitry give rise to these differences? Third, can the observed effects of individual differences be extended to older populations? If so, since the cerebellum ages more slowly than other brain regions (Horvath et al., 2015), do individual differences affect the cerebrum and cerebellum differently? Whatever the answers may be, we look forward to further studies that deepen our understanding of the diverse functions of the cerebellum.

APPENDIX A

APPENDIX A - MATERIALS

A.1 WORDS

Thirty artificial words were created using the BROCANTO language framework as a reference (Opitz & Friederici, 2003; Kepinska et al., 2017a), yet they were uniquely modified to suit the needs of the present research. There are eight nouns (N), eight verbs (v), six adverbs (m), six adjectives (M), and two determiners (d and D). Except for nouns and verbs, these artificial words feature a distinct vowel system that signals POS: "o" marks adverbs, "i" marks adjectives, and "a" marks determiners. This vowel-based categorisation facilitates the differentiation of POS while preserving ambiguity, requiring participants to infer the POS on their own. Additionally, the frequency distribution of the letters has been controlled.

Each artificial word was assigned a Chinese meaning according to the POS. These Chinese phrases were carefully chosen to include a range of antonyms (e.g., "today" and "yesterday") and several terms within the same semantic field (e.g., "apple" and "banana" are fruits), aiding participants in comparison and memorisation. Moreover, the selection process ensured that the Chinese meanings were phonetically distinct from the artificial words across Cantonese, Mandarin, and English pronunciations, thereby mitigating the potential influence of phonetic similarity. This precaution was taken despite the artificial words being intentionally challenging to pronounce, an additional measure to control for phonetic effects. To enhance memorisation, an icon representing the Chinese meaning was supplied alongside each item during the learning phase, but these visual aids were not provided during the judgement tasks. Incorrect pairings of the artificial words and Chinese phrases were created through a process of randomisation. The frequency of incorrect pairings from the same POS versus different POS was controlled at a ratio of 1:3 for each session (learning, training, and fMRI). The occurrence of all artificial words and Chinese phrases has been controlled.

It is important to highlight that, for the two fMRI sessions, pairs that were correctly matched in the first three blocks were deliberately mismatched in the last three blocks to ensure a robust evaluation of learning and retention. Additionally, the length of artificial words (2-4 letters) and Chinese phrases (1-2 Chinese characters) was carefully managed to maintain consistency across blocks. This control ensures that any differences in performance can be attributed more directly to the learning process rather than variability in word length. Table A.1 shows the artificial word stimuli used in this research.

A.2 SENTENCES

Grammatical sentences ranging from 3 to 8 artificial words in length were constructed. These sentences have a subject-verb[-object] structure. There are two types of phrases: noun phrase (NP) and verb phrase (VP). Grammatical sentences follow the structure NP VP or NP VP NP. The structure of NP is dN or DMN, and the structure of VP is v or vm. Following Kepinska et al. (2017a) and Kepinska et al. (2017b), 12 grammatical structures were used: dNv, dNvm, DMNv, dNvdN, dNvDMN, dNvmDMN, dNvmdN, DMNvdN, DMNvDMN, DMNvmDMN, DMNvm and DMNvmdN. The ungrammatical sentence violations were determiner and noun agreement violations (e.g., DNV instead of dNv, nouns should be modified by the noun determiner D rather than the adjective determiner d), POS repetitions of nouns or verbs (e.g. dNNv or dNvv), and phrase structure violations (e.g., NP NP or NP NP VP instead of NP VP or NP VP NP).

In the pilot study, not all sentences were semantically coherent, which may have led to confusion among participants and did not sufficiently encourage the processing of word meanings during grammar learning and judgement tasks, diverging from natural language processing. To rectify this and more closely mimic authentic language use, we have revised our approach to ensure that all sentences are semantically plausible. However, it is worth noting that ungrammatical sentences that fall under the second type of violation (e.g., noun phrase repetitions like the banana the apple) inherently lack semantic correctness due to their syntactic structure.

All the sentences used in learning, training, and fMRI sessions are distinct, and we con-

POS	**Artificial word**	**English meaning**	**POS**	**Artificial word**	**English meaning**
N	mlux	person	M	qi	red
N	tsoj	boy	M	thi	kind-hearted
N	lir	student	M	rix	small/little
N	te	apple	M	yi	big/grown-up
N	sta	hat	M	kdib	green
N	msuz	girl	v	pel	think
N	ko	banana	v	priz	discuss
N	zav	glasses	v	dux	criticise
m	gok	also	v	fa	look
m	fno	often	v	qok	take
m	gto	did not	v	yev	eat
m	ro	right now	v	yuf	wear
m	yo	today	v	liz	paint
m	zxo	yesterday	d	aaf	that
M	dri	young	D	aak	a

Table A.1: Artificial word stimuli in this research. N: noun, v: verb, M: adjective, m: adverb, d: noun determiner, D: adjective determiner. English meanings are translated from Chinese meanings.

trolled for violation types and sentence length. For the fMRI session, in particular, we only used sentences containing 5-6 artificial words to strictly control the covariates. For each grammatical structure (6 sentences for each structure), three corresponding ungrammatical variations were designed (7 sentences for each violation type). These ungrammatical sentences differed from their grammatical counterparts by no more than two artificial words. In the case of phrase structure violations (Type 3), the same artificial words were used, but the sentence structure was altered (from NP VP NP to NP NP VP). 12 filler sentences were also created following the rules. Half of the ungrammatical sentences were presented before their grammatical versions, and half were presented afterwards. Importantly, the ungrammatical and grammatical sentences did not occur within the same block. Table A.2 presents the controlled factors of the fMRI tasks, along with examples.

Task	Factors	Levels	Examples
Association Judgement	Block	1-6 blocks (8 critical trials and 2 fillers/block)	
	Associativity	Matched (24 critical word pairs) / Mismatched (24 critical word pairs)	ko "banana"(matched) ko "apple" (mismatched)
Grammar Judgement	Block	1-16 blocks (6 critical trials and 1 filler/block)	
	Grammaticality	Grammatical (48 critical sentences) / Ungrammatical (48 critical sentences)	aaf mlux pel (grammatical) aak mlux pel (ungrammatical)
	Sentence length	5 (24 critical sentence) or 6 words (72 critical sentences)	aak dri mlux pel gok aak dri mlux pel aaf mlux
	Violation type	Type 1: Determiner-noun-agreement violations (16 critical sentences)	aaf mlux pel aak lir (NP VP NP)
		Type 2: POS repetitions of nouns or verbs (16 critical sentences)	aaf mlux pel fe aaf lir (NP VP NP)
		Type 3: Phrase structure violations (16 critical sentences)	aaf mlux aaf lir pel (NP NP VP)
	Sentence structure	16 sentence structures.	

Table A.2: Controlled factors of the fMRI tasks. NP: noun phrase, VP: verb phrase.

APPENDIX

B

APPENDIX B - NEURAL RESULTS

B.1 THE CEREBELLUM'S ROLE IN LANGUAGE LEARNING

B.1.1 Cerebro-Subcortical-Cerebellar Cooperative Network

B.1.1.1 Associative Judgment

Region	Side	Size	Peak-level statistics			
			T value	MNI coordinates		
				x	y	z
Word > Rest						
Cortical regions						
IPL	R	199	12.78	32	-58	48
IFG	L	1035	11.09	-52	8	28
SFG	R	410	9.68	36	-12	70
SFG	L	355	8.13	-26	-10	60
IFG	R	779	7.90	58	12	24
MFG	L	231	6.09	-30	46	8
Subcortical regions						
Putamen	R	662	10.34	28	18	6

Continued on next page

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
Putamen	L	687	8.69	-24	2	4
Thalamus	L	185	7.87	-10	-18	6
Thalamus	R	206	7.35	12	-18	8
Cerebellar regions						
Crus II	L	149	8.72	-4	-70	-30
Crus II	R	127	6.95	6	-68	-32
Crus I	L	90	5.13	-36	-54	-34
Crus I	R	55	5.02	36	-50	-34
Feedback_word > Rest						
Cortical regions						
MFG	R	85	6.60	38	46	10
Cerebellar regions						
Crus I	L	48	5.69	-48	-60	-24
Crus I	L	64	4.99	-22	-86	-22

Table B.1: Activations for Word > Rest and Feedback_word > Rest in Pre-AJ (n = 18).

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
Word > Rest						
Cortical regions						
IFG	L	1934	9.96	-56	10	28
SFG	R	857	8.74	32	-12	70
IFG	R	1809	8.68	58	14	30
Subcortical regions						
Putamen	L	968	10.34	-30	-4	-6
Thalamus	R	641	9.39	12	-16	12
Putamen	R	1165	8.90	24	6	-6
Cerebellar regions						
Crus I	R	204	8.19	36	-52	-32
Crus I	L	491	7.67	-6	-76	-22
Crus I	L	323	6.93	-38	-46	-32
Feedback_word > Rest						
Subcortical regions						
Parahippocampus	L	143	7.12	-34	-44	-4
Caudate	R	183	6.84	20	14	18
Hippocampus	R	143	5.85	36	-36	-4
Cerebellar regions						
Crus I	L	135	7.29	-36	-76	-24
Crus I	L	33	5.91	-6	-86	-16
Crus I	R	48	4.35	40	-76	-24

Table B.2: Activations for Word > Rest and Feedback_word > Rest in Post-AJ (n = 38).

B.1.1.2 Grammar Judgment

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
Sentence > Rest						
Cortical regions						
IPL	R	190	13.75	32	-56	46
IFG	L	758	11.03	-44	22	26
IFG	R	658	7.35	40	14	30
MFG	R	199	6.32	34	-6	52
MFG	L	195	5.81	-28	6	60
Subcortical regions						
Thalamus	L	1048	9.33	-8	-10	6
Caudate	L	169	8.51	-6	6	6
Putamen	R	85	7.77	26	22	-2
Caudate	R	55	6.44	10	8	2
Cerebellar regions						
Crus II	L	126	6.31	-6	-86	-28
Crus II	R	20	4.96	8	-78	-34
Feedback_sen > Rest						
Cortical regions						
MFG	R	1437	8.01	34	54	6
IPL	R	184	7.08	36	-56	52
MTG	L	144	6.20	-50	-64	0
IFG	L	197	6.05	-40	22	6
MFG	L	109	5.22	-48	22	40
MFG	L	122	4.65	-40	52	8
Cerebellar regions						
Crus I	L	976	11.79	-38	-68	-26
Crus I	R	609	10.61	38	-64	-28
Crus II	L	215	7.90	-32	-72	-48
Crus II	R	312	7.78	36	-66	-44
Crus II	L	229	7.49	-8	-82	-26

Table B.3: Activations for Sentence > Rest and Feedback_sen > Rest in Pre-GJ (n = 18).

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
Sentence > Rest						
Cortical regions						
IFG	L	975	10.64	-44	4	28
IPL	R	195	9.93	32	-54	44
IFG	R	1034	8.60	40	6	30
MFG	R	366	8.28	34	-4	52
MFG	L	302	6.63	-30	-4	50
Subcortical regions						
Thalamus	L	1078	8.70	-6	-20	2
Putamen	R	120	6.78	28	20	-2
Pallidum	R	52	5.26	18	4	-2
Pallidum	L	58	5.12	-20	2	-2
Cerebellar regions						
Crus I	L	101	6.96	-4	-72	-24
Crus II	R	58	6.04	6	-68	-30
Crus II	L	27	5.95	-26	-72	-46
Feedback_sen > Rest						
Cortical regions						
MFG	R	5392	9.67	36	48	4
IFG	L	3570	8.04	-52	14	2
IPL	R	399	7.55	38	-56	50
MTG	L	111	6.84	-60	-36	22
Subcortical regions						
Caudate	L	1053	8.33	-18	-8	20
Thalamus	R	1196	7.83	22	-24	12
Cerebellar regions						
Crus I	L	1365	13.29	-12	-80	-22
Crus II	L	708	11.47	-8	-82	-26
Crus I	R	869	11.42	12	-74	-28
Crus II	R	304	10.96	8	-78	-30

Table B.4: Activations for Sentence > Rest and Feedback_sen > Rest in Post-GJ (n = 38).

B.1.1.3 Task Difference

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
Word > Sentence						
Cortical regions						
SFG	R	420	7.22	14	0	72
MTG	L	246	6.03	-44	-64	10
IFG	R	66	5.94	60	10	20
MTG	L	84	5.82	-54	-20	-6
IFG	L	103	5.67	-54	10	26
SFG	L	180	5.44	-20	-2	66
STG	L	74	5.32	-56	-42	22
MFG	L	149	5.18	-30	46	8
Subcortical regions						
Putamen	L	440	8.18	-26	-14	4
Pallidum	R	436	7.00	26	-10	4
Cerebellar regions						
Crus I	R	63	5.17	38	-52	-38
Crus I	L	30	4.47	-36	-56	-36
Feedback_word > Feedback_sen						
Cortical regions						
SFG	R	147	7.22	22	36	44
MTG	L	132	6.07	-62	-8	-16
SFG	L	373	6.07	-18	32	42
IFG	L	41	5.24	-30	32	-18

Table B.5: Activations for Word > Sentence and Feedback_word > Feedback_sen in Pre-fMRI (n = 18).

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
Feedback_sen > Feedback_word						
Cortical regions						
IPL	R	103	6.57	30	-52	44
IFG	L	639	5.57	-50	28	24
MFG	L	83	5.35	-28	0	56
MTG	L	62	5.34	-50	-64	0
MFG	R	46	5.26	38	6	62
IFG	R	245	5.00	56	20	32
MFG	L	76	4.90	-36	44	0
Subcortical regions						
Pallidum	R	169	6.65	24	-4	2
Putamen	L	161	6.63	-30	0	2
Putamen	R	71	5.84	28	16	-4
Thalamus	R	40	5.39	12	-14	2
Cerebellar regions						
Crus I	R	59	5.14	12	-74	-28
Crus I	L	37	4.65	-38	-66	-30

Table B.6: Activations for Feedback_sen > Feedback_word in Pre-fMRI (n = 18).

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
Word > Sentence						
Cortical regions						
IFG	R	3172	8.34	58	8	24
STG	L	2047	8.05	-56	-30	22
IFG	L	1142	7.26	-46	16	-12
MFG	L	1429	7.23	-36	44	24
IPL	R	290	5.31	48	-46	24
Subcortical regions						
Hippocampus	R	1710	8.23	20	-34	2
Putamen	L	1322	7.99	-28	-16	-2
Cerebellar regions						
Crus I	L	1149	8.29	-40	-50	-32
Crus I	R	810	8.13	44	-50	-34
Crus II	R	240	6.53	16	-78	-34
Crus II	L	464	5.79	-10	-74	-36
Feedback_word > Feedback_sen						
Subcortial regions						
Hippocampus	L	37	6.38	-36	-34	-6
Hippocampus	R	30	6.33	38	-34	-8
Caudate	R	60	4.91	6	18	0
Caudate	L	37	4.71	-4	16	6
Cerebellar regions						
Crus I	R	33	4.74	20	-90	-28

Table B.7: Activations for Word > Sentence and Feedback_word > Feedback_sen in Post-fMRI (n = 38).

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
Feedback_sen > Feedback_word						
Cortical regions						
IFG	L	4762	10.49	-48	18	30
IFG	R	4940	8.25	48	28	36
IPL	R	291	7.78	38	-56	48
MTG	L	540	5.63	-52	-24	-4
Subcortical regions						
Hippocampus	R	1666	8.70	22	-34	0
Putamen	L	1431	7.80	-26	-6	-8
Cerebellar regions						
Crus I	R	120	9.67	8	-74	-26
Crus II	R	243	9.23	8	-78	-30
Crus II	L	267	8.67	-10	-74	-32
Crus I	L	660	7.71	-10	-76	-22
Crus I	R	353	7.19	34	-66	-28

Table B.8: Activations for Feedback_sen > Feedback_word in Post-fMRI (n = 38).

B.1.1.4 Plasticity

			Peak-level statistics			
Region	**Side**	**Size**	**T value**	**MNI coordinates**		
				x	**y**	**z**
AJ:						
-	-	-	-	-	-	-
GJ:						
Pre-GJ Sentence >						
Post-GJ Sentence						
Caudate	L	72	7.41	-12	-10	24
IFG	R	84	6.41	40	46	-14
Post-GJ Sentence >						
Pre-GJ Sentence						
-	-	-	-	-	-	-
Pre-GJ Feedback >						
Post-GJ Feedback						
-	-	-	-		-	-
Post-GJ Feedback >						
Pre-GJ Feedback						
IPL	L	127	7.83	-60	-38	28
MTG	R	91	5.62	60	-26	-8
IPL	R	167	5.26	62	-30	28

Table B.9: Plasticity for AJ and GJ judgment and feedback.

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
AJ:						
Pre-AJ Word >						
Post-AJ Word						
STG	L	106	5.74	-58	-30	-4
Crus II	R	26	6.19	22	-56	-38
Crus I	L	22	5.97	-28	-50	-32
Post-AJ Feedback >						
Pre-AJ Feedback						
IFG	L	128	7.49	-50	22	24
MTG	R	86	6.45	58	0	-20
MTG	L	56	5.53	-56	-48	-2
GJ:						
Pre-GJ Sentence >						
Post-GJ Sentence						
-	-	-	-	-	-	-
Pre-GJ Feedback >						
Post-GJ Feedback						
Pallidum	R	153	5.13	26	-8	62
MTG	L	104	4.79	-44	-60	8

Table B.10: Regions showing positive correlations with task d-prime change for plasticity.

B.1.2 Automatic and Controlled Processing

B.1.2.1 Engagement

Seed	Region	Side	Size	Peak-level statistics			
				T value	MNI coordinates		
					x	y	z
Pre-AJ:							
-	-	-	-	-	-	-	-
Post-AJ:							
Right Crus I	Superior parietal lobule	R	65	4.72	22	-54	66
	Postcentral gyrus	R	34	4.54	54	-26	44
Left Crus II	MFG	L	49	4.67	-42	44	8
Pre-GJ:							
Left Crus I	MFG	L	28	6.17	-28	2	66
	Postcentral gyrus	L	103	5.93	-60	-22	46
	IPL	L	40	5.11	-40	-42	52
Post-GJ:							
Right Crus I	IFG	L	53	4.83	-48	24	-2
Right Crus II	IPL	L	59	4.52	-46	-44	48

Table B.11: Functional connectivity for engagement in automatic and controlled processing. AJ: Word_mat > Word_mis; GJ: Sentence_gra > Sentence_ung.

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
Pre-AJ:						
Word_mis >Word_mat						
Lobule VI	L	26	4.15	-12	-52	-26
Post AJ:						
Word_mis >Word_mat						
Crus I	R	51	4.39	42	-68	-22
Pre-GJ:						
Sentence_gra >Sentence_ung						
Lobule IV and V	R	82	5.82	10	-56	-18
Post-GJ:						
Sentence_gra >Sentence_ung						
Lobule VI	R	35	3.99	20	-56	-18

Table B.12: Cerebellar regions showing positive correlations with task d-primes in automatic and controlled processing.

Seed	**Region**	**Side**	**Size**	**Peak-level statistics**			
				T value	**MNI coordinates**		
					x	**y**	**z**
Pre-AJ:							
Left Crus I	Inferior temporal gyrus	R	32	-6.50	60	-46	-18
Left Crus II	MFG	R	103	7.22	46	18	52
	Thalamus	L	29	7.25	-10	-20	8
	MFG	R	47	6.53	34	16	46
	MTG	R	25	5.65	70	-32	-4
	Cingulate gyrus		24	5.35	0	34	10
Right Crus II	Insula	R	335	7.24	50	-14	8
	Insula	L	210	7.06	-36	-26	16
	Thalamus	L	45	6.81	-12	-14	6
	Central opercular cortex	R	73	5.82	42	6	6
	MFG	L	21	4.75	-42	12	42
Post-AJ:							
Left Crus I	SFG	L	123	-5.18	-20	6	56
Right Crus I	SFG	R	48	-4.70	22	18	54
Left Crus II	Precuneus	L	107	-5.88	-18	-50	62
	IPL	L	46	-4.58	-58	-26	26
Right Crus II	SFG	L	80	-6.17	-20	6	66
	IPL	L	37	-5.00	-64	-22	26
Pre-GJ:							
Right Crus I	Precuneus	R	173	8.42	26	-66	38
Left Crus II	Postcentral gyrus	L	68	6.63	-52	-22	40
Post-GJ:							
Left Crus I	Cuneus	R	76	-5.00	18	-88	30
Left Crus II	Cuneus	R	44	-4.66	18	-88	26
Right Crus II	Postcentral gyrus	L	46	-5.02	-66	-22	18

Table B.13: D-prime effects on the functional connectivity for engagement in automatic and controlled processing. AJ: Word_mat > Word_mis; GJ: Sentence_gra > Sentence_ung.

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
Pre-AJ:						
-	-	-	-	-	-	-
Post-AJ:						
$Word\_mis > Word\_mat$						
Lobule VIIb	L	21	4.27	-30	-74	-50
Crus I	R	22	3.95	12	-82	-28
Lobule VI	L	24	3.88	-10	-72	-22
Pre-GJ:						
$Sentence\_ung > Sentence\_gra$						
Vermis VIII	R	53	6.45	2	-66	-36
Post-GJ:						
-	-	-	-	-	-	-

Table B.14: Cerebellar regions showing negative correlations with task reaction times in automatic and controlled processing.

Seed	Region	Side	Size	Peak-level statistics			
				T value	MNI coordinates		
					x	y	z
Pre-AJ:							
Left Crus I	SFG	R	31	5.43	22	52	22
	MFG	L	30	-6.35	-54	34	18
Right Crus II	IPL	R	33	-5.81	56	-38	56
Post-AJ:							
-	-	-	-	-	-	-	-
Pre-GJ:							
Left Crus II	Cingulate gyrus	L	52	-7.49	-6	-44	6
Post-GJ:							
Left Crus I	Precuneus	R	38	-4.59	12	-76	54
Right Crus I	IFG	R	93	-5.30	30	30	4
	Precuneus	R	60	-4.94	22	-74	52
Left Crus II	MTG	L	78	5.43	-62	-32	-22

Table B.15: Reaction time effects on the functional connectivity for engagement in automatic and controlled processing. AJ: Word_mat > Word_mis; GJ: Sentence_gra > Sentence_ung.

B.1.2.2 Plasticity

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
AJ:						
Pre-AJ Word_mat > *Post-AJ Word_mat*						
-	-	-	-	-	-	-
Pre-AJ Word_mis > *Post-AJ Word_mis*						
-	-	-	-	-	-	-
(Pre-AJ Word_mat >Word_mis) > *(Post-AJ Word_mat >Word_mis)*						
-	-	-	-	-	-	-
(Post-AJ Word_mat >Word_mis) > *(Pre-AJ Word_mat >Word_mis)*						
Crus I	R	38	5.79	42	-56	-28
GJ:						
Pre-GJ Sentence_gra > *Post-GJ Sentence_gra*						
-	-	-	-	-	-	-
Pre-GJ Sentence_ung > *Post-GJ Sentence_ung*						
Crus II	L	20	4.65	-28	-80	-38
(Pre-GJ Sentence_gra >Sentence_ung) > *(Post-GJ Sentence_gra >Sentence_ung)*						
-	-	-	-	-	-	-
(Post-GJ Sentence_gra >Sentence_ung) > *(Pre-GJ Sentence_gra >Sentence_ung)*						
-	-	-	-	-	-	-

Table B.16: Cerebellar activation plasticity in automatic and controlled processing.

Seed	**Region**	**Side**	**Size**	**Peak-level statistics**			
				T value	**MNI coordinates**		
					x	**y**	**z**
AJ:							
Pre-AJ Word_mat >							
Post-AJ Word_mat							
Left Crus I	STG	L	61	7.39	-50	-22	4
	Insula	R	36	6.20	48	-10	-2
Pre-AJ Word_mis >							
Post-AJ Word_mis							
Right Crus II	Precentral gyrus	R	40	-5.93	2	-26	72
(Pre-AJ Word_mat >Word_mis) >							
(Post-AJ Word_mat >Word_mis)							
-	-	-	-	-	-	-	-
GJ:							
Pre-GJ Sentence_gra >							
Post-GJ Sentence_gra							
-	-	-	-	-	-	-	-
Pre-GJ Sentence_ung >							
Post-GJ Sentence_ung							
-	-	-	-	-	-	-	-
(Pre-GJ Sentence_gra >Sentence_ung) >							
(Post-GJ Sentence_gra >Sentence_ung)							
Left Crus I	MOG	L	42	-5.49	-48	-82	10
Right Crus I	MOG	L	69	-5.40	-28	-94	18
Left Crus II	MOG	L	62	-5.99	-42	-82	18
Right Crus II	Cuneus	L	76	-5.72	-16	-94	24
	MOG	L	62	-5.72	-48	-80	14

Table B.17: Cerebellar functional connectivity plasticity in automatic and controlled processing. MOG = Middle occipital gyrus.

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
AJ:						
Pre-AJ Word_mat > *Post-AJ Word_mat*						
Lobule VI	L	37	7.59	-28	-50	-32
Pre-AJ Word_mis > *Post-AJ Word_mis*						
Lobule VI	R	22	6.21	22	-52	-33
(Pre-AJ Word_mat >Word_mis) > *(Post-AJ Word_mat >Word_mis)*						
-	-	-	-	-	-	-
(Post-AJ Word_mat >Word_mis) > *(Pre-AJ Word_mat >Word_mis)*						
-	-	-	-	-	-	-
GJ:						
Pre-GJ Sentence_gra > *Post-GJ Sentence_gra*						
-	-	-	-	-	-	-
Pre-GJ Sentence_ung > *Post-GJ Sentence_ung*						
-	-	-	-	-	-	-
(Pre-GJ Sentence_gra >Sentence_ung) > *(Post-GJ Sentence_gra >Sentence_ung)*						
-	-	-	-	-	-	-
(Post-GJ Sentence_gra >Sentence_ung) > *(Pre-GJ Sentence_gra >Sentence_ung)*						
Lobule VI	R	26	5.69	20	-56	-20

Table B.18: Cerebellar regions showing positive correlations with task d-prime change for plasticity in automatic and controlled processing.

Seed	Region	Side	Size	Peak-level statistics			
				T value	MNI coordinates		
					x	y	z
AJ:							
Pre-AJ Word_mat > *Post-AJ Word_mat*							
-	-	-	-	-	-	-	-
Pre-AJ Word_mis > *Post-AJ Word_mis*							
-	-	-	-	-	-	-	-
(Pre-AJ Word_mat >Word_mis) > *(Post-AJ Word_mat >Word_mis)*							
Right Crus II	Caudate	R	31	7.44	8	6	14
GJ:							
Pre-GJ Sentence_gra > *Post-GJ Sentence_gra*							
Left Crus I	Lingual gyrus	L	36	6.92	-34	-58	2
	Caudate	R	50	6.82	30	-42	16
Pre-GJ Sentence_ung > *Post-GJ Sentence_ung*							
Left Crus I	Caudate	R	66	7.48	26	-36	12
	Lingual gyrus	L	42	7.02	-34	-58	2
(Pre-GJ Sentence_gra >Sentence_ung) > *(Post-GJ Sentence_gra >Sentence_ung)*							
Right Crus II	Hippocampus	L	70	11.07	-22	-38	-4
	MTG	L	36	6.40	-50	-16	-18

Table B.19: D-prime change effects on function connectivity plasticity in automatic and controlled processing.

Seed	Region	Side	Size	Peak-level statistics			
				T value	MNI coordinates		
					x	y	z
AJ:							

Continued on next page

Seed	**Region**	**Side**	**Size**	**Peak-level statistics**			
				T value	**MNI coordinates**		
					x	**y**	**z**
Pre-AJ Word_mat >							
Post-AJ Word_mat							
Left Crus I	Caudate	R	94	9.71	24	14	24
	Cingulate gyrus	L	34	-7.99	-8	-2	36
	Pallidum	R	50	-7.93	16	0	-6
Right Crus I	Caudate	R	102	8.74	24	6	24
Left Crus II	Caudate	R	42	7.14	22	14	20
Right Crus II	Superior parietal lobe	R	168	-6.61	32	-58	44
	MTG	R	58	-6.28	64	-6	-28
Pre-AJ Word_mis >							
Post-AJ Word_mis							
Left Crus II	Cuneus	R	43	5.64	18	-78	44
(Pre-AJ Word_mat >Word_mis) >							
(Post-AJ Word_mat >Word_mis)							
Right Crus I	Caudate	R	60	7.71	20	4	24
	MFG	R	93	-6.58	34	46	-8
Right Crus II	MTG	R	135	-8.68	54	-2	34
	MTG	R	194	-7.64	66	-30	-12
	IPL	R	294	-7.15	42	-48	42
	SFG	R	51	-6.77	8	46	52
	MTG	L	51	-6.30	-64	-28	-14
	Frontal pole	R	103	-5.87	36	48	-10
GJ:							
Pre-GJ Sentence_gra >							
Post-GJ Sentence_gra							
Left Crus II	MTG	L	34	5.30	-54	-44	6
Pre-GJ Sentence_ung >							
Post-GJ Sentence_ung							
Left Crus II	MTG	L	36	5.51	-56	-44	6

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Seed	**Region**	**Side**	**Size**	**Peak-level statistics**			
				T value	**MNI coordinates**		
					x	**y**	**z**
Right Crus II	MTG	R	43	6.61	54	-2	-34
(Pre-GJ Sentence_gra >Sentence_ung) >							
(Post-GJ Sentence_gra >Sentence_ung)							
Right Crus II	Precentral gyrus	R	61	5.59	44	-12	56

Table B.20: Reaction time change effects on functional connectivity plasticity in automatic and controlled processing.

B.1.3 Correct-Related and Error-Related Processing

B.1.3.1 Engagement

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
Sentence_cor >Sentence_inc						
Vermis IV and V	R	31	5.88	2	-60	-6
Crus II	L	165	5.75	-24	-86	-32
Lobule VI	R	148	5.32	18	-76	-24
Lobule IX	L	21	5.31	-6	-52	-36
Sentence_inc >Sentence_cor						
-	-	-	-	-	-	-
Feedback_pos >Feedback_neg						
Crus II	R	940	6.84	42	-68	-40
Crus I	L	437	5.76	-44	-72	-32
Lobule IV and V	L	181	5.74	-24	-50	-18
Lobule IX	L	41	5.24	-20	-48	-48
Lobule VI	L	58	4.99	-22	-76	-18
Feedback_neg >Feedback_pos						
-	-	-	-	-	-	-

Table B.21: Cerebellar activations in correct-related and error-related processing during Pre-GJ.

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
Sentence_cor >Sentence_inc						
Crus I	L	6862	8.03	-8	-82	-22
Sentence_inc >Sentence_cor						
-	-	-	-	-	-	-
Feedback_pos >Feedback_neg						
Lobule VIII	R	28	5.56	26	-48	-50
Lobule VIII	L	36	5.36	-24	-50	-80
Feedback_neg >Feedback_pos						
Vermis IX		585	7.96	0	-54	-36
Lobule VI	R	290	5.97	30	-58	-28
Lobule VI	L	153	5.48	-30	-56	-32
Crus I	L	53	4.39	-8	-76	-24
Crus I	R	49	4.13	12	-78	-28

Table B.22: Cerebellar activations in correct-related and error-related processing during Post-GJ.

Seed	**Region**	**Side**	**Size**	**Peak-level statistics**			
				T value	**MNI coordinates**		
					x	**y**	**z**
Pre-GJ:							
Sentence_cor >Sentence_inc							
Right Crus I	Cuneus	R	41	6.08	22	-78	32
Feedback_pos >Feedback_neg							
-	-	-	-	-	-	-	-
Post-GJ:							
Sentence_cor >Sentence_inc							
Left Crus I	Cingulate gyrus	L	175	-5.75	-8	34	12
Feedback_pos >Feedback_neg							
Left Crus I	MFG	R	109	5.88	24	54	0
	MFG		367	5.83	0	26	36
	MFG	R	146	5.16	32	42	14
	SFG	R	31	4.71	6	20	58
	Insula	R	63	4.59	40	16	-2
Right Crus I	Thalamus	L	51	5.38	-8	-16	12
	MFG		46	4.65	0	30	40
Left Crus II	MFG	R	489	5.71	8	40	14
Right Crus II	MFG	R	62	4.95	2	30	38
	IPL	L	173	4.88	-44	-56	-40
	IFG	L	38	4.80	-50	44	-4
	MFG	L	73	4.78	-40	32	44

Table B.23: Functional connectivity in correct-related and error-related processing.

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
Pre-GJ:						
-	-	-	-	-	-	-
Post-GJ:						
Feedback_pos >Feedback_neg						
-	-	-	-	-	-	-
Feedback_neg >Feedback_pos						
Crus II	L	197	4.92	-4	-80	-34
Crus I	R	53	4.58	48	-50	-36
Vermis VI		22	4.10	0	-64	-20
Crus II	L	23	3.82	-24	-80	-46

Table B.24: Cerebellar regions showing positive correlations with task d-primes in correct-related and error-related processing.

Seed	**Region**	**Side**	**Size**	**Peak-level statistics**			
				T value	**MNI coordinates**		
					x	**y**	**z**
Pre-GJ:							
Sentence_cor >Sentence_inc							
Right Crus II	Postcentral gyrus	R	32	-5.54	34	-28	54
Feedback_pos >Feedback_neg							
-	-	-	-	-	-	-	-
Post-GJ:							
-	-	-	-		-	-	-

Table B.25: Reaction time effects on functional connectivity for the engagement in correct-related and error-related processing.

B.1.3.2 Plasticity

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
Judgment:						
Pre-GJ Sentence_cor >						
Post-GJ Sentence_cor						
Crus I	L	50	4.60	-38	-74	-34
Crus I	R	20	4.41	-20	-90	-24
Pre-GJ Sentence_inc >						
Post-GJ Sentence_inc						
-	-	-	-	-	-	-
(Pre-GJ Sentence_cor >Sentence_inc) >						
(Post-GJ Sentence_cor >Sentence_inc)						
-	-	-	-	-	-	-
(Post-GJ Sentence_cor >Sentence_inc) >						
(Pre-GJ Sentence_cor >Sentence_inc)						
-	-	-	-	-	-	-
Feedback:						
Pre-GJ Feedback_pos >						
Post-GJ Feedback_pos						
-	-	-	-	-	-	-
Pre-GJ Feedback_neg >						
Post-GJ Feedback_neg						
-	-	-	-	-	-	-
(Pre-GJ Feedback_pos >Feedback_neg) >						
(Post-GJ Feedback_pos >Feedback_neg)						
Lobule VIII	L	468	7.08	-8	-60	-40
Lobule IX	R	25	6.25	10	-52	-52
Lobule IV and V	L	38	5.52	-4	-54	-12
Lobule VI	R	156	5.30	32	-48	-36
Vermis III	R	25	5.06	4	-42	-8
Crus II	R	158	4.88	10	-78	-30
(Post-GJ Feedback_pos >Feedback_neg) >						
(Pre-GJ Feedback_pos >Feedback_neg)						
-	-	-	-	-	-	-

Table B.26: Cerebellar activation plasticity in correct-related and error-related processing.

Seed	**Region**	**Side**	**Size**	**Peak-level statistics**			
				T value	**MNI coordinates**		
					x	**y**	**z**
Judgment:							
Pre-GJ Sentence_cor >							
Post-GJ Sentence_cor							
-	-	-	-	-	-	-	-
Pre-GJ Sentence_inc >							
Post-GJ Sentence_inc							
Right Crus I	Lingual gyrus	L	40	6.57	-2	72	2
Left Crus II	Cuneus	L	31	-5.16	-4	-82	24
	IPL	L	38	5.15	-34	-52	42
(Pre-GJ Sentence_cor >Sentence_inc) >							
(Post-GJ Sentence_cor >Sentence_inc)							
Left Crus I	Cuneus		32	5.65	0	-92	18
Right Crus I	IPL	R	32	7.92	34	-48	48
Left Crus II	Occipital lobe	R	35	5.64	10	-78	8
Right Crus II	Lingual gyrus	R	109	7.44	16	-86	-12
	Precentral gyrus	L	27	6.46	-56	2	14
	Postcentral gyrus	L	28	5.83	-26	-40	66
	STG	L	38	5.75	-52	-20	6
	IPL	R	28	4.98	38	-48	48
Feedback:							
Pre-GJ Feedback_pos >							
Post-GJ Feedback_pos							
Right Crus I	SFG	R	35	-4.93	6	38	56
Pre-GJ Feedback_neg >							
Post-GJ Feedback_neg							
Right Crus I	SFG	R	33	-4.92	8	38	56
(Pre-GJ Feedback_pos >Feedback_neg) >							
(Post-GJ Feedback_pos >Feedback_neg)							
Right Crus II	Lateral occipital cortex	L	46	-6.76	-34	-80	32

Table B.27: Cerebellar functional connectivity in correct-related and error-related processing.

Region	Side	Size	Peak-level statistics			
			T value	MNI coordinates		
				x	y	z
Judgment:						
-	-	-	-	-	-	-
Feedback:						
Pre-GJ Feedback_pos >						
Post-GJ Feedback_pos						
Lobule VIII	R	183	5.99	30	-52	-48
Lobule VIII	L	48	5.87	-24	-66	-42
Vermis IV and V	L	30	5.52	-2	-54	-18
Crus I	L	20	4.47	-40	-66	-24
Lobule VI	R	28	4.29	32	-60	-28
Pre-GJ Feedback_neg >						
Post-GJ Feedback_neg						
-	-	-	-	-	-	-
(Pre-GJ Feedback_pos >Feedback_neg) >						
(Post-GJ Feedback_pos >Feedback_neg)						
Crus II	L	25	5.74	-40	-50	-44
(Post-GJ Feedback_pos >Feedback_neg) >						
(Pre-GJ Feedback_pos >Feedback_neg)						
-	-	-	-	-	-	-

Table B.28: Cerebellar regions showing positive correlations with task d-prime change for plasticity in correct-related and error-related processing.

Seed	Region	Side	Size	Peak-level statistics			
				T value	MNI coordinates		
					x	y	z
Pre-GJ Sentence_cor > Post-GJ Sentence_cor							
Left Crus I	Caudate	R	39	-6.59	26	-36	12
	Lingual gyrus	L	32	-6.54	-34	-58	2
	Caudate	R	29	5.65	10	8	14
Pre-GJ Sentence_inc > Post-GJ Sentence_inc							
Left Crus I	Caudate	R	51	-6.64	26	-36	12
	MFG	R	40	6.31	34	52	-12
(Pre-GJ Sentence_cor >Sentence_inc) > (Post-GJ Sentence_cor >Sentence_inc)							
Left Crus I	MFG	L	74	6.66	-28	6	4
Right Crus I	Precuneus	L	33	-5.88	-12	-48	62

Table B.29: D-prime change effects on function connectivity plasticity in correct-related and error-related processing.

Seed	Region	Side	Size	Peak-level statistics			
				T value	MNI coordinates		
					x	y	z
Judgment:							
Pre-GJ Sentence_cor >							
Post-GJ Sentence_cor							
Left Crus II	MTG	L	60	-5.77	-56	-44	6
Right Crus II	MTG	R	41	-6.24	54	-2	-34
Pre-GJ Sentence_inc >							
Post-GJ Sentence_inc							
Left Crus I	SFG	L	46	-6.35	-24	68	2
Left Crus II	MTG	L	32	-5.21	-52	-46	6
Right Crus II	MTG	R	39	-6.41	54	-2	-34
(Pre-GJ Sentence_cor >Sentence_inc) >							
(Post-GJ Sentence_cor >Sentence_inc)							
Left Crus I	Postcentral gyrus	L	140	6.17	-30	-26	56
Right Crus II	Postcentral gyrus	R	43	-9.25	50	-14	10
	MFG	R	30	6.49	36	8	56
Feedback:							
-	-	-	-	-	-	-	-

Table B.30: Reaction time effects on function connectivity plasticity in correct-related and error-related processing.

B.2 CORTICAL, SUBCORTICAL, AND CEREBELLAR CONTRIBUTION DIFFERENCE

B.2.1 Automatic and Controlled Processing

B.2.1.1 Engagement

Region	Side	Size	Peak-level statistics			
			T value	MNI coordinates		
				x	y	z
Pre-AJ:						
-	-	-	-	-	-	-
Post-AJ:						
-	-	-	-	-	-	-
Pre-GJ:						
Sentence_gra >Sentence_ung						
SFG	L	452	5.64	-22	-20	62
Post-GJ:						
Sentence_ung >Sentence_gra:						
Cingulate gyrus	L	74	4.53	-4	32	30

Table B.31: Cerebrum regions showing positive correlations with task d-primes in automatic and controlled processing.

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
Pre-AJ:						
-	-	-	-	-	-	-
Post-AJ:						
Word_mis >Word_mat						
MFG	L	129	5.37	-40	50	0
IFG	L	123	4.26	-46	8	24
Pre-GJ:						
Sentence_ung >Sentence_gra						
Thalamus	R	54	8.30	10	-2	12
Lingual gyrus	R	54	8.05	14	-48	-8
Cuneus	R	166	7.44	12	-58	14
Precuneus	R	266	6.68	20	-70	38
Precentral gyrus	L	67	6.29	-50	4	-10
Caudate	R	62	5.94	16	24	-10
MTG	R	91	5.86	36	-74	24
STG	R	184	5.78	48	-28	10
IFG	L	53	5.74	-42	4	-28
STG	L	152	5.55	-52	-58	18
MTG	L	86	5.34	-42	-72	10
STG	R	73	5.20	54	4	-12
MTG	R	108	5.19	48	-62	4
Post-GJ:						
-	-	-	-	-	-	-

Table B.32: Cerebrum regions showing negative correlations with task reaction times in automatic and controlled processing.

B.2.1.2 Plasticity

Region	Side	Size	Peak-level statistics			
			T value	MNI coordinates		
				x	y	z
AJ:						
Pre-AJ Word_mat >						
Post-AJ Word_mat						
Middle occipital gyrus	L	70	5.36	-32	-82	20
Pre-AJ Word_mis >						
Post-AJ Word_mis						
-	-	-	-	-	-	-
(Pre-AJ Word_mat >Word_mis) >						
(Post-AJ Word_mat >Word_mis)						
IPL	L	184	5.27	-44	-32	60
MFG	R	30	4.57	48	24	44
(Post-AJ Word_mat >Word_mis) >						
(Pre-AJ Word_mat >Word_mis)						
-	-	-	-	-	-	-
GJ:						
Pre-GJ Sentence_gra >						
Post-GJ Sentence_gra						
Caudate	L	60	6.65	-12	-10	24
MFG	R	81	5.66	40	46	-14
Pre-GJ Sentence_ung >						
Post-GJ Sentence_ung						
Caudate	L	64	7.27	-16	-8	24
MFG	R	70	6.23	40	46	-14
(Pre-GJ Sentence_gra >Sentence_ung) >						
(Post-GJ Sentence_gra >Sentence_ung)						
-	-	-	-	-	-	-
(Post-GJ Sentence_gra >Sentence_ung) >						
(Pre-GJ Sentence_gra >Sentence_ung)						
IFG	R	74	5.05	38	26	-4

Table B.33: Cerebrum activation plasticity in automatic and controlled processing.

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
AJ:						
Pre-AJ Word_mat > *Post-AJ Word_mat*						
IFG	R	56	5.52	44	26	-8
MTG	L	87	5.46	-58	-30	-4
Post-AJ Word_mat > *Pre-AJ Word_mat*						
Parahippocampus	L	30	5.72	-28	-58	-2
Pre-AJ Word_mis > *Post-AJ Word_mis*						
MTG	L	71	4.98	-58	-30	-4
(Pre-AJ Word_mat >Word_mis) > *(Post-AJ Word_mat >Word_mis)*						
-	-	-	-	-	-	-
(Post-AJ Word_mat >Word_mis) > *(Pre-AJ Word_mat >Word_mis)*						
-	-	-	-	-	-	-
GJ:						
Post-GJ Sentence_gra > *Pre-GJ Sentence_gra*						
Cingulate gyrus	L	176	6.32	-24	-12	46
Putamen	L	52	4.95	-30	-4	-2
Post-GJ Sentence_ung > *Pre-GJ Sentence_ung*						
Parahippocampus	L	45	8.17	-38	-22	-18
(Pre-GJ Sentence_gra >Sentence_ung) > *(Post-GJ Sentence_gra >Sentence_ung)*						
-	-	-	-	-	-	-
(Post-GJ Sentence_gra >Sentence_ung) > *(Pre-GJ Sentence_gra >Sentence_ung)*						
-	-	-	-	-	-	-

Table B.34: Cerebrum regions showing positive correlations with task d-prime change for plasticity in automatic and controlled processing.

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
AJ:						
-	-	-	-	-	-	-
GJ:						
Pre-GJ Sentence_gra > *Post-GJ Sentence_gra*						
-	-	-	-	-	-	-
Pre-GJ Sentence_ung > *Post-GJ Sentence_ung*						
-	-	-	-	-	-	-
(Pre-GJ Sentence_gra >Sentence_ung) > *(Post-GJ Sentence_gra >Sentence_ung)*						
-	-	-	-	-	-	-
(Post-GJ Sentence_gra >Sentence_ung) > *(Pre-GJ Sentence_gra >Sentence_ung)*						
Insula	L	55	6.58	-46	6	2
MFG	R	103	5.07	40	36	22

Table B.35: Cerebrum regions showing negative correlations with reaction time change for plasticity in automatic and controlled processing.

B.2.2 Correct-Related and Error-Related Processing

B.2.2.1 Engagement

Region	Side	Size	Peak-level statistics			
			T value	MNI coordinates		
				x	y	z
Pre-GJ:						
Sentence_cor >Sentence_inc						
-	-	-	-	-	-	-
Feedback_neg >Feedback_pos						
Caudate	R	90	7.74	12	4	6
SFG	L	106	6.51	-4	22	54
Post-GJ:						
Sentence_cor >Sentence_inc						
-	-	-	-	-	-	-
Feedback_neg >Feedback_pos						
IFG	R	928	5.92	44	20	-14
IFG	L	251	5.82	-32	14	-28
Paraphippocampus	R	111	5.39	28	-28	-14
IPL	R	232	5.20	62	-30	44
Cingulate gyrus	R	309	5.18	6	-10	28
Cingulate gyrus	R	640	4.77	4	12	30
Insula	L	102	4.59	-40	10	4
MFG	L	110	4.57	-10	2	54

Table B.36: Cerebrum regions showing positive correlations with task d-primes in correct-related and error-related processing.

B.2.2.2 Plasticity

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
Judgment:						
Pre-GJ Sentence_cor >						
Post-GJ Sentence_cor						
SFG	R	70	6.40	22	58	14
IFG	R	82	5.85	40	48	-12
SFG	R	96	5.24	8	38	50
Pre-GJ Sentence_inc >						
Post-GJ Sentence_inc						
-	-	-	-	-	-	-
(Pre-GJ Sentence_cor >Sentence_inc) >						
(Post-GJ Sentence_cor >Sentence_inc)						
Parahippocampus	R	60	4.73	16	-42	2
(Post-GJ Sentence_cor >Sentence_inc) >						
(Pre-GJ Sentence_cor >Sentence_inc)						
-	-	-	-	-	-	-

Table B.37: Cerebrum activation plasticity in correct-related and error-related processing (judgment).

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
Feedback:						
Pre-GJ Feedback_pos >						
Post-GJ Feedback_pos						
-	-	-	-	-	-	-
Post-GJ Feedback_neg>						
Pre-GJ Feedback_neg						
IPL	L	322	7.69	-60	-36	30
IPL	R	345	6.28	60	-28	42
IFG	R	129	5.92	48	20	-8
MTG	R	207	5.86	58	-26	-8
Cingulate gyrus	R	426	5.67	14	40	20
Precuneus		370	5.59	0	-34	48
IFG	R	65	5.04	34	14	-20
Caudate	L	63	4.97	-14	-6	20
MFG	R	108	4.80	12	54	14
(Pre-GJ Feedback_pos >Feedback_neg) >						
(Post-GJ Feedback_pos >Feedback_neg)						
MFG	R	1284	8.32	46	30	16
Caudate	R	138	7.88	10	12	10
SFG	R	2355	7.64	10	16	52
Putamen	L	82	6.84	-30	-18	-2
Caudate	L	480	6.58	-12	0	16
Insula	L	516	6.22	-42	12	0
Fusiform gyrus	R	101	6.08	30	-68	-6
MFG	R	128	5.96	38	48	0
Thalamus	L	96	5.79	-18	-34	0
IPL	R	271	5.56	42	-34	36
Precuneus	R	95	5.26	6	-64	42
MTG	R	92	5.16	62	-44	0
Cingulate gyrus	R	98	4.63	6	-64	14
(Post-GJ Feedback_pos >Feedback_neg) >						
(Pre-GJ Feedback_pos >Feedback_neg)						
-	-	-	-	-	-	-

Table B.38: Cerebrum activation plasticity in correct-related and error-related processing (feedback).

Region	**Side**	**Size**	**Peak-level statistics**			
			T value	**MNI coordinates**		
				x	**y**	**z**
Judgment:						
-	-	-	-	-	-	-
Feedback:						
Pre-GJ Feedback_pos > Post-GJ Feedback_pos						
MFG	R	195	5.98	26	-8	62
Pre-GJ Feedback_neg > Post-GJ Feedback_neg>						
Precuneus	R	68	5.84	12	-46	64
MTG	L	101	5.09	-44	-60	8
(Pre-GJ Feedback_pos >Feedback_neg) > (Post-GJ Feedback_pos >Feedback_neg)						
-	-	-	-	-	-	-
(Post-GJ Feedback_pos >Feedback_neg) > (Pre-GJ Feedback_pos >Feedback_neg)						
-	-	-	-	-	-	-

Table B.39: Cerebrum regions showing positive correlations with task d-prime change for plasticity in correct-related and error-related processing.

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