CORTICAL DYNAMICS AND SPEECH PERCEPTION DURING EARLY CHILDHOOD

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Declaration

I, Ana Campos Espinoza, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

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Abstract

Early childhood is a period of important linguistic development; however, measuring the neural correlates of speech perception at this age is challenging. So far, there is no clarity about whether, between the ages of 3-6 years old, brain dynamics associated with speech perception (i) are different from those observed in adults, (ii) show atypical patterns in children with language difficulties, or (iii) are modulated by language skills.

This thesis aimed to examine cortical dynamics related to speech perception in children from 4.7 to 5.7 years old with typical language development (TLD, n=12) and developmental language disorder (DLD, n=17) and compare them to that observed in neurotypical adults (n=20). I used electroencephalography (EEG) to investigate whether young children exhibit top-down modulations on cortical speech processing and whether TLD and DLD children differed in different measures of cortical oscillatory synchrony.

Considering previous findings, we expected different EEG measures to reflect more efficient speech perception for participants with better language skills and stimuli with more informative linguistic content. We also expected an association between children's EEG responses and phonological and speech perception task performance.

Experiment 1 validated a task-free, ERP multifeature paradigm in adults to determine whether contrasts between speech stimuli elicited consistent MMN and LDN responses, compared to a non-speech control condition. In Experiment 2, we used the multifeature experiment in the speech condition to determine whether the MMN and LDN were present in children and if they resembled the adult's responses. Here, we complemented ERPs analysis with time-frequency measures, evaluating the synchrony of the neural responses independently from their amplitude (power). We also assessed the children's phonological awareness skills and investigated their association with EEG measures.

Experiment 3 examined the relationship between language skills (TLD/DLD children and adults) and the power and lateralisation of endogenous oscillations. We also related EEG resting-state measures to children's performance in speech-in-noise and filtered speech perception tests. Finally, in Experiment 4, we explored more ecological speech perception measures, recording EEG responses to unattended continuous speech. We then compared cortical entrainment to different speech features between children and adults.

Our results demonstrated age-related differences in EEG responses between adults and children, confirming that increases in neural synchrony are relevant for cortical development. A central finding is that adults also exhibited a significant effect of the linguistic content, with greater cortical synchrony for lexical stimuli, but this effect was absent in children. This indicates that adult-like top-down language modulations on speech perception could not be already in place during early childhood.

Notably, there was no evidence of differences between TLD and DLD children on most EEG measures, despite TLD children performing significantly better than DLD in phonological awareness and filtered speech perception tasks. These results indicate that cortical speech processing at the acoustic and lexical level may be preserved in young children with DLD. Although it is essential to consider methodological limitations when interpreting these findings, they were consistent across experiments.

This thesis contributes to understanding the cortical dynamics of speech perception in young children. Our findings are relevant to inform oscillatory models of typical and atypical language development and future objective clinical measures of speech processing.

Impact statement

This research holds potential benefits for both the industry and the general public, ultimately impacting society as a whole. The findings of this thesis can contribute to advancements in the field of speech processing, particularly in understanding how the brain processes and comprehends spoken language.

Industry partners

The evidence gathered in this thesis contributes to uncovering the neural patterns underlying speech perception in children and adults. This outcome directly benefits the healthcare industry, as it provides initial values for different EEG measures that can inform the development of objective speech processing measures for clinical assessment, with applications in audiology, neurology, speech and language therapy (SLT), and paediatrics.

The EEG measures related to speech processing indicated important differences in cortical activation patterns between adults and young children. This outcome can drive advancements in the hearing aid industry, such as developing new algorithms for hearing aid devices in which speech, auditory and linguistics features are weighted differently according to the user's age.

The results of this thesis could also aid the development of more refined speech recognition technologies. Improved speech recognition systems have broad applications across industries, ranging from call centres and transcription services to voice-controlled devices. Moreover, the insights gained from this thesis can contribute to developing assistive technologies (e.g., brain-computer interfaces, BCIs) for individuals with severe speech impairments, enabling them to communicate more effectively and independently.

General public and society

This research has the potential to impact the academic field in different ways by providing new evidence about the EEG signatures of speech processing during early childhood under typical and atypical language conditions. The findings and EEG analysis methods could be disseminated through national and international scholarly journals, conferences, educational instances, translational research, or academic collaborations. In addition, one practical outcome of this thesis is a database of continuous speech stimuli in Spanish, with information about their acoustic envelope values, lexical frequency, duration, and word type, among other features. This database will be made freely available for other researchers and could be expanded to include new levels of speech information, e.g. morphological or phonological.

Understanding the brain's speech processing mechanisms can aid in developing new, targeted interventions to support individuals with communication difficulties such as speech and language disorders, dyslexia, or aphasia, ultimately improving their quality of life and social interactions. This thesis could also benefit professional practice and public health outcomes in speech and language disorders, helping the development of objective speech perception measures that can be used in infants and young children and fostering earlier detection and intervention in different disorders.

This research can have educational implications in a broader societal context, providing new insights into the fundamental principles of language learning and acquisition. The findings of this thesis can inform educational approaches, curriculum development, and school policies, promoting more effective language teaching methods and support for learners with special needs. Enhanced language learning can lead to better educational outcomes, better global communication, and increased opportunities for individuals in various domains.

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List of Abbreviations

AF	Arcuate Fascicle
AST	Asymmetric Sampling in Time (AST) Hypothesis
aSTG	anterior Superior Temporal Gyrus
BA	Brodmann’s Area
CVC	Consonant Vowel Consonant
D1	Deviant 1 (non-native initial phoneme in a non-word)
D2	Deviant 2 (native initial phoneme in a non-word)
D3	Deviant 3 (native function word)
D4	Deviant 4 (native content word)
DLD	Developmental Language Disorder
DW	Difference Wave (deviant minus standard)
DW1	Difference Wave 1 (D1 minus standard)
DW2	Difference Wave 2 (D2 minus standard)
DW3	Difference Wave 3 (D3 minus standard)
DW4	Difference Wave 4 (D4 minus standard)
EEG	Electroencephalogram
ERP	Event-related Potential
ERSP	Event-related Spectral Perturbation
ECFS	Extreme Capsule Fiber System
FDR	False Discovery Rate
FOP	Frontal Operculum
HF	High-frequency oscillations
ICA	Independent Component Analysis

IFG	Inferior Frontal Gyrus
IIR	Infinite Impulse Response
IFOF	Inferior-Frontal-Occipital Fascicle
IPL	Inferior Parietal Lobe
ISI	Interstimulus Interval
ITC	Inter-trial Coherence
ITPC	Inter-trial Phase Coherence
LDN	Late Discriminative Negativity
LF	Low-frequency oscillations
MTG	Middle Temporal Gyrus
MMN	Mismatch Negativity
MMR	Mismatch Response
mTRF	multivariate Temporal Response Function
MUA	Mass Univariate Analysis
NS	Non-Speech Condition
pSTC	posterior Superior Temporal Cortex
ROI	Region of Interest
S	Speech Condition
SLF	Superior Longitudinal Fascicle
STG	Superior Temporal Gyrus
SNR	Signal-to-noise Ratio
St	Standard stimuli (native initial phoneme in a non-word)
TLD	Typical Language Development
TW	Time Window
UF	Uncinate Fascicle

Chapter 1. General Introduction

Speech perception is a crucial component of daily communication that involves transforming an acoustic signal into cortical representations for accessing linguistic meaning. Recent language processing models provide plausible explanations regarding where (neuroanatomy) and how (mechanisms) our brain perceives speech, emphasising the importance of neural synchronisation and the role of language and cognitive factors in shaping speech perception. However, these models mainly consider evidence from adult studies, resulting in a discontinuity in the theories of cortical speech processing between adults and children. Overall, we do not know what specific changes in the children brain allow them to, eventually, perceive speech as adults, at what ages these changes occur, or whether this development is disrupted in children with language disorders.

The gap in knowledge regarding the neural correlates of speech perception development could be explained by two factors: (i) with any neuroimaging or electrophysiological method, measuring brain activity in young children is a challenging task that many researchers rather avoid, and (ii) although there is an important body of evidence from different methods (EEG, fMRI, behavioural measures), these findings have not been systematically integrated into a developmental model of language processing.

Understanding the neural basis of speech perception in children is theoretically relevant because early childhood is a period of significant language development, in which spoken language is one of the bases for children's communicative skills and literacy acquisition. It is also during early childhood when many children with language disorders are first diagnosed, suggesting that some atypical patterns in language processing could become more apparent at this age.

Considering this context, the goal of my PhD was to investigate the cortical dynamics related to speech perception during early childhood (between the ages of 3-6 years) under the framework of neural oscillatory synchrony. This thesis addressed the gap in previous research by using different EEG paradigms to study speech perception in young children with typical language development (TLD) and with Developmental Language Disorder (DLD). EEG was chosen as it is a widely used method for studying neural oscillations and to acknowledge the need of determining what EEG paradigms and analysis techniques are most suitable for investigating speech perception in children.

Considering the importance of speech perception for children's communicative development and educational attainment, this thesis aims to provide new evidence for understanding how children's brains perceive speech in TLD and DLD. Considering the high prevalence of DLD among school-age children (around 7%, according to Tomblin et al., 1997), I investigated whether children with DLD exhibit atypical speech processing at the cortical level when compared to TLD peers. In the future, this work could be integrated into a developmental model of speech perception in the TLD/DLD brain, helping to inform DLD research and clinical work.

In this first chapter, I will set the theoretical framework for this thesis, outlining relevant aspects for the EEG experiments in chapters 2-5. Thus, Chapter 1 reviews the literature about speech perception in adults and young children (with typical and atypical language development) integrating multiple oscillatory findings, and presents EEG methodological considerations for speech perception research in early childhood.

1.1 Speech perception in the adult brain

1.1.1 *Brain substrates for speech perception*

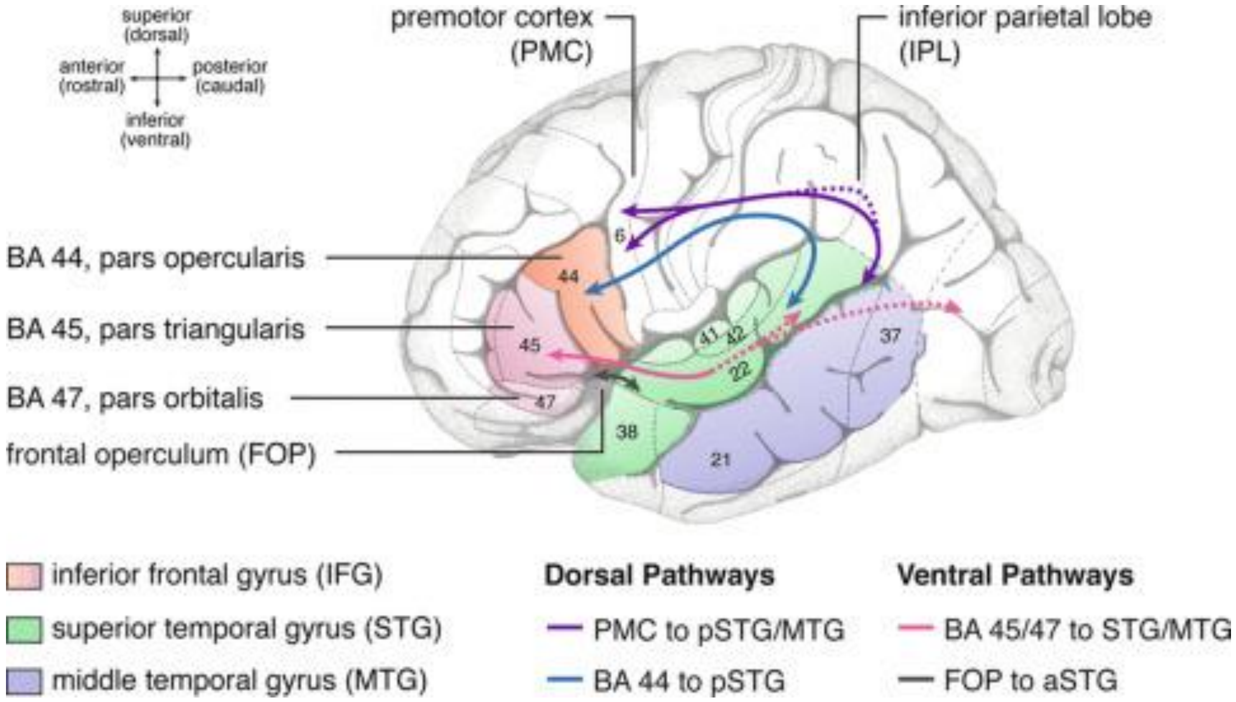
Neuroanatomy of speech perception

To understand how speech perception networks develop in children, we first need to identify the language networks in the adult brain. Current models in language neuroscience agree that there are two main networks for speech and language processing: a ventral and dorsal pathway (Hickok & Poeppel, 2016; Friederici, 2012a; Friederici & Gierhan, 2013). The ventral pathway participates in the early stages of speech perception; low-level acoustic, phonological, and lexical processing that involves temporal regions in both hemispheres, including the primary auditory cortices. The dorsal pathway participates in left-lateralised phonological processing, sensorimotor integration for speech production, syntactic and lexical-semantic processing, involving left temporal and frontal regions, as the posterior superior temporal cortex (pSTC) and the Inferior Frontal Gyrus (IFG),

On each language pathway, different tracts can be identified, which are of importance when comparing adults and children. The dorsal pathway has two subcomponents: tract Dorsal 1, the superior longitudinal fascicle (SLF), relevant for auditory to motor mapping and language acquisition (Friederici, 2011), and Dorsal 2, the arcuate fascicle (AF), involved in complex syntactic functions, such as processing distant syntactic dependencies, embedded structures, and non-canonical sentences (Brauer et al., 2011). The ventral pathway also has two subcomponents: a superficial tract (Ventral 1) corresponding to the inferior-frontal-occipital fascicle (IFOF) that is involved in semantic processing (Friederici & Gierhan, 2013), and a deep tract Ventral 2, with two subcomponents: the IFOF orbital from the orbito-frontal cortex to the frontal pole (anterior component) and the IFOF dorsal (posterior component) involved in combinatorial semantics (Brauer et al., 2013). Figure 1.1 depicts the functional neuroanatomy of the dorsal and ventral pathways according to Friederici (2015).

Figure 1.1

Language Tracts Connecting the Temporal and Frontal Cortex in the Left Hemisphere



Note. Dorsal 1 (purple): superior longitudinal fascicle (SLF), connects the dorsal premotor cortex (PMC, BA6) through the inferior parietal lobe (IPL) to the posterior superior temporal gyrus (pSTG). Dorsal 2 (blue): arcuate fascicle, connects the IFG (BA44, Broca’s area pars opercularis) to superior temporal BA41/42 and middle temporal regions 21, 22 (Wernicke's area), and 37. Ventral 1 (pink): Longitudinal Inferior-frontal-occipital fascicule (IFOF/ extreme capsule fiber system, ECFS), connects the IFG (BA45, Broca’s area pars triangularis) and BA47 to the superior and middle temporal gyrus (STG/MTG). Ventral 2 (dark grey) uncinate fascicle (UF), connects the frontal operculum (FOP) and the anterior superior temporal gyrus (aSTG) (extracted from Friederici, 2015).

Oscillatory mechanisms in speech perception

Besides understanding the functional neuroanatomy of language, research has also focused on explaining how the linguistic information in the speech signal is converted into a neural code (Hickock & Poeppel, 2016). In adults, a mechanism that could explain information processing in the brain is neural oscillatory synchrony. Neural oscillations refer to the rhythmic fluctuations in neural excitability related to different neurobiological processes (Cohen, 2014) and emerge from the synchronised firing of large groups of neurons (Buzsaki, 2006). These oscillations can be measured at different scales in the brain (for example, macroscopically using EEG) as fluctuations in voltage that exhibit timing consistency (periodicity) and can be present over several cycles, resulting in rhythmic activity at different frequency bands (Hudson & Jones, 2022).

Although not all electrical activity represented in the EEG in the frequency domain reflects neurophysiological processes, there is consensus that some of it reflects different rhythmic patterns of excitatory and inhibitory activity in brain networks (Cohen, 2014). These brain rhythms can be analysed in terms of frequency, amplitude, or phase that may reflect neural activity that occurs spontaneously (endogenous rhythms) or during perceptual or cognitive processing of exogenous stimuli (induced or evoked rhythms). In this Chapter, ‘neural oscillations’ will refer to rhythmic activity that is mechanistically related to information processing in the brain, either spontaneously or related to a task (Cohen, 2014)

The framework of neural oscillations has been a central topic in neuroscience for the last two decades, proposing that transient synchronisation of neural oscillations enables coordinated brain activity and is essential to cognition (e.g., Buszaki & Draguhn, 2004; Buszaki, 2006). The degree of neural synchronisation has been shown to correlate with different cognitive processes, including speech perception (Uhlhaas et al., 2010), with changes in the patterns of synchrony reflecting the functional coupling or decoupling of brain networks during tasks or at rest (Buzsaki & Draguhn, 2004; Lakatos et al., 2008). The synchronised oscillatory timing and phase would optimise information processing, explaining communication within local and long-range cortical networks (Varela et al., 2001).

The role of brain oscillations in speech perception has been addressed by different theories (for a review, see Meyer et al., 2020), one of the most relevant being cortical entrainment. Cortical entrainment refers to the phase alignment of brain oscillations driven by an external or internal rhythmic event (Lakatos et al., 2019). As the neural oscillatory phase reflects rhythmic changes in neural excitability (Lakatos et al., 2019), resetting to a phase of high neural excitability would optimise the brain's response to relevant inputs. In speech perception, neural entrainment has been proposed as a mechanism for the brain to encode different speech features for language comprehension (Poeppel & Assaneo, 2020).

A related concept that refers to how speech is represented in the brain is 'neural tracking', which describes the cortical activity evoked by different speech features, including the acoustic amplitude envelope, but also other types of speech features, such as phonemic or lexical information (for example, see Song et al., 2020). Some studies use the terms' tracking' and 'entrainment' in language research interchangeably. However, others consider that neural tracking represents time-synchronised (evoked) activity, whereas entrainment refers to a phase-synchronised activity (for a review see Gillis et al., 2022). In this thesis, we will use this distinction between them.

Neural entrainment to the speech amplitude envelope has been widely demonstrated in the auditory cortex, suggesting this is an essential mechanism for speech perception. Cortical entrainment to the envelope allows the brain to track the timing of individual phonemes, syllables, and words, supporting speech parsing into linguistic units (Ding & Simon, 2014; Poeppel, 2014; Meyer, 2018). In sentence perception experiments, Giraud and

Poeppel (2012) demonstrated that cortical oscillatory entrainment at different frequency bands reflects the processing of linguistic information in the speech input at multiple timescales. Slow oscillations in the delta range (1-2 Hz) correlate with the prosodic contour of the speech input and in the theta band (4-7 Hz) with the detected syllabic rate. Likewise, high-frequency gamma oscillations (30-50 Hz) correlate with phonemic and sub-phonemic elements (for a review, see Meyer, 2018). These findings have been consistently replicated over the last two decades (for a review see Poeppel & Assaneo, 2020), indicating the importance of neural oscillatory synchrony in speech perception. However, cortical entrainment occurs not only during speech processing but also for non-verbal sounds, reversed and non-intelligible speech (Ding & Simon, 2014), raising questions about its specificity as a speech perception mechanism. Notably, there is evidence that low-frequency auditory entrainment to the speech envelope correlates with speech intelligibility (Poeppel & Assaneo, 2020) and that interfering with theta entrainment disrupts speech perception performance (Zoefel et al., 2018). This evidence suggests that entrainment to speech might differ from other types of auditory entrainment and may be crucial for speech perception.

In addition to auditory entrainment, there is evidence of neural tracking of linguistic elements of speech, such as phonemes, lexical or syntactic components. This indicates that cortical tracking is involved in higher-level network activity, such as semantic processing and integration of linguistic and contextual information with an individual's previous linguistic knowledge (Meyer et al., 2020). This implies that, during speech perception (Poeppel & Assaneo, 2020), the oscillations in the auditory cortex interact with those in other brain regions. For example, high-frequency gamma oscillations (around 30-50 Hz) have been linked to the binding of word meanings to their associated context, a process that occurs beyond the auditory cortex, enabling us to understand the meaning of a sentence as a whole (Bastiaansen & Hagoort, 2006).

1.1.2 *Language modulations on speech perception*

Bottom-up and top-down interactions during speech perception

The transformation of speech into meaning involves a complex processing sequence, from low-level physical acoustic content to higher-level abstract language forms (Heilbron et al., 2022). Low-level speech processing is driven by temporal and spectral cues in the speech signal, with bottom-up mechanisms for encoding segmental (phonetic) and supra-segmental (prosodic) information in the auditory cortex. Higher-level processing involves top-down modulations from temporal, frontal and parietal areas on how we perceive incoming speech, influencing low-level speech processing.

In the brain, language knowledge means a rules-based internal structure (Martin & Doumas, 2017) acquired during native language development (Meyer, 2018). Elements such as phonemic categories, lexical status, word morphology, meaning, and grammatical structure are not present in the speech signal but in the listener's brain. Importantly, these internal rules can operate top-down to solve perceptual ambiguities during speech perception (Hagoort, 2019). This hierarchical sequence is reflected in the latencies at which speech features are encoded, with information of higher linguistic complexity processed later than the speech acoustics. Thus, the low-level speech processing (e.g., pitch, amplitude, formants, and duration) occurs early (~50-200 ms), in contrast with higher-order linguistic processing of lexical, semantic, syntactic, and prosodic information which occurs later (>200 ms).

Top-down modulations on speech perception may vary according to individual differences in cognitive skills and language knowledge (Ding & Simon, 2014; Goswami, 2011). General cognitive modulations include attention, executive control and sensory/short-term memory skills. These mechanisms are not specific to language processing and usually exploit the brain's ability to detect environmental regularities, helping to predict incoming inputs; for example, frequent items will be perceived more easily than less frequent ones (predictability) as well as related than unrelated ones (things that co-occur, e.g. context-based prediction). An example of general top-down modulations is the effect of attention on cortical entrainment which helps to understand speech in noisy environments (Song & Iverson, 2018) or when the acoustic signal is hard to discern (see review by Obleser & Kaiser, 2019).

On the other hand, language-specific top-down modulations operate only for stimuli with linguistic status (Ding & Simon, 2014; Goswami, 2011). Language knowledge (understood as an individual's language proficiency) shapes our sensitivity to speech sounds determining how they are organised into meaningful units in our brain and interpreted depending on the language context. Prior language knowledge includes skills such as phonemic categorical perception, semantic integration, and knowledge of word’s meaning. In addition, language knowledge influences the discrimination of language-specific cues contained in the speech stimuli, increasing speech redundancy via phonemic, lexical, syntactic or semantic priming (Meyer et al., 2018).

Language-specific modulations on speech perception are consistent with the fact that, despite no exact correspondence between the acoustic patterns in the input and the linguistic representations activated in the brain, perceptual discrimination is preserved even for highly variable or discontinuous speech signals, but not for their nonspeech analogues (Skipper, 2014), meaning that speech is perceived different than non-speech sounds even if they have the same acoustic information. However, there is no clarity about how language-specific and general cognitive top-down modulations can be dissociated when studying speech perception (see Zatorre & Gandour, 2008).

Importantly, it is accepted that there is an interaction between bottom-up and top-down processes during speech perception. A study byDi Liberto et al. (2015) demonstrated that the best model to describe the relationship between perceived continuous speech and neural processing in adults (n=10) was the one that combined low-level information and phonemic features. Such effects were larger at longer latencies and dissapeared when perceiving reversed speech, corroborating that speech perceived as such involves a hierarchy in the auditory/language system. Notably, although the exact neural mechanisms of this bottom-up/top-down interaction are not fully understood (Poeppel & Assaneo, 2020), they are thought to involve brain oscillations.

How does language knowledge modulate oscillatory responses to speech?

During speech perception, modulations of neural oscillations would be determined exogenously (bottom-up) by the linguistic characteristics of the speech signal and endogenously (top-down) by an individual's prior language knowledge (Meyer et al., 2019). Language knowledge is proposed to exert top-down effects on speech perception by modulating the excitability of the auditory cortex during speech encoding, thus increasing the sensitivity to linguistic stimuli (Giraud & Poeppel, 2012). A candidate mechanism is that the phase coupling of endogenous oscillations between frontal and temporal areas would stabilise entrainment with the spoken input in low-level auditory regions (Giraud et al., 2007). Top-down modulation on temporal auditory areas would occur through alpha and beta band oscillations generated in frontal cortices. In contrast, bottom-up modulations from temporal auditory to frontal areas would involve theta band oscillations (Poeppel & Assaneo, 2020).

An important factor related to language-specific modulations on speech perception seems to be the speech intelligibility, although studies so far show contradictory findings. A study by Park et al. (2015) demonstrated that high-frequency oscillations in higher-order language areas (left inferior frontal gyrus and precentral gyrus) modulated low-frequency oscillations on the auditory cortex significantly more for intelligible than for non-intelligible speech. In addition, there is evidence of lexical knowledge modulations on gamma power and delta cortical entrainment (Doelling et al., 2014; Kösem & van Wassenhove, 2017). On the contrary, Baltzel et al. (2017) demonstrated that the effects of language knowledge on the strength of auditory entrainment does not depend on the speech intelligibility, reporting similar priming effects on entrainment regardless the amount of vocoding (3 or 16-channel).

To summarise, research in adults has shown that neural oscillations are an important mecanism involved in speech perception. This mecanism seems to operate primarily through cortical synchronisation with the speech signal, with effects of language knowledge from frontal areas modulating auditory responses in a top-down process. However, less is known about how the neural activity involved in speech perception changes from birth to adulthood, how it differs between typical language acquisition and neurodevelopmental disorders and if an atypical neural activity has a causal role in language disorders.

1.2 Speech perception in early childhood

The development of speech perception skills is a complex and ongoing process that begins in the womb and continues into childhood and adolescence (Dick et al., 2015), with well-described changes during early childhood. For example, between age 3 to 6 years, children become better at segmenting and interpreting speech sounds into their corresponding phonological and semantic representations (Skeide & Friederici, 2016). Behavioural changes in speech perception emerge from interactions between brain maturation and experience, for example, with our native language; however, the relationship between these factors is not clearly described (Skeide et al., 2016). Understanding the effects of language knowledge on speech perception is relevant as it may help explain the differences between children and adults and individuals with language disorders. Therefore, this section reviews the changes in speech perception skills and brain development during early childhood in TLD.

1.2.1 *Do children perceive speech like adults?*

Speech perception skills between 3-6 years old.

Children's language proficiency increases between 3 and 6 years of age (Dick et al., 2015), but they do not yet perceive speech the same way as adults, who have more advanced speech perception skills. Adults show better phonological processing than children; for example, they are better at using acoustic cues to distinguish between speech sounds and detecting subtle acoustic differences. Essentially, adults are more likely to use top-down processing when listening to speech, exploiting the context and using their prior knowledge to solve speech perceptual ambiguities to facilitate speech comprehension (Aboitiz, 2017).

Linguistically, young children have developed some aspects of adult-like speech processing, but their word recognition skills are not fine-grained until the age of 7 years. This is evident, for example, in that their lexicon mainly comprises phonetically dissimilar, easily distinguishable items (Walley, 2005). During early childhood, the perception of phonemes is not robust and depends heavily on contextual factors such as vowel transitions and duration, consonantal context, stimulus duration or spectral information (Walley, 2005). An important finding is that consonant perception is less categorical than in adults until after the age of 6 years (Hazan & Barrett, 2000), with increases in the accuracy of phonemic identification into late childhood (Walley, 2005).

During early childhood, ongoing auditory maturation is an essential factor that underlies speech perception, with different age-related trajectories for different central auditory processing skills (Sanes & Woolley, 2011). For example, bottom-up processes such as the discrimination of frequency, intensity and duration, or the detection of amplitude and frequency modulations are not mature by the age of 6 years (Sanes & Woolley, 2011). This could explain to some extent why children are less proficient than adults when perceiving speech.

However, differences in speech perception between adults and children, and between children at different ages, not only depend on auditory maturation but are also heavily influenced by general cognitive (working memory, attention) and language-specific (vocabulary, phonological processing) top-down modulations. After the age of 8 years, children show improvements when perceiving speech with impoverished acoustic-phonetic information and speech in noise (Neuman et al., 2010), both speech perception skills known to be modulated by top-down processing. However, it is still being determined whether such modulations in children are similar or different from those observed in adults, and if so, how.

Top-down modulations and speech perception in children.

Throughout early childhood, children's speech perception skills are not only shaped by age (neuromaturation) but also by top-down modulations (Davids et al., 2011) that reflect the influence of language exposure, early experience, and social interaction. General learning mechanisms support speech perception development, helping the brain to track patterns in our native language (Saffran et al., 1996). A longitudinal study by Thompson et al. (2017) in young children (3 and 4 years old, n=59) demonstrated that age-related improvements in speech-in-noise perception were related to advanced general processing skills (intelligence, short-term memory, and attention). At the same time, children's internal language system develops with age, influencing the way they perceive speech. For example, a study by Thompson et al. (2019) in children between 4-7 years (n=104) determined that not only cognitive but also language skills measured at the age of three years predicted children's performance in a speech in noise task by the age of 5 years.

A review by Skeide and Friederici (2016) proposed two speech and language developmental stages. An initial stage of rapid acquisition of bottom-up speech processing skills (age 0-3 years) that would enable perceptual narrowing for native phonemes, speech segmentation, mapping phonological word forms with semantic representations, syntactic categorisation and grouping of words into phrase structures. Friederici et al. (2017) indicated that, during this initial stage, language processing relies on detecting linguistic statistical regularities without necessarily building syntactic hierarchies. The second stage (from age three to adolescence) is characterised by the gradual and slow development of top-down processing skills that start to emerge in the fourth year of life. This would result in the capacity for analysing semantic and syntactic relations of increasing complexity and more sophisticated prosodic processing (Skeide & Friederici, 2016). However, it is important to determine how these behavioural changes in speech perception are related to the development of language networks and neural oscillatory synchrony.

Maturation of brain language networks

Although babies are born with the neural foundations for speech and language processing (Hagoort, 2019), from infancy to adulthood, there is an important development of language networks (Friederici et al., 2017) that could explain improvements in language and speech perception skills. During early childhood, language structures in the brain mature gradually, shaped by neural pruning, myelination, and growth of white-matter tracts (Skeide & Friederici, 2016), synaptic plasticity and changes in neurotransmission (Uhlhaas et al., 2010). The evidence indicates that these brain maturation processes underlie and even predict behavioural changes in speech and language skills (Zuk et al., 2021).

In cortical language networks, different tracts show different developmental trajectories from infancy to childhood, with later maturation of the dorsal compared to the ventral pathway (Friederici, 2012b; Friederici et al., 2017). Brauer et al. (2013) used diffusion imaging to compare the maturation of functional connectivity between newborns (n=19, age 2-3 days), 7-year-old children (n=10, age range 5–8 years), and adults (n=10). For the dorsal pathway, only the dorsal tract D1 was detectable in newborns; tract D2 is not yet myelinated, meaning there is no connection between the BA 44 and pSTC. In 7-year-old children, both dorsal tracts were present, but D2 is still not fully mature compared to adults. Notably, the maturation of D2 predicts complex sentence processing performance (Friederici et al., 2017), phonological awareness skills and vocabulary knowledge (Zuk et al., 2021), which indicates it could be related to short-term verbal memory and word learning.

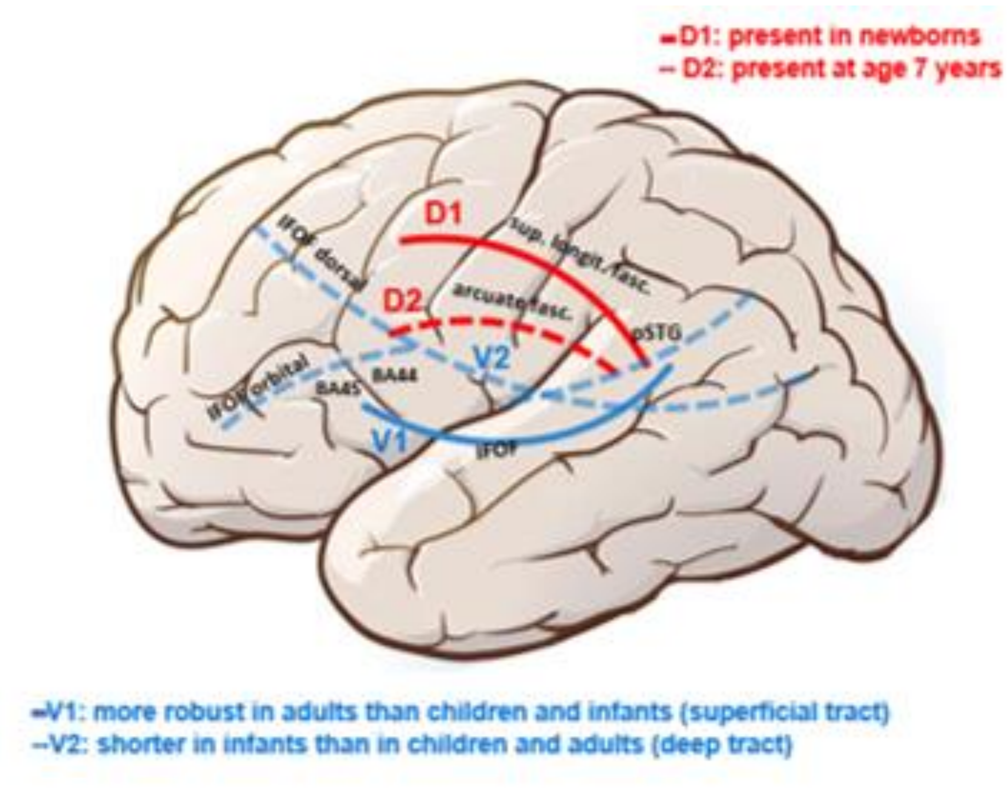
For the ventral pathway, Brauer and colleagues (2013) found that the superficial tract (V1) was present in newborns and children. However, it was more robust in adults and spread towards the parietal-occipital ending. This pathway likely supports auditory-to-motor mapping, which supports auditory feedback during infants' babbling and word/phonological learning. Finally, the deep tract V2 was present in all three groups but with much shorter middle and anterior connections and less mature in infants than in children and adults. This suggests that syntactic processing is based on the ventral system during early childhood, allowing only the processing of simple phrases and canonical sentences. Together, these structural changes support the ongoing maturation of the language network during early childhood, which could explain the development of language and speech perception skills during this stage. Figure 1.2 summarises the development of language networks.

Regarding cortical function, language lateralisation is detectable at birth (see review by Friederici, 2006). However, it is not adult-like until early childhood, although the exact age at which children show mature left-lateralisation is unclear. A systematic review of language fMRI findings by Weiss-Croft and Baldeweg (2015) indicates that left-lateralisation during speech processing is already in place by the age of 5 years. However, findings by Thompson et al. (2016) indicate adult-like oscillatory lateralisation by the age of 3 years.

Furthermore, several neuroanatomical changes during early childhood have been linked to the development of language skills. Weiss-Croft and Baldeweg (2015) reported increased activation in the superior and middle temporal gyri (bilaterally), and deactivation in the cingulate cortex from childhood to adolescence, suggesting a shift in control from high to low-level cortical areas as language processing becomes more automated and effortless.

Figure 1.2

Development of Dorsal and Ventral Language Tracts in Newborns, Children and Adults



Note. For the dorsal pathways, D1 (red solid line) is observable in newborns (a), children (b) and adults, whereas D2 (red dashed line) is absent in newborns but present from childhood onward. Both ventral tracts are observable at birth, but V1 (blue solid line) is stronger in adults than children and children than infants and V2 (blue dashed lines) is shorter and less mature in infants than in children and adults (adapted from Brauer et al., 2013).

A review by Skeide and Friederici (2016) indicates that BA44 and pSTC activate during speech perception from an early age, but their interaction is not efficient until late childhood. From the age of 3 years, they reported gradual development of top-down modulations of semantic and syntactic relations related to the maturation of the left inferior frontal cortex. At 3-4 years old, both the left temporal and left inferior frontal cortex are recruited when processing sentences, suggesting that the components for basic syntax processing are already present (Friederici et al., 2017). At 5-8 years old, increasing syntax skills correlate with the reduction of grey matter volume on the left pSTG (e.g., because of neural pruning); finally, the neuroanatomical specificity for syntax of BA 44 segregates between the ages of 7 and 10 years and gradually develops until young adulthood when it is fully efficient for processing complex syntax. Before age 10, syntactic and semantic information types recruit the same brain regions, consistent with behavioural data indicating semantic and syntactic interactions during early childhood (Friederici et al., 2017).

Considering these structural changes in cortical language network it is reasonable to think that they would involve functional changes in neural dynamics. However, it is unclear how the development of language tracts relates to the development of neural oscillations.

Development of neural oscillations.

During early childhood, neuroanatomical changes are accompanied by changes in the frequency and synchronisation of neural oscillations, which have shown to be relevant for developing and segregating cortical networks (Greene et al., 2016). Neural synchrony maturation continues until early adulthood and involves critical processes in neural networks, such as stabilisation of synaptic connections, neural pruning, and experience-dependent long-term plasticity (Uhlhaas, 2010). The mature, adult-like brain is characterised by complex, coordinated activity in particular neural populations, with greater oscillatory synchronisation reflecting more efficient neural communication (Musacchia et al., 2013).

In general, cortical activity becomes more synchronised and spatially focalised with age. Along with brain structural development, oscillatory coupling increases with age from uncorrelated to synchronous patterns in different frequency bands (Uhlhaas et al., 2010). This could be linked with some evidence reporting higher neural background noise in children than in adults (Vanvooren et al., 2015) and children than teenagers (Bishop et al., 2012; Hämmerer et al., 2013) because of less consistent neural activity.

Overall, spontaneous and task-related cortical activity shows significant age-dependent decreases in the amplitude of delta and theta oscillations and increases for the alpha, beta and gamma ranges (Uhlhaas et al., 2010). Likewise, phase synchrony increases for the theta and beta range with gamma-oscillations maturing during early childhood (Uhlhaas et al., 2010). Importantly, developmental increases in neural synchrony relate to better performance in cognitive tasks. During early childhood and until adolescence, better performance in visual perception tasks was accompanied by bilateral frontal and frontal-parietal increases in neural synchrony, which the authors interpret as top-down modulations of sensory regions (Uhlhaas et al., 2009).

In auditory development, there is evidence of similar changes in brain oscillations, with increased synchronisation from early childhood to adulthood (Bishop et al., 2010a; Doesburg et al., 2015; Müller et al., 2009). Müller et al. (2009) demonstrated differences in the amplitude and synchronisation of neural oscillations between young (9-11 years) and older children (11-13) and adults during cortical auditory discrimination. The theta and delta bands demonstrated increased synchronisation within and between electrodes. However, spectral power decreased from childhood to adolescence and adulthood, indicating an age-related shift in low-frequency activity towards more precisely synchronised oscillations (Müller et al., 2009). These findings indicate that the developing brain may show different patterns of oscillations than the adult brain. However, the relationship between activity in different frequencies and the maturation of speech perception is not yet understood.

Neural oscillations in language development

Integrating the evidence on brain maturation and neural oscillatory development, it is possible that the maturation (e.g. myelination and increased fibre density) of brain language tracts could be related to greater neural synchrony, resulting in more efficient speech perception and language processing. However, there is little research linking these lines of evidence into a functional explanation of language development.

Some studies in children suggest that age-related changes in the strength and synchrony of neural oscillations reflect speech and language skills development. A longitudinal study by Benasich et al. (2008) demonstrated that the magnitude of endogenous frontal gamma oscillations at ages 16, 24 and 36 months predicted language development at ages 4 and 5 years, with a strong correlation between phonological working memory and syntactic skills, which the authors considered related to local and long-range neural synchronisation. Doesburg et al. (2015) demonstrated age-related increases in theta synchronisation between brain language regions, which correlated with individual language skills at different ages (n=73, participants between 4-18 years). Cantiani et al., 2019, found that the amplitude and synchrony in the theta range at six months old (n=24) predicted expressive vocabulary scores at 20 months.

The evidence also indicates age-related differences in the lateralisation patterns at rest for high and low-frequency oscillations during early childhood. Kikuchi et al. (2011) investigated the lateralisation of cortical parietal-temporal oscillations in preschool children (n= 78, 3-4 years old), demonstrating that stronger left parietal-temporal theta synchronisation (6-8 Hz) correlated with better performance in language tasks. Thompson et al. (2016) showed that left-lateralisation for high-frequency oscillations (20-50 Hz) was already established at the age of 3 years and that children with better speech-in-noise skills exhibited more pronounced high-frequency leftward asymmetry (age 3-5 years, n=65). This suggests that theta and gamma oscillatory asymmetry is related to better speech perception skills in young children, which could be related to better syllabic and phonemic processing.

In terms of entrainment, Goswami (2022) highlights the importance of speech rhythmic patterns for typical language acquisition, linking the perception of linguistic units (e.g., prosodic, and syllabic stress patterns) with the rate of modulations of the speech acoustic envelope (delta and theta bands) during language development. So far, findings indicate that entrainment to the speech envelope in the delta and theta range is present in full-term infants and is observed at least until the age of seven months, although at these early stages, it is not specific for the native language (e.g., Kalashnikova et al., 2018; Ortiz-Barajas et al., 2021). On the contrary, a longitudinal study by Rios-Lopez et al. (2020) in young children (n=32) reported that at age 4-5 years, entrainment to the envelope was only present in the delta band (0 .5 Hz), with bilateral increases in synchrony in temporal areas at all testing times until the age of 7 years. Thus, there is contradicting evidence about the role of delta and theta synchrony in speech perception development.

Top-down modulations on speech entrainment are present in children but with some differences from those observed in adults. Ortiz-Barajas et al. (2021) described age-dependent changes in language experience modulations on speech entrainment during the first six months of life. They found that amplitude and phase entrainment to the speech envelope (sentences in Spanish, English or French) were already present in newborns (n=55) and did not show any differences for native (familiar) and non-native (unfamiliar) languages. However, by the age of six months, infants (n=12 longitudinal plus n=13 cross-sectional participants) only tracked the phase of native language but not the amplitude. This would indicate that speech phase entrainment to the acoustic envelope represents a basic auditory skill, but that amplitude entrainment is modulated by language experience by the first semester, with less tracking of the language infants are familiar with (or have greater experience or knowledge). Interestingly, the timing of these changes regarding the infant's age coincides with extensive evidence reporting native-phoneme specialisation in infants (e.g., perceptual narrowing) starting around six months of age (for example, see Kuhl, 2010).

In addition, there is evidence that in children, as in adults, auditory entrainment is modulated by speech intelligibility, although the patterns of modulation may differ. Vander Ghinst et al. (2019) compared cortical entrainment between adults (n=20) and typically developing children (n=20, 6- to 9-year-old) while they attended to speech embedded in multi-talker background noise. They reported two main findings: (i) children exhibited limited tracking of both the attended voice and the global acoustic stimuli at the 4–8 Hz syllable rhythm, and (ii) noise increments compromised the speech tracking significantly more in children than in adults. Likewise, Rios-Lopez et al. (2020) demonstrated that the strength of delta entrainment to speech in the right hemisphere is related to speech intelligibility measures. These initial results support the idea that top-down modulations of acoustic entrainment during the first years of life are related to prior language knowledge (or 'experience') and the speech signal itself, resembling interactions observed in adults.

In summary, changes in speech perception in young children are explained by multiple factors, such as physiological changes (e.g., auditory maturation), cognitive development (e.g., greater attention skills and memory), and increased linguistic abilities (more language experience). However, behavioural and oscillatory findings are not easily brought together in the current literature because of the variety of methods for investigating language development, such as very different age ranges, stimuli, and brain measures across studies. Nevertheless, there has been growing interest in determining the developmental trajectories of cortical language processing and whether children's language and speech perception difficulties result from atypical oscillatory activity.

1.2.2 ***Speech processing in children with DLD***

What is DLD?

DLD (formerly referred to as Specific Language Impairment, SLI) refers to children's significant and persistent difficulties in developing native language skills that are not explained by any other cognitive, motor, or sensory deficits or known medical cause (Leonard, 2014). This neurodevelopmental condition is the most prevalent language disorder, affecting 7% of children and severely disrupting educational, social and emotional development (Leonard, 2014). DLD is highly heritable, more prevalent in boys than girls, and likely to co-occur with other neurodevelopmental disorders such as dyslexia or autism spectrum disorder (ASD), suggesting complex genetic influences (Newbury & Monaco, 2010). The clinical profiles (or symptoms) are very heterogeneous but generally include deficits in syntactic, morphological, phonological and lexical processing (Schwartz, 2017).

Although the causes of DLD are not auditory, there is evidence of some speech perception deficits in children with DLD, leading to a long-lasting controversy about the role of atypical perceptual processing in this condition. Early studies indicated that children with DLD had difficulties detecting rapid auditory changes (e.g., 'Temporal Processing' hypothesis), which were linked to phonological processing difficulties, for example, when detecting the second phoneme in a consonant cluster (Tallal et al., 1997). Other studies as Ziegler et al. (2005), also focused on phonemic processing, demonstrating poorer discrimination of VCV sequences in noisy conditions in children with DLD (n=10) than in age-matched (n=10) and language-matched (n=10) controls suggesting difficulties in extracting speech features such as voicing in adverse listening environments. Cantiani et al., 2019, found that infants (n=24, six months old) at familial risk of DLD presented poorer detection of changes in F0 and the duration of nonspeech sounds compared to healthy controls. Other studies have shown difficulties in perceiving and reproducing acoustic rhythmic patterns in children with DLD compared to controls, relating them to poor processing of linguistic rhythm (for reviews, see Goswami, 2022; Ladányi et al., 2020).

However, there are several issues with the auditory accounts of DLD; firstly, speech perception and phonological deficits, although recurrent, are not universal symptoms in the DLD population (Bishop & McArthur, 2005). On the contrary, DLD-affected individuals exhibit very heterogeneous linguistic profiles, which makes their classification difficult, even into broad subgroups, such as receptive, expressive, or mixed. Secondly, it is unclear whether perceptual impairments observed in DLD overlap with those in other language disorders, e.g., speech disorders or dyslexia, meaning these speech perception deficits are not a signature (or 'marker') of DLD (Bishop & Snowling, 2004; Ramus et al., 2013). Finally, there is significant controversy about to what extent DLD should be considered a unitary condition rather than a syndrome with multiple causal components (Bishop et al., 2016; 2017).

Crucially, mounting evidence shows that individuals affected by DLD exhibit typical performance in low-level auditory tasks, with only a small proportion of them showing auditory processing deficits (see review by Rosen, 2003), which has discredited the idea of an auditory cause of DLD. In turn, some theories about the origin of DLD have argued that speech processing deficits could be a downstream consequence of this disorder, meaning that the perception of speech sounds is affected (Bailey & Snowling, 2002). For example, a less developed language system could result in reduced top-down support during speech perception in children with DLD (Bishop et al., 2012; Bishop, 2013).

Importantly, behavioural studies may be inconclusive and unreliable in young children, making it necessary to use objective brain measures for investigating speech and language processing in children with or at risk of DLD.

Neural oscillations and speech perception in DLD.

So far, there is no clear link between brain neuromaturation, oscillatory activity and speech perception deficits in DLD. Considering the developmental trajectories of language networks from birth to adulthood, it is reasonable to assume that the healthy maturation of the dorsal and ventral pathways is necessary for typical language acquisition or that atypical maturation could be related to language deficits. Researchers have tried to identify brain markers for DLD in the last decades, but findings have been inconsistent. Although some studies report abnormalities in grey and white matter volumes in children with DLD, there is no consistent evidence of significant differences in DLD brain anatomy from TLD children (Evans & Brown, 2016).

The evidence of brain functional differences in DLD is also inconclusive. Many studies have investigated whether atypical brain activity in language areas can explain language difficulties in DLD. However, findings are based on studies with very different designs, low ecological validity, and small sample sizes. An example is the widespread belief that atypical left-lateralisation could underlie poor language skills in DLD (Bishop, 2013). However, Wilson and Bishop (2018) could not replicate these findings in a larger sample of twins (n=107 with DLD and 156 with TLD, aged 6-11 years), concluding that previous findings could be spurious and explained by methodological fails.

The importance of neural synchrony for normal brain development suggests that it is relevant to investigate when explaining speech perception and language deficits at the cortical level. For example, in DLD, if reduced temporal precision of neuronal oscillations is present, it could affect activity-dependent network development (Uhlhaas et al., 2010). Notably, there is evidence of a critical role of atypical oscillatory activity in populations with other neurodevelopmental disorders; for example, there is evidence of impaired speech-related oscillations in autism spectrum disorder. Jochaut et al. (2015) reported that the severity of verbal impairment and autism symptoms in adults and adolescents (n=31) was predicted by reduced theta in the left auditory cortex and top-down gamma modulation on speech entrainment.

In dyslexia, a recent systematic review by Nallet & Gervain (2022) indicates atypical auditory entrainment to speech at the phonemic, syllabic (~5 Hz) and prosodic rates (~2 Hz) in infants and children at risk or with a diagnosis of dyslexia. Previously, Goswami (2011; 2022) proposed the ‘Temporal Sampling’ framework for dyslexia, explaining that atypical cortical entrainment with the rhythmic speech envelope at low frequencies would impair adequate sampling of speech elements that are critical for linguistic and phonological development. Together, these findings support the idea that atypical entrainment affects speech perception by interfering sampling of linguistic units and could be related to language deficits in these disorders (Molinaro et al., 2016).

Although something similar could happen in DLD, there is still little research on neural oscillations in children affected by language disorders (Maguire & Abel, 2013). Evidence from adult studies shows that atypical patterns in cortical measures as acoustic entrainment reflect speech perception differences in adults with hearing impairment, blindness, dyslexia, autism, and severe brain injury, as well as in older participants (Palan et al., 2022). Consequently, atypical oscillatory activity could be present in DLD and related to some of the symptoms observed in this disorder.

A recent perspective paper by Goswami (2022) extends the Temporal Sampling hypothesis to DLD, proposing that rhythmic processing disruptions detected in children with DLD reflect impaired neural alignment with the speech envelope, with poor encoding of key syllabic elements (onset, rhyme, stress) undermining their phonological and syntactic development. Similarly, Ladanyi et al. (2020) had previously proposed the ‘Atypical Rhythm Risk’ hypothesis, posing that atypical rhythmic processing skills are a risk factor for developmental speech and language disorders. However, both hypotheses are based on behavioural evidence from children with DLD (e.g., Richards & Goswami, 2019), as there are no studies on cortical entrainment in this population yet.

To our knowledge, only three studies have investigated the role of cortical oscillatory synchrony in DLD. Bishop et al. (2010b) compared auditory discrimination in children aged 7-16 with DLD diagnosis versus typically developing controls. The control group exhibited a drop in low-frequency power and a significant desynchronisation after cortical change detection responses (after 300 ms), which was absent in language-impaired children. The authors interpreted the lack of desynchronisation in DLD children as a poorer capacity to disengage from the cortical discrimination signals.

Heim et al. (2011; 2013) studied children aged 6-9 years with and without DLD and reported atypical oscillatory activity during rapid auditory discrimination tasks. The DLD group found significantly reduced synchronisation of early (45–75 ms) oscillations in the gamma-band range (29–52 Hz) when presenting the second stimulus of tone doublets. Cantiani et al., 2019, found that infants (n=24, six months old) at familial risk of DLD showed reduced left lateralisation in the theta and gamma bands during nonspeech auditory discrimination tasks compared to healthy, age-matched controls.

If taken together, the findings from these three studies suggest that some atypical oscillatory patterns may be present in individuals with DLD, which could have implications in terms of language processing. From Bishop et al. (2010b) findings, we could assume that less desynchronisation (or ‘less disengagement’) in later processing stages could impede higher-order language processing or disrupt speech encoding because of less available neuronal resources for processing upcoming speech. Heim et al.'s (2011; 2013) findings about reducing the gamma range could explain poorer phonemic processing and potential phonological difficulties, whereas less pronounced lateralisation could affect syllabic and phonemic processing (Cantiani et al., 2019). However, these studies used very different methods, which makes them hard to integrate and have used simple linguistic stimuli, if any.

In summary, the role of atypical entrainment in speech and language processing during language acquisition needs to be better understood. So far, there is no systematic research on the associations of DLD and neural oscillations and the role of neural synchrony in speech perception during early childhood.

1.3 EEG in speech perception developmental research

Cortical speech processing can be studied using the electroencephalogram (EEG), a direct measure of the brain's electrical activity. The EEG captures the synchronised postsynaptic activity of large populations of cortical neurons, recording it with scalp electrodes (Jackson & Bolger, 2017). The EEG reflects brain dynamics during different cognitive processes but studying them requires extracting their neural signature from the raw signal, separating it from background noise. Different EEG methods include resting-state ('or baseline')' measures, Event-Related Potentials (ERPs), and cortical entrainment analysis, all of which quantify different aspects of neural oscillatory synchrony (Bastiaansen & Hagoort, 2006). Notably, the excellent temporal resolution of EEG makes it a great tool for studying rapid neural dynamics in auditory, speech, and language processing.

1.3.1 ***EEG measures of speech perception***

Frequency domain measures: resting-state EEG

The resting state or baseline EEG measures the amplitude of the spontaneous brain activity that occurs without any external task or stimulation (endogenous or intrinsic neural oscillations). The raw EEG signal is represented in the frequency domain via spectral decomposition methods such as the Fourier transform. These methods represent the EEG signal as a linear combination of sine waves at different frequency bands (Gross, 2014).

Different features of the resting-state EEG can measure the degree of synchronisation of neural oscillations. Spectral power (in microvolts), either total or at a given frequency band, is an estimate of the signal amplitude (Varela et al., 2001), with increases in power reflecting a larger number of neurons that are active in a given location (Cohen, 2014). Resting-state frontal asymmetry uses indices to quantify power differences between frontal electrodes in the left and right hemispheres. In contrast, coherence is a measure of linear cross-correlation between two signals (e.g., pairs of electrodes) in which oscillatory phase and amplitude are intertwined (Norton et al., 2021). Baseline EEG measures may reflect brain maturation and cognitive and language processing differences.

The resting-state EEG is a valuable method to study children and other non-compliant populations (e.g., clinical groups) because it is task-free and does not require the participant to follow instructions. It is recorded during a short period while the child is quietly watching silent images on a screen, either with their eyes open or closed.

Time domain measures: ERP (MMN and LDN).

A common method to study changes in cortical activity (voltage) over time is Event-Related Potentials (ERPs). ERPs measure voltage changes over time that are time-locked (evoked) to an external stimulus and averaged for analysis (Cohen, 2014). The Mismatch Negativity (MMN) has been prevalent among ERPs in auditory and language research.

The MMN is an automatic, pre-attentional index of auditory change detection, with a temporal component generated bilaterally in the primary auditory cortex and a frontal component that reflects involuntary attentional changes (Näätänen et al., 2007). In typical adults, the auditory MMN consists of a negative deflection of 0.5-5 μV, peaking around 150-250 ms after a change (deviant stimuli) is detected within a sequence of invariant sounds (standard stimuli), known as an oddball paradigm. However, MMN amplitude and latency vary depending on factors such as the participant's age or the stimulus type (Näätänen et al., 2007). In adults, larger MMN amplitudes tend to correlate with better behavioural detection of acoustic changes, including frequency, duration, intensity, and speech contrasts (Näätänen & Alho, 1997; Näätänen et al., 2007).

A late discriminative negativity (LDN) has also been described between 350-550 ms. The LDN is more pronounced in children than adults and larger for speech than nonspeech sounds (Bishop, 2010a). An immature MMN has been identified in infants and young children, known as the Mismatch Response (MMR). The MMR can present positive polarity, longer latency, larger amplitude, and different scalp distribution than the adult MMN (Morr et al., 2002).

Time-frequency domain measures: ERSP and ITC/ITPC

Time-frequency analysis quantifies spectral changes in neural oscillations over time, for example, in response to speech stimuli. Time-frequency analysis includes indices such as power (amplitude^2) and synchrony (timing) that reflect variations for a single (local) or pairs (long-range) of electrodes (Cohen, 2014). Time-frequency measures can reflect induced neural oscillations; these are non-time locked to stimulus onset and extracted trial-by-trial to avoid cancelling out during averaging. Alternatively, evoked oscillations are power and phase-locked to an external stimulus and extracted from the final averaged ERPs (Uhlhaas, 2010). Importantly, the analysis of the phase relationship across trials is independent of the amplitude of the oscillations, except in cases when power is very low (Cohen, 2014).

Time-frequency indices include event-related spectral perturbation (ERSP), that measures event-locked changes in spectral power from a baseline, and Inter-trial coherence (ITC), which indicates the degree of phase angle clustering to a time-locking event across single trials (Makeig et al., 2004). ITC is an index that ranges from 0 (random phase angles) to 1 (identical phase angles) and is equivalent to 'Inter-trial Phase Clustering' (ITPC), 'Phase Locking Value (PLV), or 'Phase Coherence' (PC) (Cohen, 2014).

ERP components can also be analysed in the time-frequency domain to study induced activity. For example, single-trial analysis of the MMN has shown local increases in theta ITC/PLV during auditory discrimination of deviant stimuli (Bishop et al., 2010a; Bishop & Hardiman, 2010). Moreover, increased phase synchronisation for the MMN reflects more robust long-range cortico-cortical communication between temporal and frontal regions (Hsiao et al., 2010; Hsiao et al., 2009). These findings demonstrate an association between the MMN generation and oscillatory synchrony, supporting the idea that time-frequency analysis and ERPs reflect a common mechanism and are complementary for understanding neural dynamics in speech perception (Makeig et al., 2004; Müller et al., 2009).

Speech tracking measures

Different EEG measures quantify neural synchronisation to continuous speech. Neural tracking measures describe mutual speech-brain relations and how they are affected by acoustic or cognitive manipulations, for example, language modulations on speech entrainment (Obleser & Kayser, 2019). Early studies measured cortical entrainment to continuous speech as cross-correlation (coherence) between the speech envelope and the recorded brain activity (Di Liberto & Lalor, 2017). Recently, linear modelling methods can predict the EEG responses from the speech input (*encoding* or *forward* models) or reconstruct the speech stimulus from the EEG (*decoding* or *backward* models), linking cortical responses to speech features (e.g. the amplitude envelope), and higher-order information, such as phonemic (Di Liberto et al., 2015) and lexical content (Sassenhagen, 2019).

In sum, there are various EEG measures and paradigms for studying speech perception, but it is necessary to evaluate which are more suitable for developmental research. In children, speech perception has mainly been studied using ERPs. However, there is increasing interest in using alternative approaches that help overcome significant challenges of EEG research in children and infants.

1.3.2 ***Methodological considerations for EEG in speech developmental research.***

EEG is a non-invasive, portable, and relatively inexpensive method with enormous potential in neurodevelopmental science. EEG allows using the same measures from birth to adulthood, is sensitive to age-related changes in brain activity, and may predict language and cognitive skills (Norton et al., 2021). However, measuring speech perception in children is a complex task, and the EEG methodologies used in adults are only sometimes suitable for paediatric research. Despite the advantages of EEG, there are several challenges for its use in children that may lead to spurious findings and high variability between studies.

Neurobiological factors: a noisier brain?

A key aspect to consider in EEG paediatric research are the brain differences between children and adults resulting from neurodevelopment. Brain maturational processes in early childhood include changes in synaptic density, myelination of white matter tracts (Friederici et al., 2017) and increased skull thickness that influence the electrical volume conduction to the scalp and, ultimately, the EEG signal (DeBoer et al., 2006). In addition, neural activity in the developing brain is less synchronised (Muller et al., 2009), with more neural background noise in children than adults (Vanvooren et al., 2015).

Development of brain structures and cognitive functions during early childhood is reflected in ERPs components as the MMN/LDN, with significant differences in scalp distribution, amplitude, peaks, and latency from the adult's responses. For neural oscillations, there are age-related increases in the magnitude of alpha and beta bands and decreases for the low-frequency range that results from brain maturation (Uhlhaas et al., 2010).

Participant-related factors: poor quality data.

Several reviews describe good practices in infant and children EEG (see Bell & Cuevas, 2012; Brooker et al., 2020). Three common challenges in paediatric EEG experiments include how to: (i) get the child's cooperation during testing, (ii) record clean EEG data, and (iii) prevent the participants from dropping out from the studies (attrition).

Young children may get scared and refuse to wear the EEG cap or get fussy during data collection (Norton et al., 2021). Importantly, cap refusal is higher in younger children and children with special needs. This may bias the results, for example, excluding more irritable and less compliant children, such as children with neurodevelopmental disorders (Brooker et al., 2020). For paediatric EEG studies, participant attrition rates are high: up to

75% for infants, 30-45% for 2-3 years old children and 20% for children at the age of four years (Bell & Cuevas, 2012). This often results in small samples, reducing statistical power and making the findings hard to generalise. In addition, it may discourage researchers from studying children at more difficult ages, leading to gaps in knowledge in speech science.

Once a child accepts the cap, the next challenge is to obtain good-quality data. Some measures as ERPs, require large amounts of data to isolate the brain signal from noise (Luck, 2014). This results in long testing times, which are hard to tolerate for young children. They may become restless, bored, or sleepy, resulting in movement-related artifacts, alpha band contamination or blinks (Debnath et al., 2020). Importantly, drastic differences in data quality between participants or stimulus conditions may alter the results, for example, resulting in ERP amplitude and latency differences (DeBoer et al., 2005).

Finally, defining strict participant inclusion/exclusion criteria may improve EEG data quality by reducing sample heterogeneity but results in a lack of diversity that compromises the generalisability of EEG findings. According to Norton et al. (2021), there is a need to increase the participation of underrepresented groups in EEG studies, such as participants from deprived backgrounds or racially, culturally and ethnically diverse (e.g., those with thick hair or non-English speakers).

Experimental factors: stimuli and paradigms.

So far, much of the ERP work in speech perception has used highly controlled and isolated stimuli, such as tones or phonemic contrasts in consonant/vowel in syllables (e.g., /ba/-/da/). Thus, they inform about acoustic and phonological discrimination but not about higher-level linguistic modulations (e.g. words) for which they may lack ecological validity to explain the complexity of speech perception (Alexandrou. Saarinen, Kujala & Salmelin, 2018). Nevertheless, there is growing interest in studying speech perception in daily-life contexts, using naturalistic stimuli as continuous speech (Walley, 2005).

Regarding EEG paradigms, ERP speech perception studies often use an oddball paradigm, which is repetitive and hard to tolerate for children. Alternatively, the multi-feature (or *optimal*) paradigm (Näätänen et al., 2004) represents an efficient tool to include multiple acoustic contrasts and reduce ERP testing time without losing statistical power (Niemitalo-Haapola et al., 2013). Considering potential clinical applications, EEG/ERP experiments have been introducing paradigms and analysis techniques that reflect not only group-level but also individual differences in speech perception, for example, machine learning methods.

Data analysis issues: EEG pre-processing and measures.

There are different toolboxes available for analysing adult EEG data. However, because of the differences between children and adults, adult analysis cannot be extended to paediatric EEG. So far, there is no gold standard on what pre-processing steps to use, how to define a priori the electrodes or time windows of interest or the more suitable EEG measures for comparing children and adults' neural responses to speech.

Regarding pre-processing steps for paediatric EEG, high inter-lab variability hinders reproducibility and large-scale studies. Despite some recent standardisation attempts as the MADE Pipeline (Debnath et al., 2020) and new pre-processing tools that minimise artefact-related data loss, it is necessary to investigate how different methods work with children's data. For example, EEG adult absolute thresholds for artefact rejection cannot be applied to children's data because infants and young children show inherently greater EEG baseline power in lower frequency ranges and higher amplitude ERPs than adults (Brooker, 2020), requiring higher thresholds for artefact rejection.

Moreover, a critical question is whether it is appropriate to compare adult and children's EEG data quantitatively and what measures to use. For example, in the resting-state EEG, adult and children frequency bands are not necessarily equivalent: band boundaries are lower for infants and children (Saby & Marshall, 2012), whereas peak frequency and power change with age (Bell & Cuevas, 2012). For ERP components, there are age-related differences in morphology, latency and scalp topography (DeBoer et al., 2006). During speech discrimination tasks, theta phase synchronisation increases, and power decreases from childhood to adolescence (Bishop et al., 2011) and adolescence to adulthood (Müller et al., 2009). Paradoxically, larger amplitudes in EEG responses in children do not represent better speech discrimination than adults but result from brain maturation (DeBoer et al., 2006).

Finally, children show high within and between-participant variability in EEG amplitude and latency measures, especially for clinical groups. This variability results from developmental differences in brain synchrony and may significantly affect EEG measures based on signal averaging, such as ERPs. Signal averaging for isolating ERP components removes important neural activity that contributes to cognitive processing, but that in children may not be robustly time-locked to an event (Makeig et al., 2004). Alternatively, EEG measures of oscillatory synchrony (PC, PLV, and ITC) could be more suitable to reflect differences in cortical responses to speech than amplitude-based measures.

In summary, this literature review shows essential differences in speech processing skills between children and adults, and between children with TLD and DLD. These differences are associated with the maturation of auditory and language networks and language knowledge acquisition during early childhood, among other factors. Importantly, these multiple research areas (for example, evidence from EEG studies) need to be integrated into language development models that are consistent with those proposed for adults.

1.4 Thesis outline

Previous findings highlight the role of neural synchrony in normal brain development and its potential importance for understanding neurodevelopmental disorders such as DLD (Uhlhaas et al., 2010). Using EEG as an objective measure of brain oscillations, it would be possible to characterise cortical responses to speech in young children with different language skills. However, this requires determining what EEG measures and paradigms are sensitive to language and speech-processing behavioural differences.

This thesis aims to investigate cortical activity associated with speech perception in young children with different language developmental statuses (TLD and DLD) using a range of EEG paradigms, also comparing children's responses to those observed in adults (expert language status).

Specifically, this thesis addresses the following research questions:

(i) Do cortical responses associated with speech perception vary according to young children's language status (typical versus impaired)?

(ii) What EEG indices reflect group-level differences in language skills: expert (e.g., adult-like), typical development (TLD children) or atypical development (DLD children)?

(iii) Do EEG measures relate to children's behavioural measures of speech perception and phonological processing?

We conducted four EEG experiments to address these questions: a resting state, multi-feature MMN/LDN, and continuous speech perception paradigm. Children's speech perception and phonological skills were also tested to determine relationships between their neural responses and language performance.

The general hypothesis is that during early childhood, brain oscillations involved in speech processing will reflect neuro-maturation (age-related changes) but also, the effects of acquired language knowledge. As speech perception relies on cortical oscillatory mechanisms modulated by language knowledge, neural synchronisation in processing speech stimuli should differ under different linguistic abilities. For example, language modulations may vary during language acquisition because of the accumulation of language experience (knowledge) and in language-impaired children because of limited top-down language influences.

Thus, as children acquire language, better language skills may enhance speech representation at the cortical level until they reach adult-like speech perception. However, this effect would be absent or less pronounced in children with DLD.

Specifically, my predictions (P) were:

P1: EEG indices would reflect more efficient speech processing in adults than in children.

P2: EEG indices would reflect more efficient speech processing in children with TLD than children with DLD at the same age.

P3: Better language skills will facilitate the perception of speech at the cortical level, especially with higher-order linguistic content (e.g. lexical than functional words)

P4: Cortical responses (EEG) and behavioural measures of speech processing will show a positive, direct association.

The first study of this thesis (Chapter 2) validated an ERP multifeature experiment (Näätänen et al., 2004) in a group of healthy Spanish-speaking adults, comparing cortical discrimination responses (MMN/LDN) for speech stimuli versus their nonspeech analogues using very controlled stimuli (CVC monosyllables). In the second study (Chapter 3), we used the stimuli from the adult experiment, but only in the speech condition to investigate discrimination of phonemic contrasts in children with TLD and DLD (ages 4.7 to 5.7 years). We compared ERP and time-frequency measures and their associations with phonological awareness processing performance.

The third study (Chapter 4) used a less-controlled task-free paradigm to examine the relationship between resting-state power, oscillatory lateralisation, and speech perception tests between TLD and DLD children. The fourth experiment (Chapter 5) compared, for the first time, speech tracking in children with DLD versus TLD, using multivariate temporal response functions (mTRFs) to map EEG responses and continuous speech features (Di Liberto et al., 2015). Finally, Chapter 6 discusses the potential neurophysiological mechanisms underlying our EEG findings and their interpretation regarding current knowledge in language neuroscience and speech perception development.

This thesis contributes to understanding the neural basis of speech perception in children by exploring different measures of cortical activity related to speech perception. It further informs research in speech perception development by using a range of paradigms with different ecological validity, relating EEG to behavioural measures of phonological and speech processing. In the future, these findings could help clinical practice by aiding the diagnosis of speech and language disorders and monitoring interventions' efficacy.

Chapter 2. Validating a multifeature experiment in adults

2.1 Introduction

For humans, spoken language is a relevant input for which our brain has an innate preference (Zatorre & Gandour, 2007). At the same time, some linguistic content in the speech input is perceived more easily than others. In the brain, this is supported by complex mechanisms and involves integrating multiple bottom-up and top-down processes. However, it is still being determined to what degree speech perception is guided by auditory and linguistic features of the speech signal and how these features interact with prior language knowledge (or language skills).

An objective, accurate measure to investigate how the brain perceives speech is the Mismatch Negativity (MMN). The MMN can be elicited without conscious attention to the stimuli, helping to separate attentional and linguistic processing. The MMN patterns are also sensitive to different levels of linguistic representation in the speech signal, for example, phonemic or lexical content. However, MMN experiments usually use a few contrasts, providing little information on higher-order language influences. In addition, there is a need to test previous MMN findings in new populations, for example, Spanish speakers.

This chapter investigated cortical discrimination of speech stimuli of varying linguistic complexity. We aimed to validate an MMN experiment in adult Spanish speakers, providing reference values for future studies with children (Chapter 3). Instead of a typical oddball design, we used a multifeature (optimal) paradigm (Näätänen et al., 2004), partially replicating a study by Gansonre et al. (2018). This allowed us to contrast multiple linguistics content while considerably reducing the EEG testing time for future studies in children.

2.1.1 *Language influences on speech perception*

Speech perception is hierarchically organised, involving successive stages of increasing complexity during which linguistic features are integrated (Cutler, 2008; Peelle et al., 2010). During word recognition, a hierarchical sequence for speech processing involves early, low-level acoustic features (e.g., pitch, amplitude, formants) and later, higher-level sub-lexical phonological (individual sounds and syllables), lexical (words) and semantic (word meanings) content (Kujala et al., 2007). However, to what extent each stage is influenced by the linguistic properties of the input, language representations in our brain or their interplay still needs to be fully understood. Although the amount of sensory detail in the speech signal (speech intelligibility) is undoubtedly a crucial factor determining how well we perceive spoken language, there is consistent evidence for top-down effects on different speech perception stages. Perceiving speech (but not other sounds) would activate language representations in the listener's brain, reducing the impact of acoustic variations in the input and enhancing the perception of features relevant to speech comprehension (Cutler, 2008; van Linden et a., 2007).

One type of top-down language modulation that shapes how the brain responds to speech relates to an individual's experience with a given language (Leonard & Chang, 2014). More experienced language users (e.g., adult-like, native speakers) will perceive a given speech input more easily than less experienced or less language-proficient ones. A typical example is the innate brain preference for our native language; multiple studies have demonstrated that after the age of two years, cortical responses are more significant for native than non-native phonemes, indicating better phonological discrimination for the language we are familiar with (Näätänen et al., 1997; Kuhl, 2010). This indicates that speech perception is driven by implicit language knowledge acquired through cumulative experience, for example, with our native language's phonological rules or vocabulary.

A second type of language top-down modulation on speech perception is the listener's language knowledge. Although the literature here is vast, a clear example of language knowledge manipulation is the study by Sohoglu et al. (2012). They tested fourteen adults by showing them a text before presenting spoken sentences with different levels of acoustic degradation. They found that when participants knew sentence content beforehand (matching text condition), their ratings of perceptual clarity were significantly better than when the text did not correspond to the upcoming sentence (mismatching text condition), with prior language knowledge predicting how the speech was perceived. The authors concluded that increasing the amount of prior knowledge improved speech perception, similar to when the speech signal was physically enhanced (greater intelligibility). However, other studies using objective measures have found no such effects. Millman et al. (2015) used MEG to measure cortical tracking of the speech envelope before and after training participants (n=16) to understand unintelligible speech. They found no enhancement in the responses for the same sentence after they became intelligible, concluding that speech perception was driven by acoustic processing with no effects of prior language knowledge. This discrepancy between subjective and objective measures could be explained to a great extent by the great variety of paradigms used to investigate top-down language effects.

A third factor that interacts with language representations in the brain is the type of linguistic content in the speech input, such as phonemic categories, lexical status, word morphology and meaning. Previous studies indicate that some elements of speech are perceived more easily than others, generally those that activate higher-order language representations. Shtyrov et al. (2011) reported enhanced cortical responses for words than non-words in adults (n=18), indicating easier phonological processing when phonemes (native) are presented in a meaningful configuration (lexical status effect). Similarly, a study by Mai, Minnet and Wang (2016) in adult Mandarin speakers (n=21) confirmed the effects of lexical status on different EEG measures when presenting sentences containing real words and non-words with similar acoustical structures. The authors detected different EEG patterns for real words and non-words, concluding that phonological and semantic tasks engage different cortical networks during speech processing. This indicates that findings about linguistic content effects on cortical speech processing may need further replication, ideally in different languages.

Regarding neural mechanisms, it is believed that top-down language modulations interact with incoming speech through top-down feedback loops from frontal to temporal auditory areas. Notably, interactions between language knowledge and linguistic content occur during the late and early stages of speech processing (less than 200 ms). Sohoglu et al. (2012) reported that the effect of prior language knowledge involves activation in the STG shortly after speech onset, even before sensory cortices are recruited. Similarly, there is evidence of significant lexical effects peaking within 200 ms with enhanced cortical responses for stimuli with lexical status (Shtyrov et al., 2011). Moreover, a provocative claim by Leonard and Chang (2014) posits that neural activity in the STG reflects context-dependent spectro-temporal representations of speech, meaning that this low-level speech processing area would also encode linguistically and behaviourally relevant information.

Together, these findings indicate that prior language knowledge and the type of linguistic representations in the speech input modulate speech perception in the brain, even at low-level processing stages. However, a common issue with previous research investigating these effects with neural measures is that they frequently use very small samples, very different paradigms and have yet to replicate their findings. In this context, the MMN has emerged as a reliable index suitable for studying the effects of language knowledge and linguistic content on speech perception with millisecond precision.

2.1.2 *Speech perception and the MMN*

The MMN is the negative frontal deflection elicited by the detection of any unexpected auditory feature, e.g., frequency, duration, intensity, or speech contrast. It is commonly elicited during passive listening using an oddball paradigm, consisting of an infrequent (deviant) stimulus within a sequence of repeated (standard) sounds. The MMN is measured on different waveforms computed by subtracting the ERP responses for the standard from that of the deviant stimuli (Luck & Kappenmann, 2011). The amplitude of the MMN is thought to reflect the magnitude of physical difference detected between a deviant and the preceding standards, but also the stimulus probability, as deviant stimuli are less likely to occur than standards. The latency varies according to the stimulus complexity, but roughly, the MMN typically spans from 100-250 ms (Kappenman et al., 2021) with an additional late discriminatory negativity (LDN) in the 350 (or earlier)–500 ms range. The LDN is more reliable in young children, larger for speech than non-speech sounds and decreases in amplitude with age (Cheour et al., 2001). Larger amplitudes and shorter latencies are typically interpreted as more efficient cortical processing.

Since the 1990s, many studies have used the MMN to study speech perception in passive listening conditions, measuring the detection of sub-lexical contrasts as phonological differences in syllables and between larger units as words and sentences (Näätänen, 2003). For example, Kuuluvainen et al. (2014) used EEG–MEG in healthy adults (n=15) to measure cortical change detection of syllables with consonant, vowel, sound duration, frequency, and intensity contrasts. After controlling for acoustic and linguistic differences, they reported larger MMN for speech than for non-speech analogues. Thus, the MMN is useful to study top-down modulations on speech perception and the effects of different linguistic content.

At early processing stages, larger MMNs reflect an enhanced perception of speech with higher-order linguistic content. For example, a study by van Linden et al, (2007) in adults (n=16) reported greater MMN amplitude when the stimulus lexical information helped to disambiguate the phonemic content, demonstrating that lexical influences operate at pre-lexical processing stages. Shtyrov et al. (2011) detected an early effect of word frequency at 100-120 ms originating bilaterally in the left inferior frontal areas, with significantly greater MMN amplitude for high-frequency words. This indicates frontal top-down modulations interplay with linguistic content at early processing stages. Similarly, a study in German speakers (n=23) by Jacobsen et al. (2021) demonstrated early effects of word type in the MMN amplitude, with more significant frontal responses for nouns than function words in the 80-200 ms interval.

At later processing stages (>200 ms), modulations on the MMN include lexical status and word type effects. Shtyrov et al. (2011) reported that a later lexicality effect originated bilaterally in perisylvian areas, with significantly larger responses for word than for non-word deviants in the 200–350-time window. Similarly, Gansonre et al. (2018) reported later phonological, lexical, and lexical-semantic enhancement effects. They found significantly larger negative responses for native vowels than for non-native analogues with a centrally distributed peak at 248 ms. Real words elicited significantly larger negativity than non-words at 320 ms, whereas action verbs exhibited a more robust frontal negative response than concrete nouns, peaking at 310 ms. Together, these results indicate later MMN-like responses consistent with the LDN time course. However, focusing on the LDN as a cortical measure for adult speech perception studies could be less appropriate than the MMN because the LDN decreases with age, and could be hard to differentiate from the N400 component.

An important methodological aspect is that most MMN studies use a simple oddball paradigm with one standard stimulus interspersed with one or two deviants that differ in one critical acoustic feature. Such strict acoustic control is hard to achieve in speech perception research as speech naturally involves multiple phonological contrasts. Many studies try to control acoustic differences by restricting the number of speech contrasts, ending up with very restricted distinctions such as /ba/-/da/. Although these conditions provide reasonable experimental control, they limit the number of contrasts that can be studied in each experiment, resulting in long EEG recording times if wanting to introduce more variables. More importantly, such controlled conditions are not very informative about speech perception, such as how low-level speech features are modulated by language knowledge and linguistic content.

In response to this, a variant of the oddball paradigm, the multifeature paradigm, attempted to sort out this limitation by including several deviants versus one standard, allowing different contrasts in a much shorter time without losing statistical power (Näätänen et al., 2004). Gansonre et al. (2018) used a multifeature paradigm to study the perception of different speech contrasts in monosyllabic word forms in a group of adult Danish speakers (n=21). Although they used parent waveforms[1] instead of the MMN difference waveforms, their experiment demonstrated that it is possible to successfully elicit ERP responses for multiple linguistic conditions in a single testing session.

From a theoretical perspective, there are different interpretations of the MMN. A classical hypothesis is that the MMN reflects the formation of sensory memory traces and is elicited as an error signal when an incoming deviant mismatches previous representations of a standard stimulus (Näätänen et al., 2005). Memory traces would involve language-specific representations in the posterior left auditory cortex for speech perception, working as templates for automatic speech sound recognition (Näätänen, 2003; Näätänen, et al., 1997; Pulvermüller et al., 2001). Alternatively, the neural adaptation account suggests that the MMN is not a response itself but a part of the auditory N1 component, which is suppressed

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[1] In recent MMN research, ‘parent waveforms’ (e.g., Kappenmann et al., 2021) refer to the original standard and deviant grand averages before calculating the difference waveform deviant minus standard.

and delayed, reflecting passive neural attenuation in the auditory cortex for repetitive sounds, including speech (Jaaskelainen et al., 2004). This bottom-up, pre-attentive gating of novel stimuli into conscious perception would leave out irrelevant, less-informative stimuli (Heilbron & Chait, 2018). Finally, the predictive coding framework proposes that the MMN is an index of "prediction error" between the brain's prediction about future sensory events and upcoming sensory information (Garrido et al., 2009). This error signal updates higher-order processing levels and facilitates low-level processing of new inputs (Heilborn & Chait, 2018). Although predictive mechanisms are not exclusive to language, evidence supports predictive coding during phonological, lexical, semantic, and grammatical processing (Heilbron et al., 2022).

Although the MMN theories may overlap in some respects, as they are all somehow based on memory, Heilbron and Chait (2018) pointed out an important distinction between them: Predictions operate prospectively, representing future stimuli, whereas memory comparisons act retrospectively by comparing the incoming input with previous traces. There is a need for more MMN studies contrasting different language processing levels. To determine which of these approaches better explains linguistic modulations on speech perception, for example, using the multifeature paradigm.

2.1.3 *The current study*

This study investigated the effects of different types of linguistic content on the cortical detection of speech contrasts in adults, as indexed by the MMN. Given the few studies assessing cortical speech processing in Spanish speakers and the need for EEG paradigms suitable for young children, we partially replicated an experiment by Gansonre et al. (2018) in a group of Chilean adults (n=20). Using a multifeature paradigm, we investigated the

MMN responses to phonological changes in a set of speech (S) deviants that differed hierarchically in their linguistic content: native versus non-native phonemes in non-words, non-words versus words, and function versus content words. We also compared the MMN for each deviant type with the responses to their non-speech (NS) analogues (control condition).

The aims of this study were twofold; firstly, to determine if our experiment elicited a consistent MMN (and LDN, for exploratory purposes), and secondly, if the MMN was influenced by the linguistic differences between stimuli.

Thus, we addressed three questions:

(i) Are there significant MMN/LDN responses?

(ii) If an MMN is present, are there any differences in amplitude or latency when stimuli are presented in a speech versus a non-speech configuration?

(iii) Is there any effect of the linguistic content on the MMN patterns?

We hypothesized that our experiment would elicit robust MMN responses for all deviants and that early effects of linguistic content would be observed as differences in the MMN amplitude and latency. Specifically, we predicted an effect of linguistic content, with MNN differences between pairs of speech and non-speech stimuli.

For contrasts in the speech condition, we predicted an effect of the linguistic processing level, with different MMN responses for (i) native than non-native phonemes in non-words, (ii) words than non-words (lexical/ non-lexical status), and (iii) content words versus function words (word class). However, for the direction of these effects, our hypotheses were exploratory and considered possible outcomes according to the MMN frameworks described earlier, summarised in Table 2.1.

Table 2.1

Possible Linguistic Effects on the MMN According to Different Theories

Hypothesis	MMN prediction	Rationale
Predictive coding	either (a) no effect of condition or linguistic content on the MMN, or (b) reduced MMN amplitude for more predictable stimulus (speech), because of less prediction error.	because (a) the probability of occurrence is equal for all deviant types, or (b) language status could make the speech stimuli easier to predict than meaningless non-speech analogues.
Memory traces	Larger MMN amplitude for more familiar, higher-order stimulus (speech than non-speech, but only for words; for words than non-words, and for content than function words).	If a language-specific memory effect is present, we should observe larger responses because of stronger long-term memory traces.
Neural adaptation	either (a) no difference in MMN between conditions, or (b) smaller responses for speech than non-speech items, but with no differences within the speech condition.	either (a) all type of changes should trigger equal neural refreshment. or (b) repeated speech stimuli could generate neural habituation faster.

2.2 Methods

2.2.1 *Participants*

Twenty adults (age range 24.9-44.11 years, *M*=34.2, *SD*= 4.8, 12 female) were recruited for the study through advertising on social media groups. All participants were native Chilean Spanish-speaking adults who lived in London (UK), used Spanish as their first language at home and, despite having English as a second language, did not speak a language other than Spanish (Chilean variant) before the age of 5 years. None of the participants reported a history of hearing loss, neurological or psychiatric conditions, or learning or language difficulties, as determined by an online screening survey.

This study was approved by the Research Ethics Committee of the Division of Psychology and Language Sciences, University College London (UCL). Before participating in the study, all participants read an information sheet and provided written informed consent. All participants received compensation of £15 for their time.

2.2.2 *Stimuli*

Two sets of acoustic stimuli were created: a ‘speech’ (S) and a ‘non-speech’ (NS) condition. Each set consisted of five stimulus types: one standard stimulus (288 in total) and four deviants (72 stimulus for each type, 288 deviants in total) with a total of 576 stimulus per condition (S and NS).

Speech condition

Five CVC monosyllables were created according to the Spanish language phonotactic rules. Stimuli were recorded by a female native Chilean Spanish speaker in an acoustically shielded booth with a condenser microphone RODE NT-1A, an RME Fireface UC interface and the Audacity software with 44.100 Hz sampling rate, stereo channels and a 16-bit format as settings. The recorded string was converted to mono, and each stimulus was cut from the whole set to the nearest zero crossing, defining the stimulus beginning/end.

The five stimuli consisted of one standard (St) and four deviants (D1 to D4) that were produced by changing the initial phoneme of the standard stimulus while keeping constant the vowel nucleus and the final consonant. These phonemic changes resulted in acoustic and phonological contrasts between the standard and deviant stimulus aiming to elicit the MMN but also involved different levels of linguistic processing: (i) phonological: native versus non-native phonemes in non-words (phonotactically allowed word forms without meaning), (ii) lexical: non-words versus real words, and (iii) semantic: function versus content words.

Stimuli were controlled as much as possible for acoustic and linguistic differences known to influence cortical speech processing measures, such as the MMN. According to Guardia (2010), the initial phonemes were selected to maximize their similarity in terms of linguistic (e.g., syllable structure, word length/stress) and lexical factors (age of acquisition and oral frequency). Thus, the stimuli should meet the all the following criteria: (i) St and D2 are non-words with a Spanish native initial phoneme, (ii) D1 is a non-word with an initial phoneme that is non-native in Spanish, (iii) D3 is a Chilean Spanish function word, (iv) D4 is a Chilean Spanish content word, (v) D3 and D4 are similar in their age of acquisition and oral frequency and are acquired before the age of 4.6 years (to be used in future experiments with young children), according to databases by Corral et al., (2009) and Alonso et al., (2015).

As illustrated in Table 2.2, “fus”, a non-word in Spanish, was selected as the standard (St) stimulus. To create deviant 1 (D1), the initial phoneme was changed into /ʃ/, but the vowel and final consonant were preserved (/u/ and /s/, respectively), resulting in the non-word /ʃus/ (“shus”) which is non-native in Spanish. For deviant 2 (D2), the initial phoneme was changed into /x/, a native Spanish phoneme that produced the non-word /xus/ (“hus”).

For deviant 3 (D3), the initial phoneme was /t/, resulting in the function word /tus/ ("tus", meaning "yours"), and for deviant 4 (D4), the initial phoneme was /l/, producing the content (lexical) word /lus/[2] ("luz", meaning "light"). Although a fricative onset consonant (in St, D1 and D2) and the /u/ vowel nucleus could make the stimulus less salient (because of greater noise and lower amplitude, respectively), only these CVC combinations met all our criteria.

Table 2.2

Linguistic Parameters for Stimuli in the Speech Condition

Type	Class	Initial Consonant	Vowel	Final Consonant	Age of Acquisition	Oral Frequency
St	Non-word	/f/ Native, labiodental, unvoiced fricative	/u/	/s/	--	--
D1	Non-word	/ʃ/ Non-Native, postalveolar, unvoiced fricative	/u/	/s/	--	--
D2	Non-word	/x/ Native, velar, unvoiced fricative	/u/	/s/	--	--
D3	Function word (determiner)	/t/ Native, dental, unvoiced, alveolar	/u/	/s/	4.24 [a]	2.63 [b]
D4	Content word (noun)	/l/ Native, alveolar, voiced, lateral	/u/	/s/	3.18 [a]	2.53 [b]

Note. St: Standard, D1: Deviant 1, D2: Deviant 2; D3: Deviant 3; D4: Deviant 4.

[a] Subjective AoA in years (Alonso et al., 2015)

[b] Among the 100 most frequent words and monosyllables in Spanish (Corral et al., 2009)

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[2] Note that /lus/ is valid for the Chilean and other Hispano-American Spanish pronunciation but not totally for peninsular Spanish, in which the phoneme /s/ is pronounced interdentally, as in many areas in Spain.

Non-Speech condition.

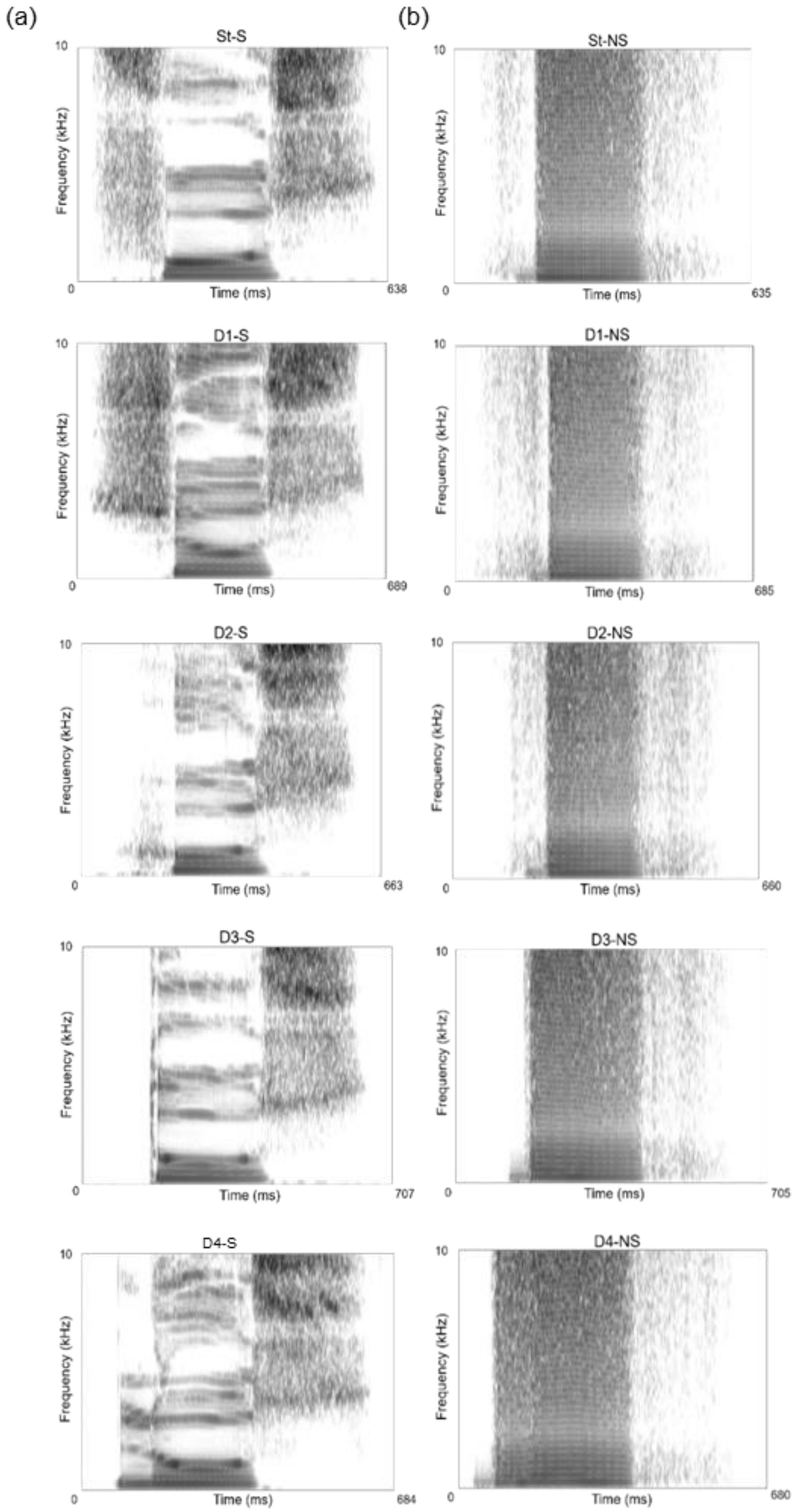
A set of standard-deviant stimuli were spectrally matched to each one of the original stimuli but could not be perceived as speech. These non-speech analogues acted as a control condition, differentiating the MMN effects resulting from acoustic changes from any potential linguistic effects.

The NS analogues were created from the original stimuli using TANDEM-STRAIGHT (Kawahara et al., 2008), a speech modification system that decomposes the speech into a carrier and a spectral filter. Before resynthesis, the spectral filter was averaged across the entire frequency range, preserving the temporal fluctuations in amplitude and voiced/unvoiced/mixed distinctions but no other variations in spectral content. The result was similar to what would be obtained in a traditional single-channel vocoder (Dudley, 1939). Finally, the ensemble of five non-speech sounds was spectrally matched to the average spectrum of the five originals. The spectrograms for the stimulus in both conditions are presented in Figure 2.1.

To control for acoustic factors, all stimuli were matched as much as possible in pitch, intensity and duration using PRAAT (Boersma & Weenink, 2018). For stimulus with a voiceless initial consonant (all except D4-S), the initial consonant was defined from time=0 to the last time point in which the signal was aperiodic. *Vowel duration* was defined as the time from the start to the end of periodicity. The final consonant duration was defined from the first aperiodic sample after the vowel end to the stimulus end time. The initial consonant for D4-S (voiced) was identified from the vowel by visual inspection of the spectrogram, and the vowel onset was considered as the time when there was a sudden and sustained rise in $f0$, confirmed by auditory inspection of the consonant-vowel transition. After pre-processing, stereo format was restored. Table 2.3 presents the acoustic parameters for all stimuli.

Figure 2.1

Spectrograms of Each Stimuli



Note. Column (a) Speech (S) condition; (b) Non-speech (NS) condition.

Table 2.3

Acoustic Parameters for Stimulus in the Speech and Nonspeech Conditions

	Mean values			Vowel[c]			Consonant	
Condition/ Stimulus type	Duration (ms)	Pitch (Hz)	Intensity[b] (dB)	Duration (ms)	Mean pitch (Hz)	Mean intensity (dB)	Initial (ms)	Final (ms)
Speech								
St	610	264	66.7	240	264	70.8	140	210
D1	660	264	66.7	220	264	71.3	190	230
D2	630	267	66.7	210	268	71.5	170	240
D3	680	267	66.7	250	266	71.0	140	270
D4	660	264	66.7	230	269	70.7	130	280
Non-speech								
St	610	264	66.7	280	264	70.2	110	200
D1	660	264	66.7	240	265	71.1	170	230
D2	630	267	66.7	250	268	70.8	140	230
D3	680	267	66.7	290	267	70.5	110	260
D4	650	262	66.7	230	268	70.2	140	270

Note. St: Standard, D1: Deviant 1, D2: Deviant 2, D3: Deviant 3, D4: Deviant 4.

Stimulus duration ranged from 610 to 680 ms with a 15 ms ramp on/off segment.

[b] Intensity of all stimuli was normalised to the root-mean-square (RMS) at 66.7 dB

[c] Vowel intensity differences within 1 dB and in vowel pitch within 1 Hz for each S-NS pair.

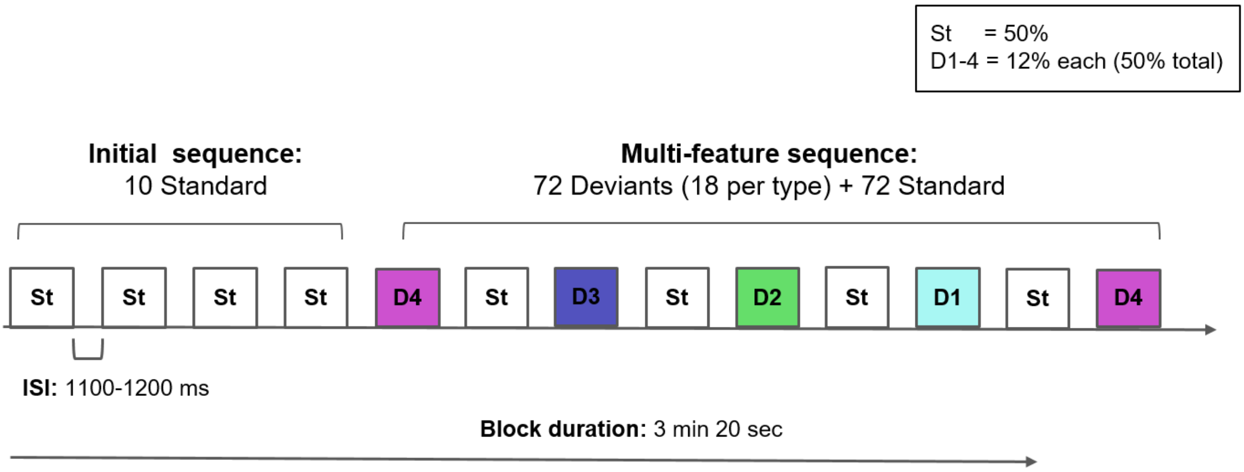
Importantly, some inevitable differences in the acoustic complexity between stimulus pairs in the S and NS condition persisted, even after maximum efforts to match them as can be confirmed by visual inspection of the spectrograms in Figure 2.1. For example, D1-S has a lower intensity in the initial fricative than its NS analogue.

2.2.3 *Procedure*

Stimuli of the S and NS condition were divided into four blocks of 3 min 20 seconds duration (8 blocks in total, with a total duration of 28 minutes). Each experimental block consisted of an initial habituation sequence of 10 standards, and a multi-feature sequence of 144 stimuli (Figure 2.2). In the multi-feature sequence, the four deviants (12% of the trials each) stimuli interspersed in a randomised order with the standard stimulus (50% of the trials). The inter-stimulus interval (ISI) was randomly jittered between 1100-1200 ms, and the presentation order of the speech and non-speech blocks was randomised across participants.

Figure 2.2

Structure of each Experimental Block for the Speech and Non-Speech Conditions



Note. Each experimental block consisted of an initial sequence of 10 standards (white squares), and a multifeature sequence, in which D1 (light blue), D2 (green), D3 (blue), and D4 (pink) were randomly alternated with the standard. Total number of stimuli per block= 154. ISI: Inter-stimulus interval.

Participants were tested in a single 2-hour session at the UCL Infant and Child Language Lab. After providing informed consent, they completed a language background questionnaire and received an air conduction pure tone audiometry according to the British Society of Audiology procedures (BSA, 2011). They also completed the Block Design test of the Weschler Abbreviated Scale of Intelligence, WASI (Weschler, 2011), a standardised measure of nonverbal IQ.

The participant's hearing and nonverbal skills were assessed to confirm that they (i) presented mean pure tone average (PTA) air-conduction thresholds ≤20 dB for both ears at octave frequencies from 500-4000 Hz, or a threshold of ≤25 dB at any given frequency from 250-8000 Hz, and (ii) performed no more than 1 SD below the normative mean (M=50, SD=5) on the Block Design test. Table 2.4 summarises participant's auditory and non-verbal test results.

Table 2.4

Participant's Hearing Thresholds and Non-Verbal Scores

Measure	M	SD	CI (Lower-upper)	Range
PTA right ear (dB HL)	6.2	3.7	4.4 - 7.8	0 - 13
PTA left ear (dB HL)	6.9	3.6	5.1 - 8.5	0 - 13
Block Design (*T* -score) [a]	60.7	7.8	56.9 - 64.4	44 - 79

Note. n=20. Group Means, Standard Deviations (SD), Confidence Intervals (CI) for the Mean (95%), and Ranges for pure tone average (PTA) and the Block Design test.

[a] One missing value (n=19)

2.2.4 *EEG acquisition and pre-processing*

EEG was recorded in a sound attenuated booth. Participants were instructed to sit in a chair comfortably and still, ignoring the acoustic stimuli while watching a silent video, with no response required. All auditory stimuli were presented free field at 70 dB SPL via one loudspeaker placed in front of the participant.

Continuous EEG was recorded with a 32- channel Biosemi ActiveTwo System (https://www.biosemi.com), at a 2048-Hz sampling rate. The electrodes were positioned according to the 10-20 system in the following sites: Fp1/2 - AF3/4 - F7/8 - F3/4 - FC1/2 - FC5 /6- T7/8 - C3/4 - CP1/2 - CP5/6 - P7 /8- P3/4 - Pz - PO3/4 - O1/2 - Oz - Fz – Cz. A1 and A2 were placed on the left and right mastoids, respectively and CMS-DRL were used as online reference. The vertical and horizontal electro-oculogram were recorded by electrodes in the left supra and infraorbital sites and right and left eye canthus, respectively. For all electrodes, DC offsets were kept under 25 µV.

The EEG was pre-processed using EEGLAB v.14 (Delorme & Makeig, 2004), MATLAB v.2018a (The Mathworks Inc) and ERPLAB v.5.1.1.0 (Lopez-Calderon & Luck, 2014). Data were resampled to 500 Hz and re-referenced off-line to the average of both mastoids. The continuous EEG was high-pass-filtered with an IIR Butterworth filter (2nd order, 12 dB/octave attenuation, half-frequency cut-offs 0.1Hz, zero-phase shift) to remove slow drifts and DC offsets (Luck, 2014). Bad channels were removed after visual inspection and Independent Component Analysis (ICA) was applied to reduce blinks and eye movements. After ICA, the removed channels were interpolated, and data were re-referenced to the head average.

A total of 619 epochs of 1000 ms duration were extracted for each participant, defined from -200 to 800 ms, with baseline correction between -200 to 0 ms. Epochs with artifacts exceeding an absolute threshold of 100 µV were excluded. The EEG noise level was quantified as the individual percentage of epochs rejected for each stimulus type and condition, considering 30% of the trials per stimulus type as individual maximum artifact rejection. No participant exceeded this criterion. Table 2.5 presents the group averages per condition and stimulus type (see Appendix 2.1 for individual rejection values).

Table 2.5

Percentage of Rejected Epochs per Condition and Stimulus Type

Stimulus Type	Speech		Non-Speech	
	M	SD	M	SD
St	11.8	12.4	10.7	9.3
D1	7.6	8.8	8.7	7.2
D2	9.2	7.9	9.0	7.8
D3	8.4	7.2	9.4	7.8
D4	8.8	6.6	11.9	15.3

Note. n=20. Group Means, Standard Deviations (SD) for the total percentage of rejected epochs.

2.2.5 *ERP data analysis*

Individual ERP datasets were created for each participant and the grand average was calculated across all subjects for each stimulus type in both conditions. Then, four difference waves (DWs) were computed for all the stimulus type per condition, by subtracting the average responses for the standards from the average responses for each deviant type. Difference waveforms were then analysed to determine if the MMN response was present and quantify its amplitude and latency.

To reduce the number of statistical comparisons (Luck & Gaspelin, 2017), electrode Fz was selected *a priori* for all data analyses as previous literature has reported it as a site of maximum MMN amplitude (Näätänen et al, 2004). Pre-processed DWs at 500 Hz were decimated for statistical analysis by a factor of 4 to 125 Hz, by low pass filtering with a boxcar moving average and baseline correction from -194 to 0 ms.

For the first analysis, significant responses and their polarity were detected by point-by-point, 2-tailed t-tests applied in the 50-450 ms time window. Using a broad time window would allow us not only to detect the MMN but to explore other responses as the LDN for informing future studies. A response was considered present if the amplitude of a DW was significantly smaller than 0 µV for a continuous period of at least 16 ms (Gurthrie & Buchwald, 1991). The MMN time window was defined between 100-250 ms whereas exploratory LDN analysis comprised the 250-450 ms interval. All between and within-condition analysis were performed in the MMN time window: peak latency was calculated as the largest negative deflection in the 100-250 ms interval, and mean amplitude as the average over a 50 ms interval centred in the peak latency. Qualitatively, we reported the temporal patterns and scalp distribution for the MMN.

2.2.6 *Statistical analysis*

Statistical analyses were performed using SPSS v.27, Matlab 2018a and the Mass Univariate ERP Toolbox, MUA (Groppe et al., 2011) and considered a critical alpha level of 0.05 for all analysis, except when correction for multiple comparisons was required.

MUA was used to identify determine reliable responses by performs point-by-point t-tests throughout a given time window(s) and electrode(s) of interest, testing the null hypothesis that the difference between a given ERP waveform is not significantly different from 0 µV. The results of each test are expressed as a t-score for each time point, with greater t-scores indicating more reliably differences (Groppe et al., 2011). As this is a validation study, the MUA approach was preferred over other MMN/LDN identification or quantification methods (e.g., average measures over a time window), because it provides a fine-grained analysis of the time course (start/ending points) and the direction (polarity) of any significant responses for each DW type and between/within-condition effects.

To control for the substantial number of comparisons, the significance of each t-test was assessed by applying a False Discovery Rate (FDR) control procedure at a 5% nominal level (Benjamini & Hochberg, 1995). FDR controls for the average proportion of significant test that are, in fact, false discoveries (type I error) within a family of comparisons, as occurs across electrodes or between consecutive time points for the same electrode (Fields & Kuperberg, 2020). The FDR correction assumes that a family of test are positively correlated and ensures that the likelihood of false discoveries will be limited to the nominal level, regardless their dependency (Benjamini & Hochberg, 1995). FDR-corrected p-values referring the critical threshold for statistical significance are known as q-values. For example, for a family-wise error rate of q=0.05 (α=0.05), any t-test result with $q \leq 5\%$ will be considered statistically significant (Groppe et al., 2011).

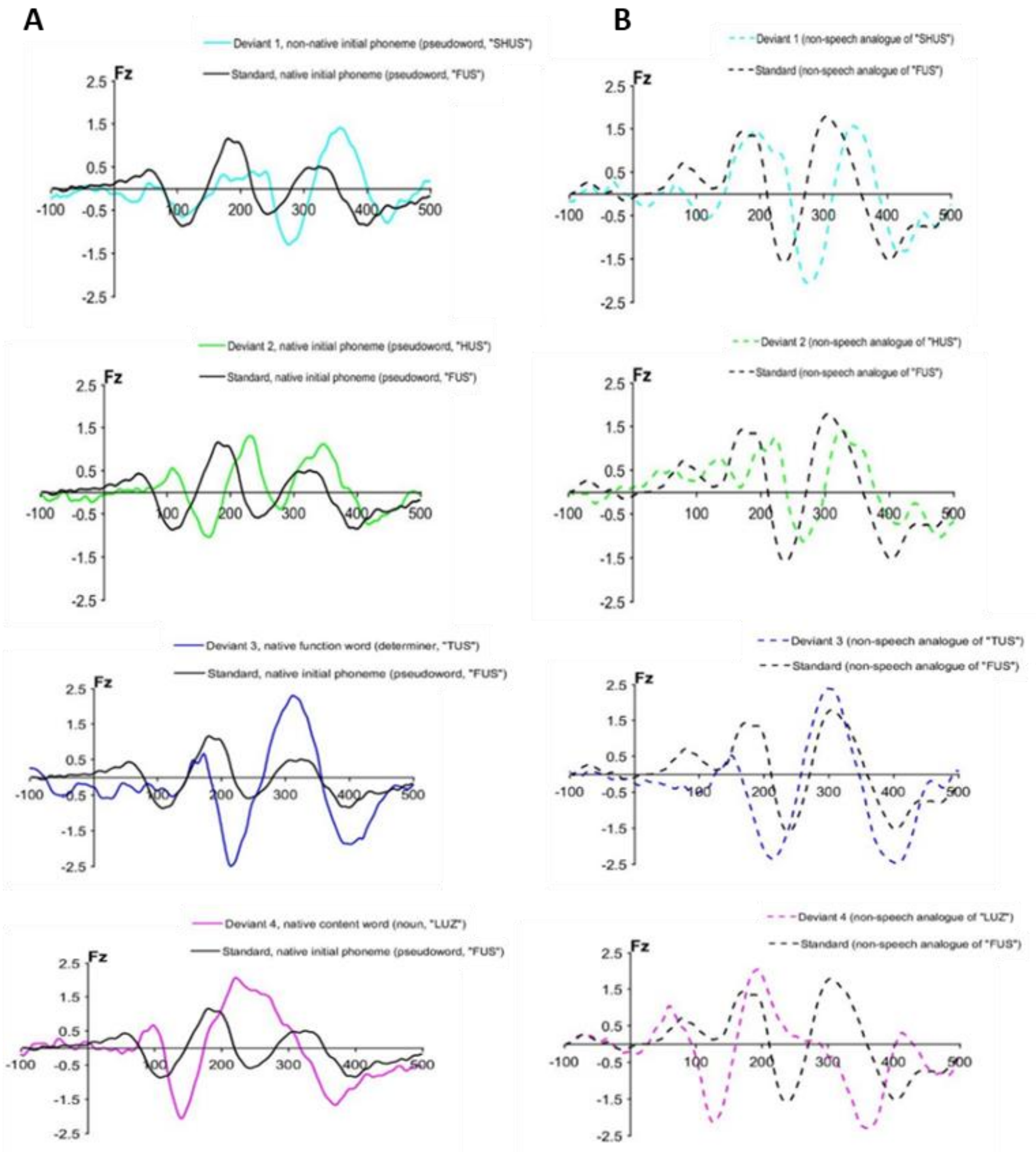
2.3 Results

2.3.1 *Identification of significant ERP responses*

Figure 2.3 displays the ERP grand average waveforms for all stimulus in the S and NS condition, indicates typical auditory responses for all the stimulus types. For the S condition (Figure 2.3a), peaks on D1 and D2 are clearer for the standard stimulus, but the opposite pattern is observed for D3 and D4. In the NS condition (Figure 2.3b) the amplitude of deviant and standard stimuli looks very similar.

Figure 2.3

Grand Average Parent Waveforms at Fz, for all Stimuli



Note. ERP waveforms for stimuli in the in the Speech (column A, solid lines) and Non-Speech (column B, dashed lines) condition. First row: standard (black) - deviant 1 (light blue). Second row: standard (black waveforms) versus deviant 2 (green waveforms). Third row: standard (black) versus deviant 3 (blue). Fourth row: standard (black) versus deviant 4 (pink).

MMN/LDN identification in Difference Waveforms

The first validation step for our experiment focused on determining whether it elicited statistically significant MMN and LDN responses in each of the difference waves and if so, in describing their temporal patterns. We computed four difference waveforms (DW) from individual ERP sets and averaged them across subjects for each condition resulting in two pools of deviants; one for the speech (DW1-S, DW2-S, DW3-S and DW4-S) and another for the non-speech condition (DW1-NS, DW2-NS, DW3-NS and DW4-NS).

MUA was applied at electrode Fz for each DW, to determine (a) if statistically significant responses were present, (b) their latency and duration (start-end time points), and (c) the polarity of other responses (positive or negative), using a broader time window around 50-450 ms (exact boundaries for a 125 Hz rate: 46-446 ms).

Significant responses of the same polarity (either positive or negative) were detected for all DW types at similar latency ranges for both conditions (see Table 2.6). In general, the duration of these responses was longer in the non-speech than in the speech condition, except for DW type 2. Amongst these significant ERP responses, the MMN was identified as negative deflections occurring in the 100–250-time window for an interval of at least 16 ms (Guthrie & Buchwald, 1991).

The results of the MUA confirm the presence of significant MMN responses at Fz the 100-250 ms time window for all DW types in both conditions (Table 2.6, values in bold). In addition, significant negative responses are observed for the 250-450 interval in both conditions (Table 2.6, underlined values) for all DW types, except for DW2_S, suggesting LDN responses are also present. Table 2.7 presents the parameters of the MUA in the 50-550 ms time window, with a family-wise alpha level of 5% (q=0.05) for each DW type, in both conditions.

Table 2.6

Significant ERP Responses Detected in the 50-450 ms Time Window

	Speech			Non-speech		
DW type	Start/end time (ms)	Response duration (ms)	Response Polarity	Start/end time (ms)	Response duration (ms)	Response Polarity
DW1	--	--	--	78-102	24	Neg.
	--	--	--	**102-126**	24	Neg.
	182-198	24	Neg.	**--**	--	--
	238	8	Pos.	214-246	32	Pos.
	278-294	16	Neg.	262-318	56	Neg.
	350-390	40	Pos.	342-398	56	Pos.
DW2	102-118	16	Pos.	--	--	--
	158-182	24	Neg.	**166-182**	16	Neg.
	222-246	24	Pos.	214-246	32	Pos.
	--	--	--	270-310	40	Neg.
	358-366	8*	Neg	358-404	60	Pos.
DW3	--	--	--	62-110	48	Neg.
	190-230	40	Neg.	**166-222**	56	Neg.
	278-334	56	Pos.	262-270	8	Pos.
				366-374	8	Neg.
	414-430	16	Neg.			
DW4	86-110	24	Pos.	54-62	8	Pos.
	126-174	48	Neg.	**102-158**	56	Neg.
	214-278	64	Pos.	206-254	48	Pos.
	326-374	48	Neg.	286-374	88	Neg.
	--	--	--	398-422	24	Pos.

Note. Time points and/or intervals for which the DW amplitude differed significantly from 0 µV, presented in chronological order after stimulus onset. Significant intervals corresponding to MMN responses are marked in bold, in the shaded cells. Significant intervals corresponding to the LDN response are underlined. (*) This response is too short to be considered significant.

Table 2.7

Results of the Mass Univariate Analysis for the 50-450 ms Time Window

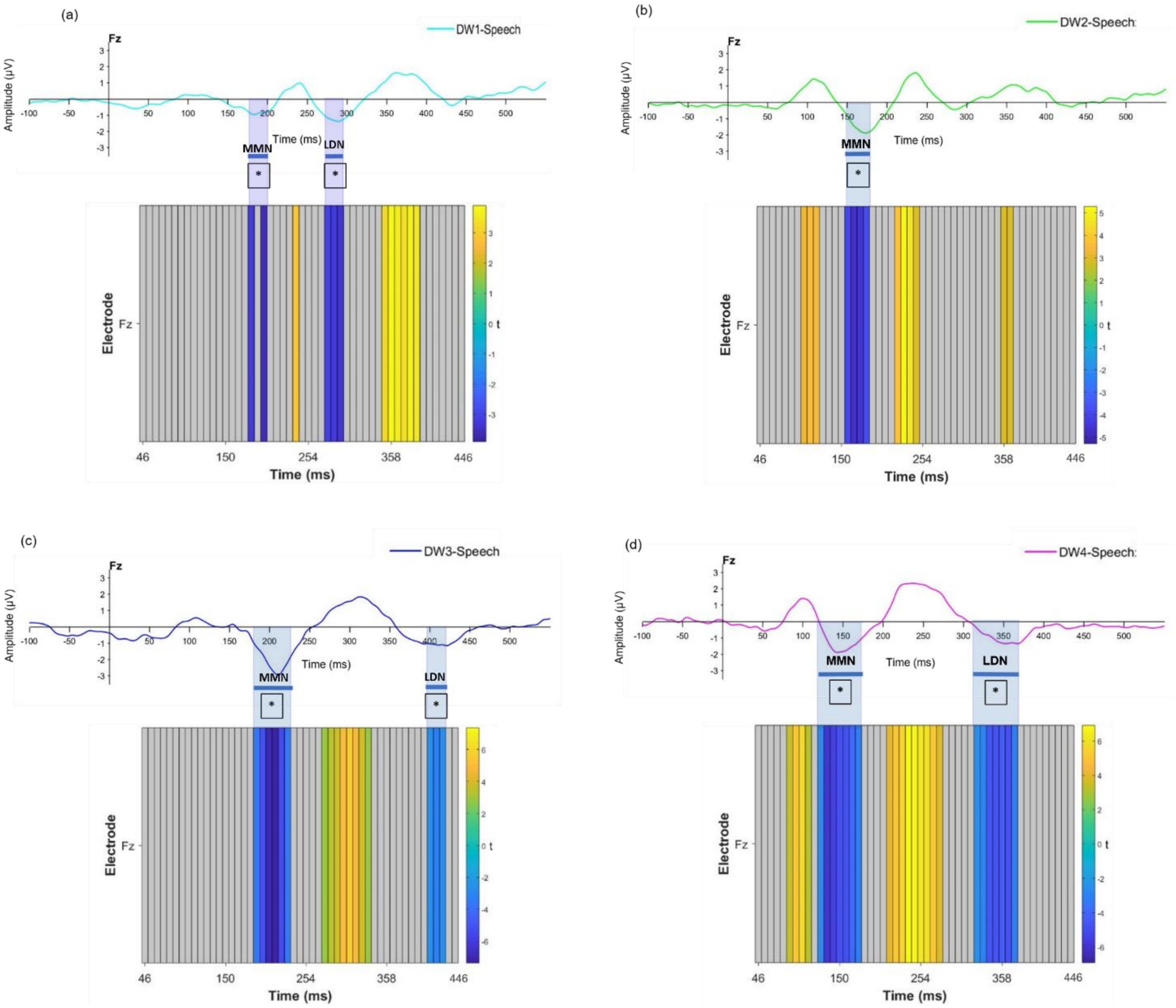
Stimulus type	Speech			Non-speech		
	Critical t-scores	Test-wise alpha	Estimated upper bound FDR	Critical t-scores	Test-wise alpha	Estimated upper bound FDR
DW1	-2.85 /2.85	0.01	0.6	-2.40 / 2.40	0.03	1.4
DW2	-2.80 /2.80	0.01	0.7	-2.73 / 2.73	0.01	1.0
DW3	-2.69 /2.69	0.02	0.9	-2.70 / 2.70	0.02	1.0
DW4	-2.41 /2.41	0.03	1.4	-2.37 / 2.37	0.03	1.7

Note. Critical t-scores (2-tailed) indicate the values at which the point-by-point t-scores computed for each DW start to significantly deviate from 0 µV. The test-wise alpha corresponds to the corrected q values whereas the estimated upper bound corresponds to the expected proportion of false rejections of the null hypothesis, this is, the FDR.

To help understand the MMN/LDN patterns, MUA raster diagrams in both figures were projected on the grand average difference waveforms. Figure 2.4 and 2.5 illustrates the intervals of significant responses for each DW type in both conditions. Each rectangular bin in the raster plot equals to 8 ms (at a 125 Hz sampling rate) and represents the value (*q*) of a t-test at electrode Fz. Colour towards green-yellow and blue indicate significantly positive and negative difference from zero, respectively. Grey squares, non-significant differences from 0 µV. Significant MMN and LDN were detected for all stimulus in both condition, except for LDN in DW2-S.

Figure 2.4

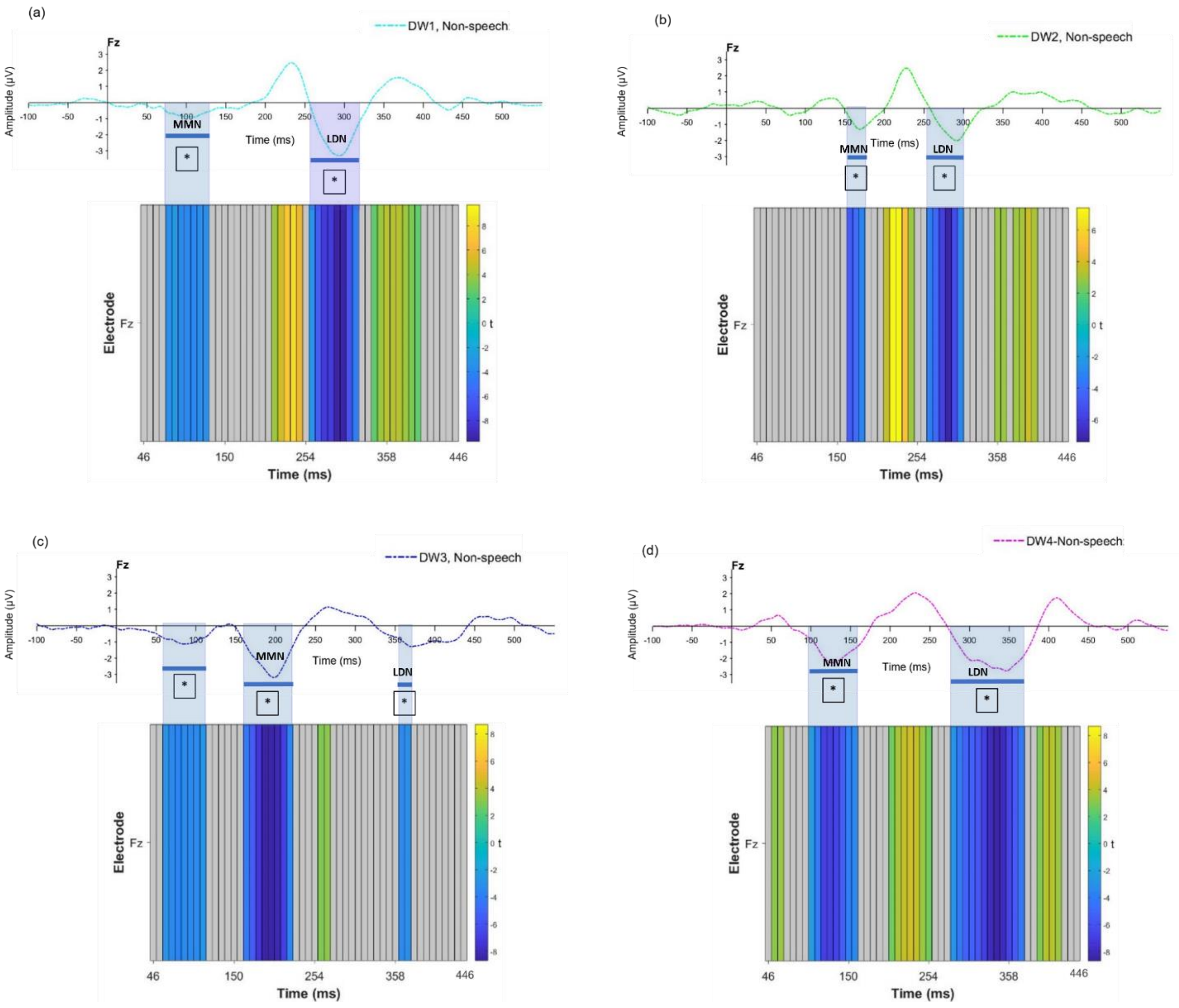
Significant MMN/LDN Responses at Fz for all DW in the Speech Condition



Note. Panel (a) DW1, (b) DW2, (c) DW3, and (d) DW4. Coloured bins in the raster plots indicate the time periods when the response amplitude is significantly different from 0 µV, at *q*=0.05, after correcting for multiple comparisons. Colour bar: t-scores for the MUA. Significant MMN/LDN responses were detected for all deviants, except LDN in DW2. All waveforms were low-pass-filter at 35 Hz (Butterworth IIR) before plotting.

Figure 2.5

Significant MMN/LDN Responses at Fz for all DW in the Non-Speech Condition



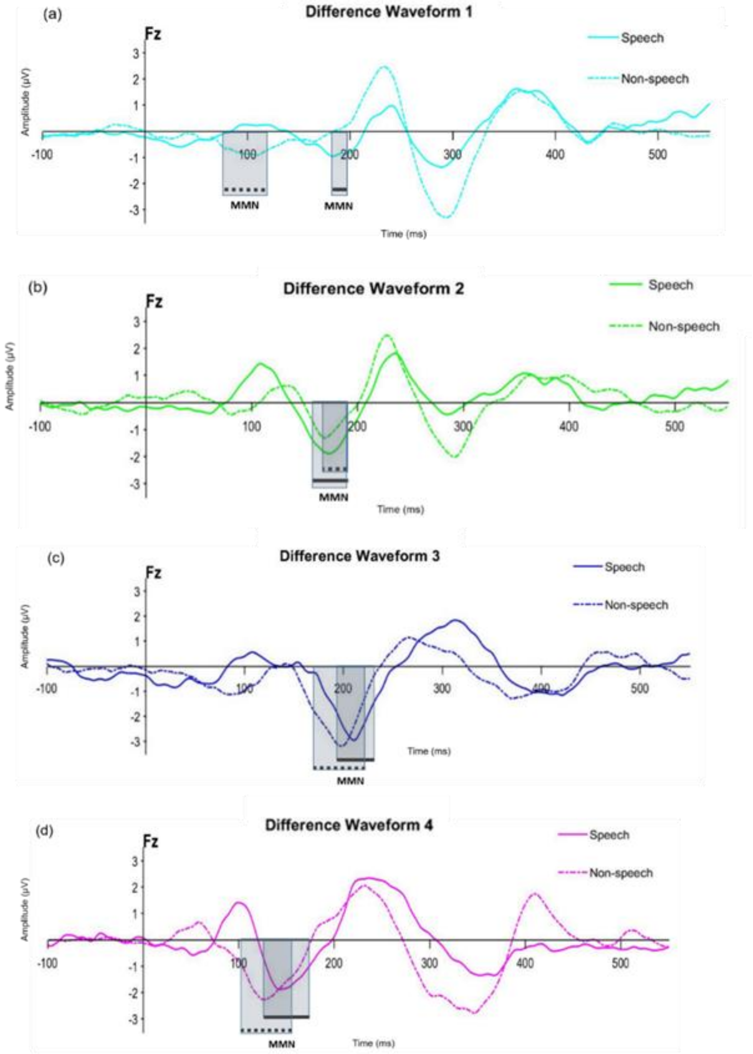
Note. Panel (a) DW1, (b) DW2, (c) DW3, and (d) DW4. Coloured bins in the raster plots indicate the time periods when the response amplitude is significantly different from 0 µV, at *q*=0.05 after correcting for multiple comparisons. Colourbar: t-scores for the MUA. MMN and LDN responses were detected for all NS deviants. All waveforms were low-pass-filter at 35 Hz (Butterworth IIR) before plotting.

2.3.2 *Comparison of MMN responses between conditions.*

The second analysis investigated between-conditions differences in MMN patterns for each S-NS pair (Figure 2.6). All DW pairs showed some MMN overlap except for DW1, which appeared much earlier and has longer duration in the NS than the S condition. In terms of latency pair DW2 had an earlier onset and longer response for the S condition, whereas DW3 and DW4 showed earlier MMN onsets and longer duration for NS stimuli.

Figure 2.6

Comparison of the Significant MMN Responses for Speech/Non-Speech Pairs at Fz



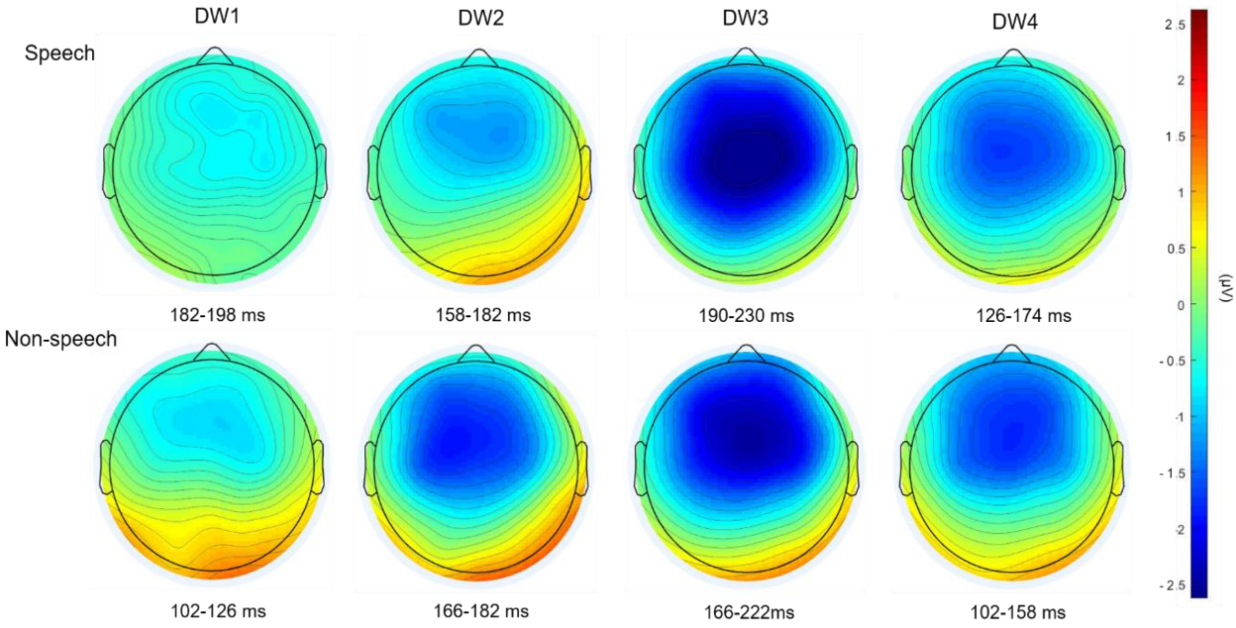
Note. MMN: shaded area; S: continuous line, NS: dotted line.

Differences in MMN Topography

In terms of the scalp topography, the MMN responses presented a similar pattern between conditions for S and NS stimuli on each DW type (Figure 2.7). This pattern consisted in amplitude shifts towards negative values with a frontal-central distribution that was more pronounced for DW3 and DW4 than for DW1 and DW2, in both conditions.

Figure 2.7

Scalp Distribution of the MMN Effects for each DW Type



Note. First row: Speech condition, second row: Non-speech condition. Numbers indicate the significant MMN interval for each DW type. Columns 1-4: DW type. Colourbar indicates mean amplitude (μV) across the time range (green/blue: negative values, yellow/red: positive values).

Differences in the MMN latency

The MMN overlapped for each S-NS pair (except for DW1, with earlier onset for NS), with longer responses in the NS condition except in DW2 (see Table 2.7). Peak negative latency was measured in the 100-250 time window and averaged across participants (see Table 2.8 for descriptive statistics).

Table 2.8

MMN Peak Negative Latency (ms) *for all S-NS Pairs in the 100-250 Interval*

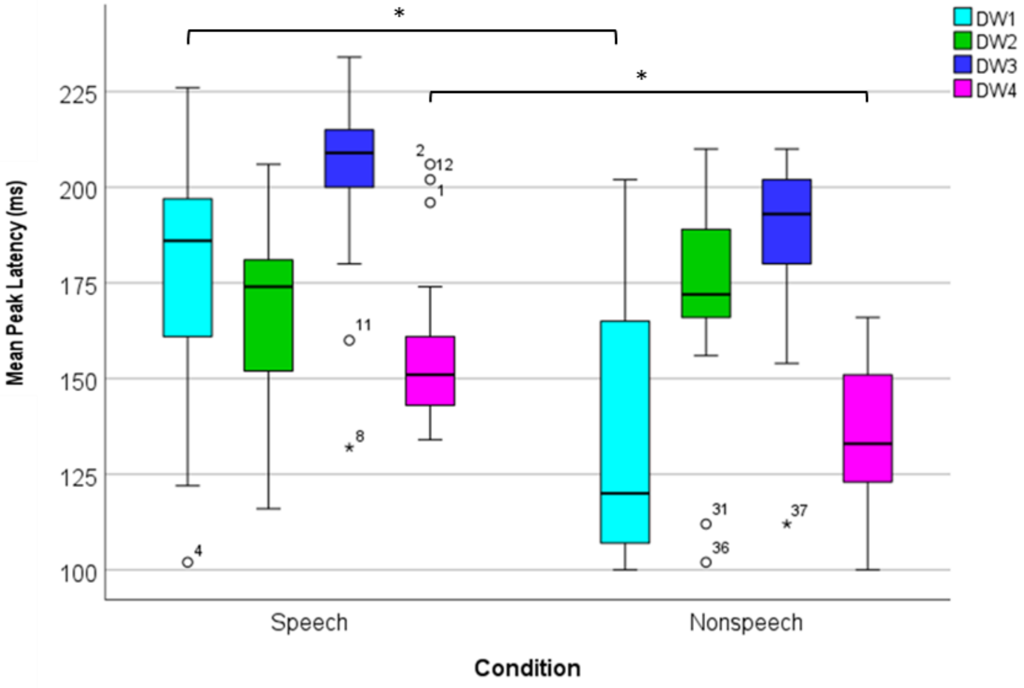
	Speech			Non-speech		
	M	*SD*	*Md*	*M*	*SD*	*Md*
DW1	178.5	29.8	186	137.1	36.17	120
DW2	167.4	22.5	174	172	26.35	172
DW3	202.5	23.2	209	186.4	23.36	193
DW4	157	21.3	151	135.9	17.53	133

Note. n=20.

After confirming non-normal distributions for peak latency in all DW (except for DW1-S, DW2-S and DW4-NS) by Shapiro-Wilk tests (results in Appendix 2.2), we conducted planned comparison with pairwise Wilcoxon signed rank test (Bonferroni-corrected alpha= .013). Results indicate significantly shorter peak latency in the NS than the S condition for DW1 (*Z*= -2.857, *p*= .004, *r* =-0.452) and DW4 (*Z*=-2.999, p= .003, *r* =-0.474) with large effect size, but no differences for DW2, (*Z*= -.841, *p*= .041. *r* = -0.133) and DW3 (*Z*=-2.013, *p*=. 044, *r* =-0.318) with small and medium effect size, respectively. Figure 2.8 presents mean values for peak latency per condition and DW type.

Figure 2.8

Box Plots for MMN Peak Latency Values in the Speech/Non-Speech Condition at Fz



Note. n=20. (*) indicates significantly shorter latency in NS condition at the 0.13 level.

Differences in the MMN Amplitude

To get an initial insight of the MMN magnitude and reference values for future studies, we calculated MMN mean amplitude over a 50 ms time window centred in the peak latency (Calcus et al., 2020). Table 2.9 presents descriptive statistics for mean amplitude.

Table 2.9

MMN Mean Amplitude (µV) for all Speech/Non-Speech Pairs

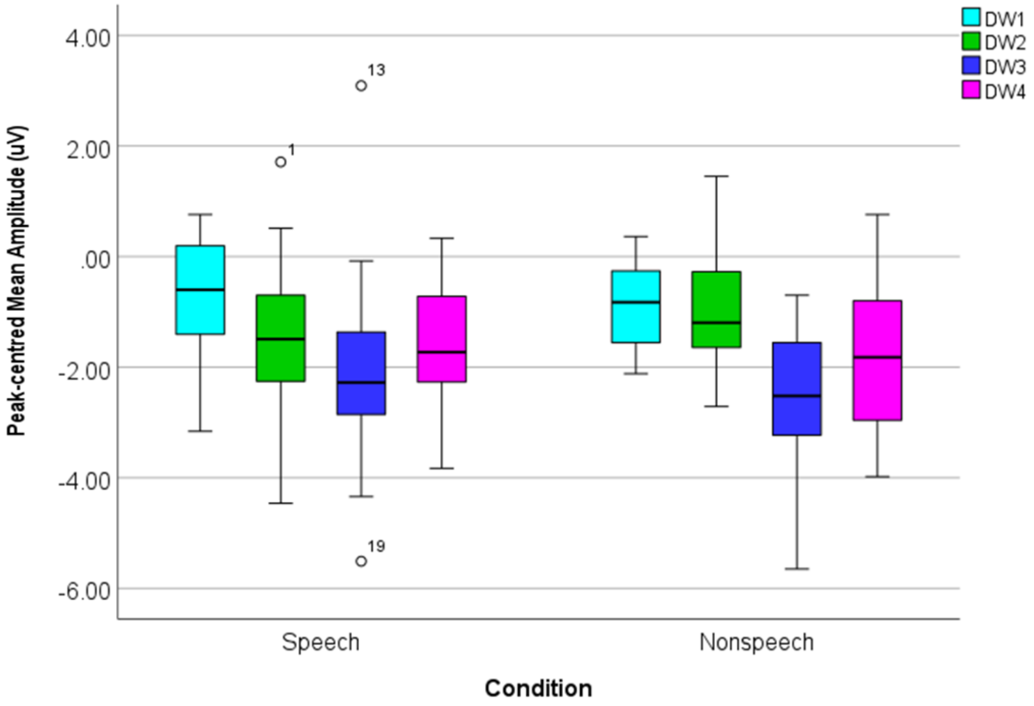
	Speech		Non-speech	
	M	*SD*	*M*	*SD*
DW1	- .76	1.13	-.91	.82
DW2	-1.59	1.51	-.82	1.23
DW3	-2.08	1.77	-2.58	1.25
DW4	-1.58	1.11	-1.78	1.36

Note. n=20. Peak-centred mean amplitude *M* and *SD* in the MMN interval.

In general, mean amplitude tended to be larger in the NS than the S condition, except for DW2, that showed the opposite pattern (Figure 2.9). Non-significant Shapiro-Wilk (append 2.4) tests indicated normal distribution for mean amplitude for all stimuli.

Figure 2.9

Box Plots for MMN Mean Amplitude in the Speech/Non-speech Condition at Fz



Note. n=20. Peak-centred mean amplitude, all S-NS stimuli.

To avoid double-dipping[3], we did not statistically compare peak-centred mean amplitude between conditions. Instead, S versus NS analysis of MMN amplitude was based on planned MUA comparisons of each S-NS pair over the whole 100-250 ms time window and not on peak-centred mean amplitudesignificant MMN period. For future studies this would be more informative about the time course of any effects than comparing mean latency

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[3] Or 'circular inference' refers to biasing results by using a data selection method that it is not independent of the intended statistical contrast (Cohen, 2016; 2017).

values. MUA demonstrated that the amplitude difference between conditions (S minus NS) was significantly different from 0 µV, for all DW pairs. Table 2.10 presents the time points with significant between-condition differences and the MUA results (*q*=0.05).

Table 2.10

MUA results for Between-Condition Amplitude Differences for the 100-250 ms Time Window

	Time points (ms)	Duration (ms)	Critical t-scores	Test-wise alpha	FDR Estimated Upper bound
DW1/S-NS	102-118 [a]	16	-2.55 / 2.55	0.020	0.6
	182-238	56			
DW2/S-NS	102-110b	8	-4.02 / 4.02	0.001	0.1
DW3/S-NS	102-110[a]	8	-2.88/ 2.88	0.010	0.2
	174- 190[a]	36			
DW4/S-NS	102 -126[a]	24	-3.27 / 3.27	0.004	0.2

Note. MUA for MMN amplitude for all *speech minus non-speech pairs.*

[a] *NS> S at* q=0.05.

[b] Positive polarity interval, not an MMN.

For DW1, significant larger negativity was detected for NS than S between 102-118 ms, whereas the opposite was observed in the 182-238 ms interval, consistent with the non-overlapping MMN on each condition for this pair (see Figure 2.10). For DW2/S, significantly larger amplitude were observed in the 102-110 interval for the S than in the NS condition, but for a positive polarity interval and only for 8 ms, so this should not be considered a MMN difference. For DW3/S-NS, MMN amplitude was significantly larger for the NS condition in the 102-110 ms, but only for 8 ms, and the 174-190 interval, for 36 ms. For DW4/S-NS, MMN amplitude was significantly larger for the NS condition in the 102-126 interval.

Finally, an exploratory MUA in a later LDN interval (250-450ms) detected significantly larger responses in the non-speech condition for DW1 (278-318 ms) and between 270-358 ms for DW4. No significant differences in amplitude were observed for DW3. Although a significant amplitude difference was observed for DW2 (286-302 ms), previous analysis detected no LDN for this DW type.

In summary, we observed significantly larger MMN amplitude in the NS condition for early DW1, DW3, and DW4, but the smaller for late DW1 and no differences for DW2. MMN peak latency was significantly shorter in the NS condition only for DW1 and DW4.

2.3.3 *Comparison of the MMN for different speech contrasts*

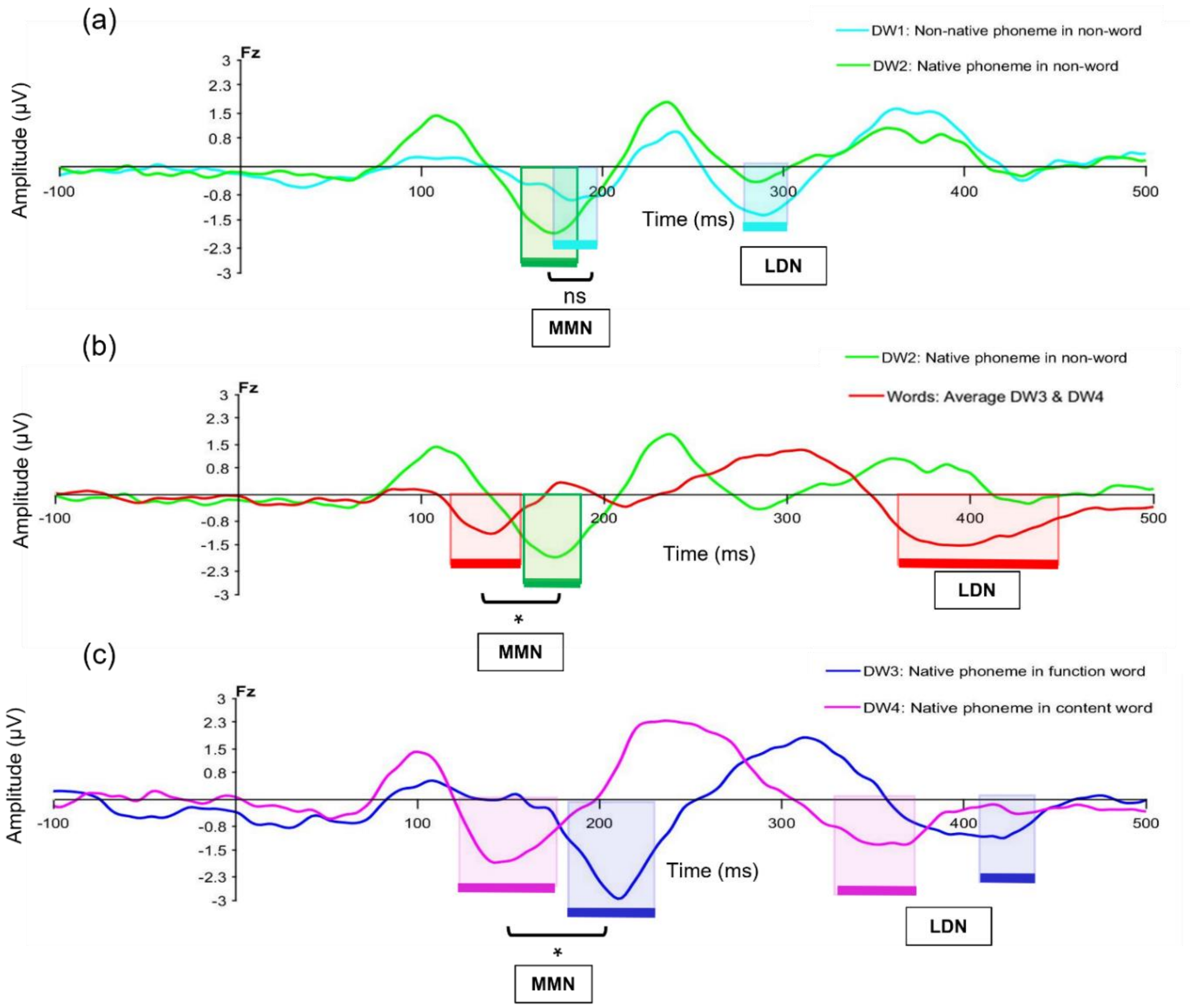
Considering that there were inevitable acoustic differences between the initial phonemes between speech stimuli, the final MUA was mostly focused on characterising the MMN patterns for future comparisons with groups of children.

To compare deviants with lexical vs non-lexical status we merged the responses for function and content words, into a new waveform “Words” (Wrds). For Words, MUA indicated a significant MMN response between 118-150 ms (duration of 32 ms), with mean peak latency at 154.4 ms (*SD*= 35.73) and mean amplitude of -1.55 µV (*SD*=1.08) along with an LDN response between 366-446 ms, with mean peak latency at 400.1 ms (*SD*=24.14) and mean amplitude of -1.72 µV (*SD*=1.68).

Figure 2.10 compares the significant MMNs (and LDNs, for reference purposes) for speech stimulus, contrasting three linguistic levels: (a) phonological (non-native versus native phonemes in non-words), (b) lexical (non-words versus words), and (c) semantic (function versus content words).

Figure 2.10

MMN Amplitude Differences in the Speech Condition



Note. Significant MMN responses for a) native (light blue) versus non-native (green) phonemes in non-words, b) non-words (green) versus words (red), and c) content (blue) versus function (pink) words. LDN shown only for illustrative purposes. (*) indicates significant differences in MMN amplitude (*q*=0.05).

Planned comparisons of peak latency using pairwise Wilcoxon signed rank test with Bonferroni-corrected alpha=0.0167 indicated significant differences only for word type, with shorter latencies for content than for function words (*Z*= -3.74 , *p*<.001, *r*= -0.6, large effect size), but no differences between native and non-native phonemes in non-words (*Z*= -1.91, *p*= .06, *r*= -.03) or between non-words and words (*Z*= -1.55 , *p*= .121, *r*=-.025), both with small effect. For the MMN amplitude, planned comparisons with MUA indicate significantly larger responses for non-words than words, and for function words than content words, but no differences between native and non-native phonemes in non-words (Table 2.11).

Table 2.11

MUA results for Amplitude differences between Stimuli in the Speech Condition

	Significant time points (ms)	Critical t-scores	Test-wise alpha	Estimated upper bound FDR
Non-native vs native phonemes (in non-words)	--	--	>= 0.017	--
Non-words vs words	166-198	-3.41/ 3.41	0.003	0.2
Function vs content words	102-126	-3.10/3.10	0.006	0.3

Note. Results of the MUA with a family-wise alpha level of 5% (*q*=0.05),

2.4 Discussion

2.4.1 *Summary of findings*

This study investigated the effects of the linguistic content of speech stimuli in the MMN patterns, aiming to validate a multifeature experiment in Spanish-speaking adults for future use in speech perception studies in young children. Our main results confirm our hypotheses, indicating that (i) significant MMN/LDN were detected for all stimuli (except in DW2-S for LDN), demonstrating that our experiment successfully elicited the responses of interest, (ii) between-condition differences were present, characterised by significantly larger amplitude in for all pairs in the NS condition (except DW2), and significantly shorter peak latency for DW1 and DW4 for the NS condition, suggesting different processing of linguistic versus non-linguistic sounds, and (iii), in the S condition, the MMN amplitude was significantly larger for non-words than words, and for function than content words, also with significantly earlier peaks for content than function words, indicating an effect of linguistic content. However, it is worth noting that despite their analogue acoustic structure, S-NS pairs were not an exact acoustic match.

Nevertheless, our first finding confirms the suitability of the multi-feature paradigm to contrast several linguistic and non-linguistic stimuli. Our MMN results are in line with previous research using MUA that reported similar temporal and amplitude patterns, for example, the CORE (Compendium of Open Resources and Experiments) initiative for ERP standardisation, developed by leading scientists at the University of California (see Kappenman’s et al., 2021). They reported MMN responses for contrasting tones distributed over the medial frontocentral electrodes, detected in the 113- 231 ms time window, with a peak latency of 187 ms and a mean amplitude of -1.86 µV, consistent with the patterns we observed in our data.

On the contrary, our exploratory analysis for the LDN indicated larger or equal amplitude in the NS than in the S condition, contradicting previous findings about larger LDN for S and its interpretations as an index of complex phonological processing (David et al., 2020). The fact that LDN for DW2-S was too short to be considered significant could be explained because we combined the MUA with Guthrie and Buchwald's (1991) recommendations, which could be too conservative and increase type II errors. It is possible that a less conservative approach would be able to identify an LDN response in DW2-S as well, especially considering that an 8ms significant response is already present. For example, instead of a priori defining time windows for analysis, it is possible to use peak-centred intervals for MMN detection and measurement, as in Calcus et al. (2020). Although the approach is less informative for a validation study like ours, future studies could use our results to select empirically justified time windows of interest.

A second main finding of this study was that MMN differed significantly between S-NS pairs. Larger responses in the NS condition for DW3 (function words), DW4 (content words) and early DW1 (non-native non-words), but the opposite happened for late DW1. This contradiction between early and late DW1 amplitude results could be explained because there was no MMN overlap between this pair of stimuli as in the other pairs. Future studies could elucidate it using measures other than point-by-point MUA (e.g., mean latency). Notably, smaller MMN amplitude for DW3-S and DW4-S indicate smaller responses for speech containing meaning than for their NS pair. Thus, our findings contradict previous evidence of no amplitude differences between S and NS analogues (Sussman et al., 2004), but also, those studies reporting significantly larger MMN amplitude for S than NS because of a language enhancement effect (Kuuluvainen et al., 2014; Näätänen, 2011).

The patterns we observed for S-NS pairs could be explained because our participants were all adult language users who processed their native speech automatically, especially if presented as isolated word forms. For them, the detection of NS may have been driven purely by acoustic processing. In contrast, detecting S would activate feature-specific language top-down effects (Heilbron et al., 2022) with smaller MMNs indexing more automatic processing of easy-to-detect speech. A simple way to investigate this further could be to average the MMN amplitude over the significant interval to analyse the main effects of the condition and stimulus type and their interactions. However, for this study, this would constitute double-dipping (Cohen, 2014). Regarding latency, some NS stimuli peaked earlier than the S ones but with no apparent pattern regarding the linguistic content (DW1 and DW4). Importantly, the MMN differences could be also explained by acoustic differences between S-NS pairs.

Although between-condition MMN differences in our study may reflect different cortical processing for linguistic and non-linguistic stimuli, interpreting the direction of these effects under the MMN hypotheses is not straightforward. Our findings do not support the memory-based account because there was no speech enhancement effect for S over NS, especially for meaningful words, whose long-term memory traces should be more robust than for non-words. From the neural adaptation view, smaller responses for S than NS for words could represent faster neural adaptation in the auditory cortex for less novel stimuli. Stimulus repetition in our experiment could have suppressed the MMN amplitude, but this should be equal for both conditions. Nevertheless, attenuation could be greater for S stimuli because having only five stimuli per condition would have made the S stimuli easier to remember (e.g. because of a more stable memory trace) and thus more likely to be suppressed than NS. According to Baart and Samuel (2015), saturation by repetition of a small pool of stimulus could confuse the lexical status of words and the non-lexical status of non-words. From the predictive coding perspective, the contextual prediction would be easier for S than NS stimuli, resulting in less prediction error and smaller MMN amplitudes for the S condition, especially for stimuli that are “less surprising” because of easier-to-retain linguistic content.

This is supported by evidence that predictive mechanisms do not only include anticipation but top-down language predictions (Heilbron et al., 2022; Wacongne et al., 2021).

A third central finding of this study is the significant differences in the MMN amplitude and latency between speech stimuli. Although their interpretation should be cautious because of inevitable acoustic differences in the initial phonemes, previous research indicates that our results could reflect genuine top-down language influences on low-level auditory processing. Our final analysis showed that the MMN amplitude and latency differences depended on the linguistic content only when meaning was involved, with lexical and semantic but no purely phonological effects. Interestingly, larger MMNs were detected for less informative linguistic representations (non-words than words and function than content words), which would be consistent with the predictive coding interpretation. Similar findings were reported by Scharinger et al. (2016), who observed larger MMNs for less predictable than more predictable vowels, indicating a top-down effect of the stimulus linguistic category on the MMN amplitude. In terms of MMN timing, the opposite pattern was observed, with significantly shorter latency for content than function words. Qualitatively, earlier onset was observed for more informative linguistic content as words than non-words and content than function words, suggesting faster cortical responses for higher-order linguistic content than for more phonological-based processing, as in non-words.

Notably, the direction of the linguistic content effects again contradicts previous studies that reported enhanced amplitude for words versus non-words using similar designs (Näätänen et al., 2007). Methodological differences between studies could explain this finding. For example, Gansonre et al. (2018) used a later time window (~300 ms after stimulus onset) and ERP parent (non-subtracted) waves instead of difference waveforms, reporting semantics effects for different classes of words but only in terms of scalp topography. In addition, our study used MUA for between-condition analysis which was not optimal for comparing MMN amplitude for DW1S-NS as the significant intervals did not overlap and may not necessarily correspond to the significant MMN. This reinforces the idea that discrepancies in results between MMN studies may arise from methodological differences, making it hard to compare findings across studies without a data analysis gold standard and large-scale replication.

Overall, our results indicate that the magnitude of the MMN reflects top-down language influences in line with predictive processing but contradicts previous findings by demonstrating that easier, more automatic detection for more informative linguistic content is reflected in the MMN as smaller amplitude for speech stimuli. On the contrary, the timing of the MMN (latency) agrees with previous findings, at least at the single-word processing level.

2.4.2 *Strengths, limitations, and future research*

An important contribution of this study is that our experiment elicited consistent MMN responses for all the DW types, characterising different aspects such as timing, amplitude and scalp patterns, which can inform future studies in Spanish speakers. Moreover, these responses were obtained in an EEG testing time as short as 30 minutes making these materials and findings a valuable resource for future studies in groups of participants that are less able to tolerate long testing sessions, for example, young children or clinical populations. Another contribution of this study is that we provided empirical evidence of the effects of linguistic content on the MMN amplitude and latency at the single-word level. However, further research is needed to investigate to what extent the top-down effects operate beyond isolated words (Hagoort, 2019).

An essential point for speech perception experiments is selecting good non-speech analogues as control conditions to avoid potential acoustic confounds (Rosen & Iverson, 2007). The main limitation of this study is that, despite selecting adequate non-speech analogues as a control condition, changing the initial phonemes entails inevitable acoustic differences that generate an MMN response but may also act as a confound when comparing language effects between speech stimuli. Because this experiment is intended for children, the selection of function and content words prioritised phonological processing factors, such as the age of acquisition and oral frequency (Guarda, 2010), even if this implied larger acoustic variations in the initial phonemes. For this reason, the initial consonants for non-word stimuli involved only fricatives between standards and deviants, but the word stimuli involved other differences: stopped and lateral distinctive features for function words and voicing for content words, resulting in more pronounced acoustic/phonetic differences for meaningful stimuli (D3 and D4). These differences are especially relevant when using Spanish consonants, in which voiced/unvoiced contrasts are easier to detect (Guarda, 2010). Thus, it is essential to acknowledge these differences in acoustic complexity between S-NS pairs when interpreting our MMN results and conducting similar studies in the future.

Our statistical analysis attempted to reduce the influence of other acoustic differences by contrasting only speech/non-speech stimuli that were analogue pairs. However, as between-condition MUA requires subtracting the MMN non-speech for each corresponding speech stimulus to test against 0 µV, the statistical power to detect true effects could have been reduced when avoiding type II error. Moreover, as MUA does not inform about effect size and power, our results could have been affected by a small effect size and low power to detect any potential effects of linguistic content. In the future, these results could be used as reference values to a priori define more precise time windows of interest and use peak-centred mean amplitude instead of MUA as it seems a more appropriate measure for comparing different speech stimuli, especially those that do not overlap in time. This could increase power without the risk of double-dipping.

A second limitation is that our decision to include multiple contrasts and two experimental conditions, although beneficial from the perspective of time optimisation and confound control, resulted in a smaller number of deviant trials per stimulus type so we could keep the testing session to a reasonable duration. Even when the minimum number of trials that were obtained for each stimulus type (50 per deviant type and 200 for standards) is considered adequate (Luck, 2014), in the future, the signal-to-noise ratio might have been increased by reducing the number of deviants or by extending the number of deviants per condition. Interestingly, this limitation could be solved by using new analysis methods that are more powerful even with fewer trials, for example, linear modelling and multivariate methods (see Chapter 5).

Finally, future research could further investigate the effect of language content on the response temporal patterns using this paradigm, including a more detailed analysis of the MMN latency and duration. In addition, time-frequency analysis could complement these results, as the study of neural oscillations may be especially suitable for studying language development and comparing different age groups. Thus, our next step is to analyse these data using power and inter-trial phase coherence measures, comparing the results to those obtained by children in the speech condition of this experiment.

2.4.3 *Conclusions*

In sum, this study showed the validity of our experiment in eliciting consistent MMN responses that not only detected acoustic contrasts but support an effect of the stimulus speech status and linguistic content. As predicted, linguistic modulations on the MMN amplitude were observed as an effect of the stimulus speech versus non-speech configuration, lexical status and word type, suggesting differences in the cortical processing of speech depending on the linguistic content. However, these results also could be explained by acoustic differences between our S-NS pairs. Importantly, this experiment can be replicated in other Spanish-speaking populations or applied to different age/clinical groups.

Chapter 3. Language modulations on speech perception in children with typical language development and DLD

3.1 Introduction

Between the ages of 3 and 6 years old, children can understand spoken language effortlessly, but they are still less proficient than adults. This suggests that there are differences in how the brain of adults and children process speech, but many aspects in this field are yet to be investigated. For example, it is unclear whether children exhibit the same top-down modulations on speech perception observed in adults (see Chapter 2). In addition, despite language acquisition follows well-defined trajectories, not all children present the same skills at the same age, for example, those affected by Developmental Language Disorder (DLD). Thus, children with typical language development (TLD) may process speech differently than those with DLD, because of less effective or disrupted language top-down modulations, as proposed by Bishop et al. (2012), although there is little evidence on this regard.

So far, the mismatch negativity (MMN) and the late discriminative negativity LDN, as well as their less-mature version, the mismatch response (MMR), have been widely used to study language and speech perception development. However, there are methodological issues when comparing adults and children ERPs (see Chapter 1), especially because of the intrinsically smaller-scale responses in adults. This study addressed this issue by complementing ERP measures with time-frequency (TF) analysis, using an amplitude-free measure as inter-trial phase coherence, (ITPC) to inform about non-time-locked cortical activity. We aimed to determine whether the MMRs (MMN/LDN) for different speech content reflected group-level differences in top-down modulations because of different language status, by comparing children with TLD and DLD, and children versus adults (Chapter 2). For children, we also examined the associations between the MMRs and their phonological skills.

3.1.1 MMR in speech perception development research

In infants and young children, the MMN and LDN may present a negative or positive polarity, so *mismatch response* (MMR) is a generic term to refer them. Although negative, MMN-like responses can be detected in the first six months of life (Cheour et al., 1998), there is great variation within and between children, with some studies reporting positive MMRs until the age of 6-7 years (Maurer et al., 2003). Like the adult MMN/LDN, the MMR reflects the brain's sensitivity to physical and abstract changes in a sequence of regular inputs (MacLean & Ward, 2014), as occurs in speech contrasts. Moreover, the MMR can be elicited with speech stimuli using a multifeature paradigm to optimise data collection (Lovio, et al., 2009; Niemitalo-Haapola et al., 2013), and during unattended listening, making it a valuable measure in speech developmental research.

As for other ERPs, the MMR patterns change from birth to adulthood (De Haan, 2007; Sussman et al., 2008) reflecting typical auditory maturation (Morr et al, 2002). In children, MMRs may show a more distributed scalp localization than in adults (Cheour, 2007), or reversed polarity (Paquette et al., 2013). However, there is great variability in the literature about the MMR latency, amplitude, scalp distribution and polarity for each age, especially in clinical groups (Bishop, 2007). Overall, the MMR seems to become more stable with age, showing greater amplitude, shorter latency, and the typical negative polarity.

MMRs in TLD children

In typically developing children, multiple studies have described age-related changes for the MMR/MMN/LDN measures (see Näätänen et al, 2019). Näätänen (2003) states that language-specific phonetic memory traces for the native language develop during the first few months of life and are reflected in the MMN. For frequency deviants MMN peaks between 120-400 ms post-deviant detection at age 3 years-old, whereas for 5–8-year-olds MMN peak latencies for occur between 190 and 270 ms, a more adult-like range (Maurer et al., 2003). When using smaller age bands (4–5- and 6–7-year-olds) the MMRs appears to be delayed and longer in children (Shafer et al., 2010) whereas for older children (6-13 years), latency becomes more like that observed in adults (Csepe, 1995). In general, the MMR latency correlates negatively with age during early childhood because of neuromaturational changes leading to faster information transmission in the brain (Bishop, et, al, 2010a; Shafer, et al., 2000).

The MMR/MMN amplitude, however, seems not to follow a linear trajectory but a U-shaped curve during development (De Haan, 2007) with adult-like amplitudes in infants but significantly smaller responses in early childhood, until late childhood, when their amplitude increases again until adolescence (Bishop, et, al, 2011). Paquette et al., (2013) reported smaller MMRs in children than adults (n=14), with greater negativity in older (n=14, age 8-13 years) than younger children (n=12, age 3-7 years) both for speech and non-speech contrasts. Bishop, et al., (2010a) measured the MMRs for tones and syllables in children (n=30, 7-12 years), teenagers (n=23, 13-16 years), and adults (n=32, 35-56 years), reporting significant age-related increment in mean amplitude for the MMN and a decrease in the LDN. Other studies report that over the age of 6 years, the MMN amplitude is as large as, or even larger in children than in adults (Cheour et al., 2001; Csepe, 1995). Although the literature reports inconsistent findings, there seems to be changes in the MMR latency and amplitude that suggest ongoing maturation of cortical speech processing during early childhood.

As occurs in adults, the type of acoustic contrast determines the patterns of the MMR in children, with different latency and amplitude values for non-speech versus speech stimuli (Dehaene-Lambertz & Baillet, 1998; Paquette et al., 2013), and for speech with different linguistic content (e.g., syllables versus words). For example, Kuuluvainen et al (2016) used a multifeature paradigm to investigate cortical discrimination in 6-year-old typically developing children (n=63), reporting larger MMN for contrasts in syllables than for their acoustically matched non-speech equivalents. In young children, MMR is sensitive to changes in various acoustic features of speech sounds, such as frequency, duration, intensity, and phoneme identity (Kraus et al., 1993). However, the MMRs do not only depend on processing of the acoustic features of speech but are influenced by psycho-linguistic factors as phonological structure, word grammatical function and word distributional frequency.

Previous literature has described the effects of different linguistic content on the MMR at different ages, for example, more consistent responses for native than non-native phonemic contrasts between the ages of 6-12 months (Rivera-Gaxiola, et al., 2005). In syllables, for vowel contrasts, a study in 3-year-old Finnish children showed MMN-like responses peaking in the 300-400 ms range (Čeponienė, et al., 2003), whereas in French-speakers aged 3 and 7 years-old, changes in initial consonants elicited MMN peaking at 270 ms (Paquette et al., 2013). Strotseva-Feinschmidt et al., (2015) studied discriminative responses for two German function words differing in the final phoneme (articles der/den) and frequency of occurrence in 34 children at age 3 years-old. They found that for *der* (high frequency) both an MMN and a LDN response were observed, whereas the less-frequent word *den* elicited only a LDN, suggesting easier processing of higher-frequency words. All these differences in the MMR, MMN and LDN were attributed to linguistic content, but it is noteworthy that they could results from acoustic differences between the stimuli, for example, different duration or spectral content.

In addition of the speech information itself, the MMRs are modulated by the linguistic context in which the speech sounds are presented (Čeponienė et al., 2003). For example, there is MMR enhancement when a deviant syllable occurs in a word compared to when it occurs in isolation. David et al., (2020) investigated MMRs to non-words with different phonological complexity in school-age children (n=22, age: 6-10 years) and adults. They observed that for more complex syllables, the MMN was smaller, but the LDN was larger in children than adults, in agreement with interpretations of the LDN as an index of speech processing complexity (Kujala & Leminem, 2017). These findings indicate that the MMN/LDN patterns not only age-dependant but influenced by the stimuli, contexts, and measures used to study them.

In children with TLD there is evidence of associations of MMN patters with language skills. From the age of 7.5 to 24 months, multiple studies have reported a positive correlation between the MMN amplitude for native phonemic contrasts with behavioural phoneme discrimination measures (Kuhl & Rivera-Gaxiola, 2008; Rivera-Gaxiola et al, 2005), and suggest they may predict receptive language skills at later ages. For example Guttorm et al., (2010) found that the MMN measured at birth in infants with (n=12) and without (n=11) risk of dyslexia predicted their language skills at age 5 years. A study by Linnavalli et al., (2017) showed that children (n=70, age 5-6 years) with better phoneme processing performance showed larger MMN that those with poorer behavioural results. Similarly, a study in pre-schoolers (n=166, mean age= 5 years 6 months) by Norton et al., (2021) found significantly larger MMNs in the late window (300-500 ms) for /ba/-/da/ contrasts in children with typical phonological awareness (PA) skills than in those with low PA skills. These results relate the

MMN to phonological processing abilities, however, other studies show no relationship between the MMN and behavioural measures (e.g., Bishop & Hardiman, 2010).

MMR findings in DLD

In children with DLD, cortical speech processing and its MMR signatures during early childhood are less understood, especially when compared with other neurodevelopmental disorders as dyslexia or autism (Nallet & Gervain, 2022). Nevertheless, some studies have suggested that atypical cortical processing of speech may explain some symptoms (Evans & Brown, 2016). Overall, studies have found that children with DLD exhibit reduced MMR amplitude and/or delayed MMR latency compared to typically developing children (Bishop & McArthur, 2005; Friederich et al., 2004; Kujala et al., 2007). Some MMN findings suggest that children with DLD have difficulties in processing the acoustic features of speech and in detecting phonemic contrasts. A review of MMN findings (Kujala & Leminem, 2017) concluded that children with DLD show poorer and slower neural discrimination of speech sound, resulting in smaller MMN amplitudes, delayed latencies, atypical scalp distributions and less left hemisphere lateralization than TLD children.

However, other studies have reported no differences in MMR between children with DLD and typically developing children. For example, a MEG study by Pihko et al. (2008) in children between 5–7 years, compared cortical discrimination of syllables with changing vowels or consonants and detected no MMN differences between children with DLD (n=11) and controls (n=11). Similarly, Bishop, Hardiman, & Barry (2010b) compared discrimination of tones and phonemes with small and large differences in children and teenagers with DLD and TLD aged 7-16 years. They reported no group differences for the MMN and LDN amplitude for large deviants, although LDN were reduced in the DLD group for the small deviants. Thus, results so far are inconsistent and have important methodological differences, hindering their interpretation and replication (Bishop, 2007).

As in TLD children, several studies suggest a connection between the MMN/LDN and language skills in DLD-affected children. Kujala et al. (2007) found that the MMR amplitude correlated positively with language abilities in children with DLD (as in TLD children), with stronger MMRs associated with better language outcomes. A review of MMN findings in DLD by Kujala & Leminem (2017) indicates an amplitude reduction particularly over the left scalp areas, and delayed latency in infants and children at familial risk for language deficits or with DLD diagnosis. Furthermore, they linked atypical neural responses with DLD, and indicate an association between the MMR and language skills in children be a useful tool for predicting language outcomes in children with DLD. However, none of the studies reviewed by Kujala & Leminem (2017) investigated processing of meaning, only of phonemic contrasts in syllables (e.g., /ba/ versus /da/) and no null findings were reported in this review.

Different factors may explain reduced MMRs in children with DLD, for example, impaired neural mechanisms underlying the MMR generation, although there is little evidence in this regard. Some studies have shown that MMR is generated by the same sources as the MMN in the auditory cortex (Näätänen et al., 2007) which could involve some cortical differences in children with DLD at this level, despite DLD is not an auditory deficit. Another possibility is that the reduced MMR response in children with DLD could reflect specific difficulties in processing speech sounds. Children with DLD can have poorer phonological processing skills than typically developing children which may affect their ability to detect changes in speech sounds, but not in other sound contrasts (Bishop et al., 1999). So far, findings only seem to confirm that language processing networks in the brain as well as the auditory pathways are still developing during early childhood.

This discrepancy and lack of evidence in MMR developmental findings is mostly explained by the many different methodological approaches. For example, the lack of a gold standard method to determine the presence of an MMR, studies grouping participants in broad age ranges instead of narrow bands, or the use of peak measures which are sensitive to age differences in waveform variance may introduce spurious effects in children speech perception studies (Bishop, et al., 2010a; 2010b; Bishop, 2007). In addition, most MMR findings come from studies using non-speech and non-meaningful speech stimuli, which may not be easily generalised to phonological or speech processing in natural settings. All these factors limit the utility of the MMR, for example, as a tool to help explain speech perception development.

3.1.2 Time-frequency ERP analysis and speech perception development

Although time-frequency analysis (TF has been less used than ERPs to study auditory development, it may be a useful method to help further our understanding of language and speech perception development. TF analysis preserves non-stimulus locked oscillatory activity that is abundant in children and which otherwise are averaged-out by the ERP technique (Maguire & Abel, 2013). Moreover, TF analysis tends to increase the SNR, especially for frequencies below 20 Hz (Cohen, 2014) which is an advantage when dealing with noisy data, as children's, making it more reliable than time-domain measures for MMN identification (Bishop & Hardiman, 2010). In MMN experiments, the amplitude of this response has been considered to reflect phase realignment (increased synchrony) in the theta range, (Bishop, et al., 2010b; Bishop & Hardiman, 2010; MacLean & Ward, 2014), whereas the LDN would reflect event-related desynchronization in a broader range of low frequencies, including delta, theta and alpha (Bishop et al. , 2010b).

In adults, studies using time frequency analysis of the MMN have found increased inter-trial phase coherence (ITPC) for detection of deviant than standard non-speech sounds. A study in adult's (n=16) by Fuentemilla et al. (2008) found larger theta ITPC for duration deviants than for standards at temporal and frontal sites, and larger event-related spectral perturbation (ERSP) for deviants at frontal sites only, interpreting them as evidence of different MMN generators. Similarly, two studies by Hsiao and colleagues (n=10 adults) showed larger theta phase locking values (PLV) and spectral power for duration deviants than for standard stimuli (Hsiao et al., 2009; 2010). Bishop & Hardiman (2010) also examined adult's (n=17) responses to duration contrasts, reporting no changes in ERSP power but significant increase in theta ITPC, which they considered an index of event-related phase-resetting. Another study by Bishop, Hardiman & Barry (2010a) using tones and syllables contrast concluded that MMN resulted from greater theta (4-7 Hz) phase synchronization for deviants than for standards, correlating theta ITPC with behavioural discrimination thresholds For frequency deviants, Ko et al., (2012) found that theta power and ITPC were larger at frontal-central electrodes. Although these findings consistently indicate a role of increase theta ITPC in auditory deviance detection, most of them were elicited by non-speech stimuli, so it is unclear whether they can be generalised to speech perception.

MMN and theta oscillations in TLD children

In paediatric MMR research, few studies have used time-frequency analysis, but those that have, report enhanced cortical synchronization at different frequency bands during detection of deviants in comparison to standards, as has been also described in adults. Previous studies suggest a relationship between increased stimulus-induced phase synchronisation, and ERP changes between childhood and adolescence (Müller et al., 2009; Poulsen et al., 2009). Studies in infants using speech stimuli suggest that age-related increases in power and ITPC in the delta, theta and gamma bands between 6 and 12 months of age may reflect selective enhancement and perceptual narrowing for native phonemes (Kuhl, 2010; Ortiz-Mantilla, et al 2013).

From childhood to early adolescence, time-frequency analysis of the MMN shows increases in theta phase synchrony for detection of deviant in comparison to standards, indicating more efficient sound processing with age. Bishop, Hardiman & Barry (2010a) studied cortical discrimination of deviant tones and syllables in children (n=30, 7 -12 years), adolescents (n=23, 13-16 years) and adults (n=32, 35-56 years), reporting theta phase locking increases with age, with largest phase locking values for adults and larger for adolescents than children. A longitudinal study by Bishop et al., (2011) in 7 and 9 years-old children (n=150), showed that two years after a first EEG, there was an increase in theta inter-trial phase coherence for tone contrasts in frontal but not in temporal regions.

Together, these findings support the idea that the maturation of the MMN neural substrates is accompanied by age-related increases in oscillatory synchronization. During early childhood synchrony increases seem to occur in the theta range and mostly in with frontal than temporal scalp distribution, suggesting more involvement of top-down processing. In adults, theta synchronization is thought to play a key role in syllabic segmentation (Giraud & Poeppel, 2012). However, there is very little research about the role of theta synchronisation in children with TLD and DLD, and how theta synchronisation is related to manipulation of the speech linguistic content, with a lack of clarity about the developmental trajectories.

Atypical oscillations in DLD

Although the role of oscillatory dynamics in DLD has been far less investigated than in other neurodevelopmental disorders such as dyslexia or autism spectrum disorder (for a review see Nallet & Gervain, 2022), some evidence indicates that atypical activity may as well underlie language disorders. Bishop et al. (2010b) compared cortical discrimination of tones and speech sounds in children with DLD (7 to 16 years old) and TLD measuring low-frequency-band synchronization in the MMN/LDN intervals. Although no between-group differences were detected in the MMN responses, they observed that the TLD but not the DLD group, had a significant drop in power in the LDN interval in relation to the MMN range for the low frequency bands (delta, theta, and alpha). The authors suggested that this lack of event-related desynchronization for LDN but with an intact MMN indicates an inability of disengage neural activity in the DLD group, after initially 'normal' auditory change detection (Bishop et al., 2010). Although this is an interesting theory, no further evidence has emerged regarding this interpretation.

Heim et al. (2011; 2013) studied oscillatory dynamics during rapid auditory processing of tone doublets in children between 6-9 years with and without language disorders. They found atypical gamma activity (29-52 Hz range) in the language-impaired group, with significantly reduced amplitude and phase-locking values of early (45–75 ms) oscillations for the second tone in the doublet. The authors interpreted these findings as evidence of altered oscillatory timing in language-impaired children when processing rapid sequences of tones. Again, they used non-speech or simple speech stimuli, making it hard to differentiate higher order language modulations and effects of the stimulus linguistic content.

In conclusion, the MMR is a valuable tool for investigating the neural mechanisms underlying speech processing in children. In typically developing children MMR has been shown to be sensitive to speech contrasts, showing a positive correlation with language development and somewhat identifiable developmental trajectory. In children with DLD, MMR has been found to be reduced in amplitude and/or delayed in latency, suggesting difficulties in processing the acoustic features of speech sounds. However, further research is needed to determine important aspects as if MMRs are modulated by top-down language effects in children if they are reduced or atypical in children with DLD, and how account for important methodological issues, some of which will be addressed in the present study.

3.1.3 The current study

The aim of this study was to verify the presence of adult-like MMN/LDN responses in children with TLD and DLD for stimulus with different linguistic content and compare their parameters with those observed in adults in our previous experiment (Chapter 2).

To account for the need of more cross-linguistic research in this field, we recruited a group of Spanish-speaking children with DLD and age-matched controls from the same preschool in Santiago, Chile. This would allow us to determine if a top-down effect of language skills was present during early childhood and if it was reduced in DLD children.

Specifically, we addressed the following research questions:

(i) Is cortical speech processing modulated by top-down language skills in early childhood?

(ii) Do cortical responses to speech vary with children's language proficiency (e.g., phonological skills)?

Based on previous findings, we hypothesized that an MMR would be present in children in response to phonological contrasts, but the patterns of these responses would vary between the TLD and DLD groups, and between children and adults, because of the differences in language skills between the groups and the interaction of these skills with the linguistic content of the stimuli.

Specifically, we expected that responses at electrode Fz would be (1) more immature (e.g., positive instead of negative polarity of MMRs), (2) less robust (e.g., smaller mean amplitude), 3) less synchronized (e.g., reduced ERSP and ITPC) in DLD than TLD children, and in children than adults, and 4) correlated with measures of phonological awareness.

3.2 Methods

3.2.1 Participants

Twenty-nine Spanish-speaking children between 4.9 and 5.7-year-old were invited to this study but twenty-seven completed this experiment, as two children refused to wear the EEG gear. Participants were divided in two groups according to their language developmental status: a group with a previous diagnosis of expressive-receptive Developmental Language Disorder (DLD, n=16, 6 female, *M*age 5.2 years, range 4.9-5.7 years) and a group of controls with typical language development (TLD, n=11, 7 female, *M*age 5.2 years, range 4.10-5.6 years). In addition, data from 20 adults from our previous study (Chapter 2) was included for age-related comparisons.

Children in the DLD group were diagnosed at least one year before this study by a Speech and Language Therapist (SLT), as part of the initial assessment for preschool admission of children at risk or with parental concern of language difficulties. The diagnosis was based on the Chilean legislation for Language Special Preschools[4], and is requested by paediatricians, child neurologists or psiquiatrists whenever a language disorder is suspected. The SLT diagnostic procedures include full parent or carer interview and medical history, functional assessment of orofacial structures and hearing, speech sound production screening, and three standardised language tests that assess comprehension and production skills. These tests have been adapted and normed for Chilean children between the ages of 3.0 and 6.11 years and comprise the Exploratory Test of Spanish Grammar by A. Toronto (STSG; Pavez, 2003), the Test for Auditive Comprehension of Language by E. Carrow, Chilean Application (TECAL; Pavez, 2004), and the Test to Evaluate Processes of Phonological Simplification,

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[4] Decreet 170 and 1300, available at https://especial.mineduc.cl/wp-content/uploads/sites/31/2018/06/DTO-170_21-ABR-2010.pdf, and https://especial.mineduc.cl/wp-content/uploads/sites/31/2016/08/201304231710590.DecretoN1300.pdf

revised version (TEPROSIF-R; Pavez, Maggiolo & Coloma, 2008). The STSG assesses the comprehension and production of morfosyntactic structures, the TECAL measures comprehension of vocabulary, morphology and syntax, whereas the TEPROSIF-R assesses expressive language, measuring the amount and type of phonological simplification processes.

Although for this study we were not able to access the school assessment records because of privacy restrictions, all children in the DLD group had previously received a diagnosis of expressive-receptive DLD variant. This provided some homogeneity for this group, as all children met the following criteria according to the Chilean legislation: (i) being affected by language difficulties that significantly impair their day to day communication, (ii) exhibit significant poor performance in the three aforementioned language tests, indicated by scores 2 SD below the age-expected norm, and (ii) not being affected by other concomitant neurodevelopmental disorder, health condition or environmental factor that explains the language deficit. Importantly, the tests used for diagnosis were not used again as variables in this study to avoid introducing circularity, but their outcome provide a way to

To control for socioeconomic factors, all children were recruited from the same preschool in Santiago, Chile, from the special education and mainstream division, respectively. For the control group, children were invited to participate after checking they were native monolingual Chilean Spanish-speakers, used Spanish as their first language at home and had no history of any neurodevelopmental disorders, learning, language, or hearing difficulties. For the DLD group, children were pre-selected by the preschool SLT, to make sure they had no concomitant difficulties. Children who passed a hearing screening and were able to complete a non-verbal reasoning task were invited to participate in the study. Table 3.1 presents the screening information for both groups of children.

This study was conducted according to the Declaration of Helsinki and was approved by the University College London (UCL) and the University of Chile, Research Ethics Committees. In all cases, participant’s parents/guardians received an information sheet plus a verbal explanation of the study, completed a developmental questionnaire and signed a consent form before the screening phase. Children provided verbal assent before start testing. Parents received £10 for travel expenses and children received a small age-appropriated gift.

Table 3.1

Participant’s Age, Hearing Levels and Non-Verbal Test Scores

	TLD (n=11)			DLD (n=16)		
Measure	*M*	*SD*	min-max	*M*	*SD*	min-max
Age (months)	62.4	2.94	58-66	61.9	3.92	57-67
PTA left ear (dB HL)	20.9	1.69	20-25	20.6	.91	20-22.5
PTA right ear (dB HL)	21.3	1.58	20-25	20.6	1.12	20-23.8
Block design (Z score)	18.1	1.58	15-19	15.7	2.98	10-19

Note. Group mean values, SD, and minimum/maximum values for age, play audiometry and the Block Design test.

3.2.2 Stimuli

Participant’s phonological processing skills were assessed using the syllabic subsection of the Phonological Awareness Assessment Test, PECFO (Varela & de Barbieri, 2015). This test has been normed and standardised for Chilean children between 4 and 7.11 years. The syllabic subsection of this test measures six different phonological awareness (PA) skills: syllable segmentation, initial syllable recognition, rhyme recognition, initial syllable deletion, rhyme deletion and syllable inversion. Each task consisted of five items, with one point assigned for each correct item and a maximum score of 30 for the subsection (Appendix 3.1).

For the EEG experiment, we used the multifeature experiment, stimuli and recording settings as in the adult's experiment. However, this time we only used the stimuli for the Speech condition, resulting in four blocks of 3 min 20 seconds duration (Chapter 2).

3.2.3 Procedure

Children were tested in three sessions, all conducted in separate days in Santiago, Chile. The first session took place at the children’s preschool after their parent/guardian signed the informed consent and answered a developmental questionnaire. Children who provided verbal assent underwent a hearing screening consistent in otoscopy and a play audiometry (pass/fail at 500-1000-2000-4000 Hz, 40 and 20 dB), and performed the Block Design task.

The second session was conducted three months later in research facilities at Neurosystems Lab, University of Chile. Here, the EEG was recorded in a sound attenuated booth, with stereo stimuli presented sfree field at 70 dB through right and left loudspeakers at 90 cm in a 75 degree angle. During the experiment no response was required and children sat comfortably in an armchair with their parent next to them while watching a silent cartoon in a tablet (screen), placed at eye level in front of them at a distance of 100 cm. Each EEG session lasted around 15 minutes (with breaks when needed) plus a set up time of 20 minutes.

The final session was held three weeks later, again at Neurosystems Lab, University of Chile, and consisted of the phonological awareness task and speech perception tests for experiment 3 (see Chapter 4).

3.2.4 Design

This study considered a between-subject design, for comparing speech processing under different language status; typically developing, atypically developing and adult-like. The between-subjects factor (IV) was different language status (operationalised as ‘Group’), with three levels; TLD children, DLD children, and adults (Ad). Our EEG dependent variable (DV) was cortical responses to speech, operationalised as ERP (peak latency, in ms and mean amplitude, in µV) and time-frequency measures (ERSP, in dB power and ITC, in a 0-1 range). At the behavioural level, the DV consisted of the phonological awareness scores for the syllabic awareness test subsection.

3.2.5 EEG acquisition and processing

Continuous EEG was recorded with a 32-channels Biosemi system, at a 2048 Hz sampling rate. Electrodes were positioned according to the 10-20 electrode system as in Chapter 2, with offsets kept under 30 µV. Vertical and horizontal electrooculogram were recorded in the right supraorbital area and right eye canthus, respectively. The EEG was preprocessed with EEGLab and ERPLab.

EEG data were downsampled to 500 Hz and re-referenced off-line to the full head average. A high-pass IIR Butterworth filter (non-causal, zero-phase shift, 2nd order) with cut-offs of 0.1Hz (roll-off 12 dB/octave attenuation, half amplitude -6dB, half-power -3dB), was applied to the continuous EEG remove slow drifts (Luck, 2014).

An initial threshold of 350 µV was applied to remove data portions with excessively large artifacts. To retain as much data as possible, we visually inspected each dataset and removed noise-contaminated data portions and channels. Then, we performed ICA to remove blinks, eye movements and other artifacts. After data cleaning, we interpolated the removed channels and re-referenced the data to the full head average. Then, separate pipelines were applied for the ERP and time-frequency analysis.

For ERP analysis, epochs were defined from -200 to 800 ms, with baseline correction between -200 to 0 ms. In total, 619 epochs of 1000 ms duration were extracted per participant. Epochs with artifacts exceeding an absolute threshold of 200 µV were excluded. We quantified EEG noise level as the percentage of epochs rejected per participant for each stimulus type and condition, with an individual maximum artifact rejection criterion of 35% of the trials per stimulus type (see Table 3.2 for group measures and Appendix 3.2 for individual rejection values) and a minimum of 44 trials per deviant condition.

All ERP statistical analysis were performed in the subtracted difference waveforms (DW, deviant minus standard), using MUA, peak-centred mean amplitude and peak latency as measures, calculated in two time windows: TW1 (100-250 ms) and TW2 (250-400 ms). Importantly, no participants were excluded on any of the groups as all datasets were below the rejection threshold after data cleaning and artifact correction.

Time-frequency analysis was performed with Fieldtrip (Oostenveld et al., 2011) in the parent waves for each standard and deviant type, following previous literature (e.g., Gansonre et al., 2018). We used Morlet wavelets for spectral decomposition of each trial into 19 log-spaced frequencies, from 2 to 45 Hz. Morlet wavelets parameters were defined according to previous literature (e.g., Cohen, 2014), using 3 cycles at the lowest, and 14 at the highest frequency (0.8 cycles increase), and a window length of 1670 ms.

Table 3.2

Percentage of Rejected Epochs per Condition and Stimulus Type

Stimulus Type	TLD		DLD	
	M (%)	SD	M (%)	SD
Non-native Non-words	8.72	11.65	11.05	8.82
Native Non-words	7.07	8.12	10.64	6.91
Function Words	5.82	5.69	9.31	6.63
Content Words	6.33	8.70	8.77	7.25
Standard(NN-Nwords)	6.91	8.45	10.59	6.91
Total	10.03	9.56	10.33	6.93

Note. TLD, n=11, DLD, n=16. Group means (M) and standard Deviations (SD) for the percentage of rejected epochs, in total and for each stimulus type.

To avoid edge artifacts, non-overlapping epochs of 3000 ms duration were defined between -1000 to 2000 ms for each trial, and then averaged across deviant types for each participant. Baseline correction was applied from -500 to -200 ms to avoid spectral leakeage from the following epoch in the low frequencies. Running the decomposition trial by trial allowed us to obtain induced activity and avoid cancelling out responses that were not time-locked. As time-frequency analysis is sensitive to differences in the number of trials per condition (Cohen, 2014), we found the participant with the minimum number of trials for a given condition (60 trials) and matched this number in all other participants and conditions by randomly selecting 60 trials from each participant's pool.

The brain's oscillatory synchrony in a given frequency band was examined through two time-frequency measures: ERSP and ITPC. ERSP quantified how much energy did the signal had for each frequency at each time point and was measured as power change relative to the -500 to -200 baseline (in dB), averaged across conditions for each group (Cohen, 2014). ITPC was calculated as an index between 0 and 1, and reflected how consistently the oscillations reach the same point in the cycle across stimulus types.

3.2.6 Statistical Analysis

Statistical analyses were conducted with Matlab, the MUA toolbox, and SPSS v26-29. For the ERP analysis, we identified significant MMRs in the TLD and DLD groups using MUA (successive point-by-point t-tests with FDR control) in a broad time window between 100 and 500 ms. Then, we ran between-groups comparisons of peak centred mean amplitude in an early (TW1, 100-250) and late (TW2, 250-400) windows, for the children and adult groups.

For TF analysis, we wanted to avoid bias when selecting the time windows for ERSP and ITPC. Thus, we determined regions of interest (ROI) for the theta and alpha bands in a way that was blind to the stimulus type, by averaging together the responses for all stimulus type for each group (Figure 3.1). We compared ERSP and ITPC between participant groups and using separate mixed repeated measures ANOVA for each ROI, with Bonferroni correction for multiple comparisons. Effects sizes were measured with eta squared (η^2) and partial eta squared (η_p^2), considering large effect≥ 0.14; medium effects ≥ 0.06; small effects ≥ 0.01, and Cohen's *d* (large effect = 0.8; medium effect= 0.5; small effect= 0.2), when corresponding.

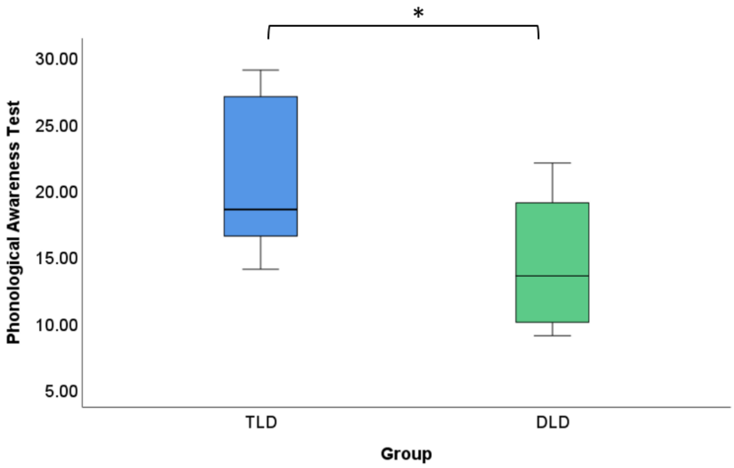
3.3 Results

3.3.1 Phonological awareness test

After confirming data normality (Appendix 3.3), independent-samples t-tests revealed that the DLD group (*M*=14.57, *SD*=4.67) showed significantly lower scores than the TLD group (*M*=20.87, *SD*=5.86) for the phonological awareness test [*t*(19)=2.778, *p*= .012,] with a small effect size, *d*=1.23**.** Figure 3.1 present mean values for the phonological awareness test.

Figure 3.1

Box Plots for Mean Scores on the Phonological Awareness Test for the Children Groups



Note. (*) indicates significant difference at the 0.05 level.

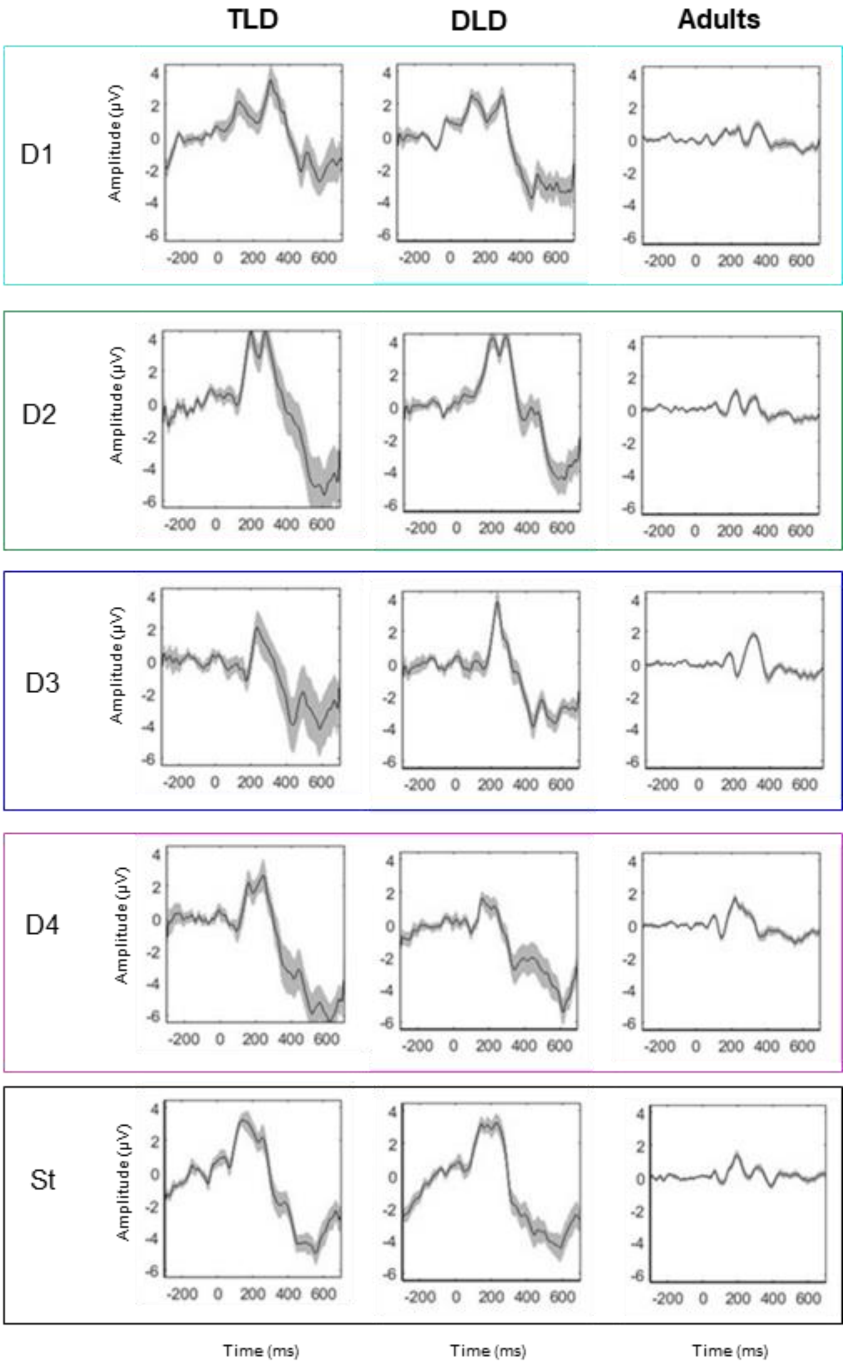
3.3.2 ERP analysis

Grand averages

Grand average waveforms were computed at Fz for all stimulus types, indicating similar patterns in the TLD and DLD group (Figure 3.2). Visual inspection of the waveforms in Figure 3.2 indicates obligatory auditory responses in both groups, with positive peaks around 200 and 300 ms, and negative responses before 200 and after 400 ms. Importantly, children responses are considerably larger and more variable than Adult's responses in Chapter 2 (Figure 3.2).

Figure 3.2

Parent Waveforms at Fz, Grand Average for all Groups and Stimuli



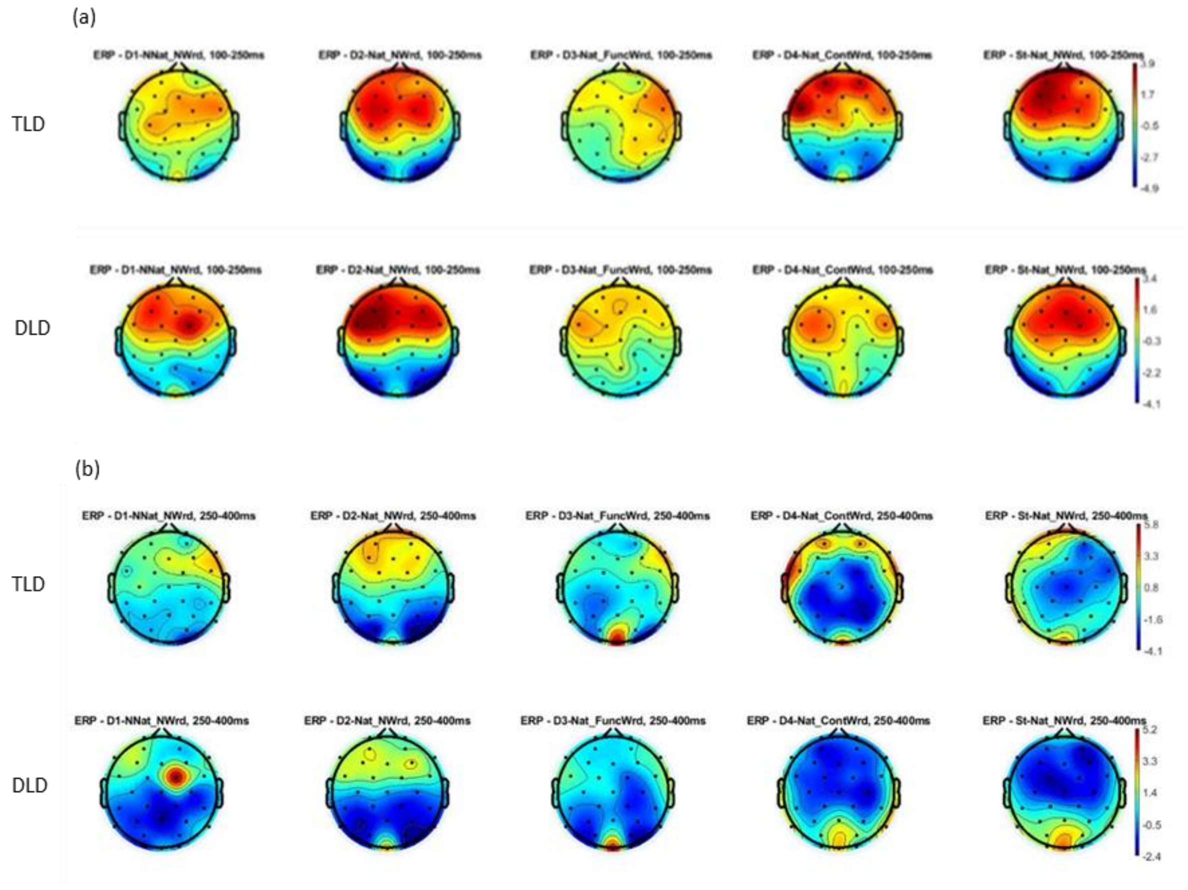
Note. Parent waveforms for the TLD (left column), DLD (middle column) and Adult group (right column). D1: non-native non-words (light blue box); D2: native non-words (green box); D3: function words (blue box); D4: content words (pink box) and St: native non-words (standars, black box). Central lines: Mean; shaded areas: Standard error (SE). Time 0= onset.

Scalp topography

Scalp distributions were computed for TW1 and TW2 (Figure 3.3). For TW1, activation was predominantly frontal-central, with similar patterns in TLD and DLD children for native non-words and function words. The TLD group showed greater positivity for non-native non-words, but the opposite pattern for content words. For TW2, all responses tended to central-posterior negativities, more broadly distributed in the DLD than the TLD group.

Figure 3.3

ERP Scalp Distribution for each Stimulus Type between Groups of Children



Note. Panel (a) 100-250 ms; Panel (b) 250-400 ms. Left to right, column 1: non-native non-words; 2; native non-words, 3: Function words; 4: Content words; 5: standard stimuli. Colourbar: µV

Identification of MMRs on Difference Waveforms

The first analysis focused on determining the presence of statistically significant MMRs, and if so, on characterising their latency and polarity. Five difference waveforms (DW) were computed at electrode Fz from individual ERP sets, and averaged across subjects on each group: DW1: non-native, DW2, native, etc. Statistical significance was determined in the 100-500 ms time window on data down sampled to 125 Hz. We used MUA by point-by-point t-tests with Benjamini & Hochberg FDR control procedure to test the null hypothesis that a given DW has a mean of 0 µV deflections against the alternative hypothesis is that the DW differs from 0 µV (i.e., two-tailed test). Table 3.3 presents the results of the MUA.

Table 3.3

MUA Results for MMR Identification at Fz for TLD and DLD in the 100-500 ms Interval

	TLD				DLD			
	Critical t-scores	Test-wise alpha	Upper bound FDR	Differences	Critical t-scores	Test-wise alpha	Upper bound FDR	Differences
NN-NW	-3.24 / 3.24	0.009	0.6	12	-3.25 / 3.25	0.005	0.4	7
N-NW	-3.07 / 3.07	0.012	0.7	14	-2.78 / 2.78	0.014	2.0	39
Function	-3.19 / 3.19	0.010	0.6	11	-2.81 / 2.81	0.013	1.1	21
Content	--	0.002	--	0	-3.34 / 3.34	0.005	0.4	7
Words	-3.74 / 3.74	0.004	0.3	6	-2.98 / 2.98	0.010	0.6	12

Note. NN-NW: non-native non-words; N-NW: native non-words; Function, Content and Words (combined). Comparisons (all tests)= 57. TLD group, df =10; DLD group, df =15.

Table 3.4 presents the cluster of significant responses detected in both groups in the 100-500 interval, indicating differences in their timing and polarity patterns. Negative MMRs were detected only within 200 ms and positive ones only after 182 ms. Early, MMN-like responses were not detected for non-native non-words (DW1), but were present for Words in both groups, and only in TLD for native non-words (DW2). Later, positive MMRs were present for non-words (DW1 & DW2) in both groups, and for function words (DW3) only in the DLD group, but were absent for content words and words. No LDN-like responses were detected on either group between 250-450 ms. Figures 3.4-3.8 illustrate the significant MMR for each DW.

Table 3.4

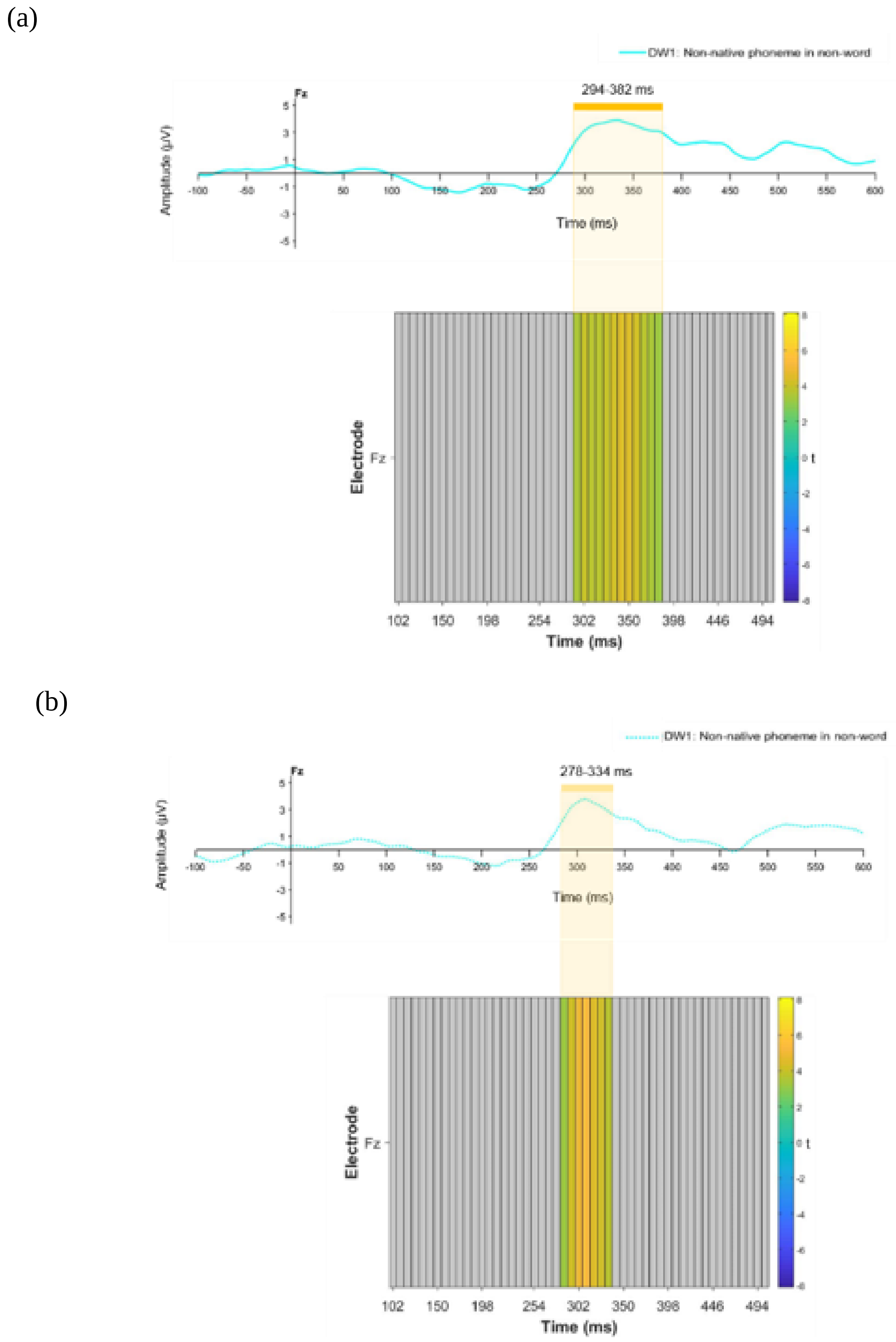
Significant ERP Responses for all DW Types in the 100-500 ms Time Window

Group	TLD			DLD		
DW Type	Significant responses (ms)	Duration (ms)	Polarity	Significant responses (ms)	Duration (ms)	Polarity
NN-Nwrd	294-382	88	Positive	278-334	56	Positive
	102-134	32	Negative	--	--	--
N-NWrd	(190-198)	8	Positive	182-346	164	Positive
	286-342	56	Positive			
	102-182	80	Negative	**102-182**	80	Negative
Function	--	--	--	(230-238)	8	Positive
	--	--	--	294-374	80	Positive
Content	**(102-110)**	8	Negative	**102-150**	48	Negative
Words	**102-142**	40	Negative	**102-174**	74	Negative

Note. NN-NW: non-native non-words; N-NW: native non-words. MMN-like responses are marked with in bold type. Responses in brackets may be considered too short to be significant.

Figure 3.4

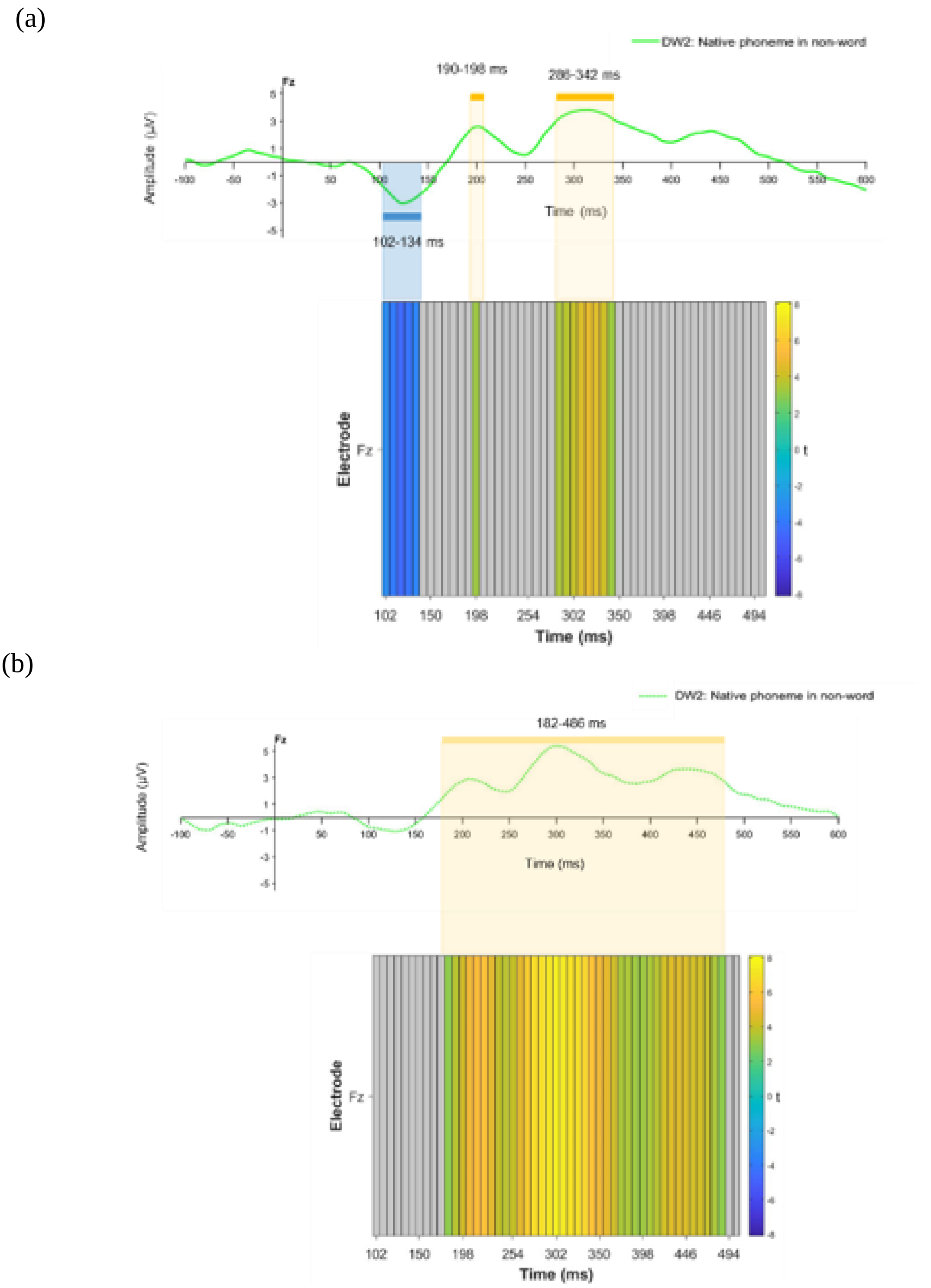
Difference Waveforms per Group at Fz for DW1



Note. MUA results for non-native phonemes in non-words. (a) TLD group (continuous line); (b) DLD group (dotted line) stimuli. Time 0 = stimulus onset. Colourbar: t-scores for the MUA

Figure 3.5

Difference Waveforms per Group at Fz for DW2



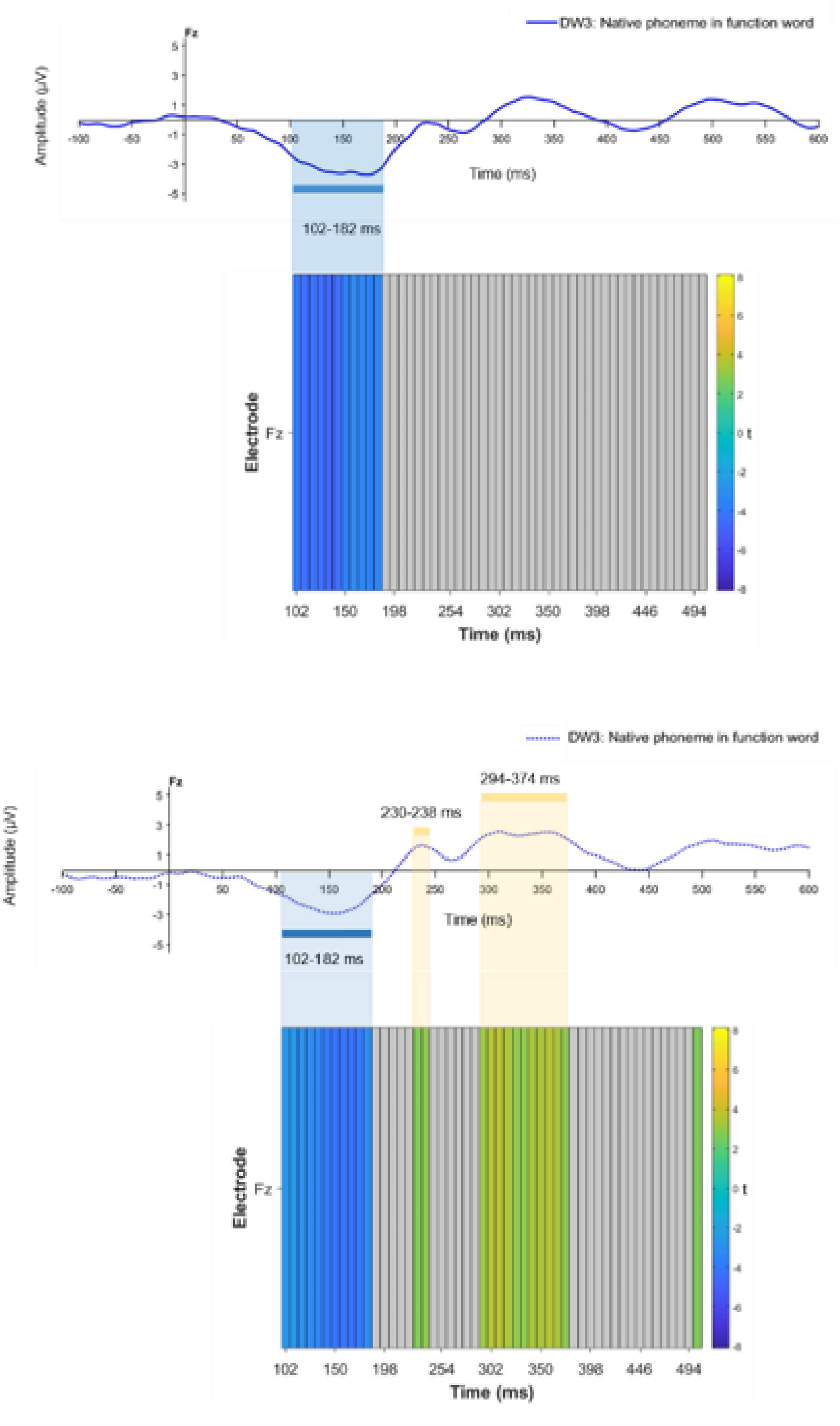
Note. MUA results for native phonemes in non-words. (a) TLD group (continuous line); (b) DLD group (dotted line) stimuli. Time 0 = stimulus onset. Colourbar: t-scores for the MUA

Figure 3.6

Difference Waveforms per Group at Fz for DW3

(a)

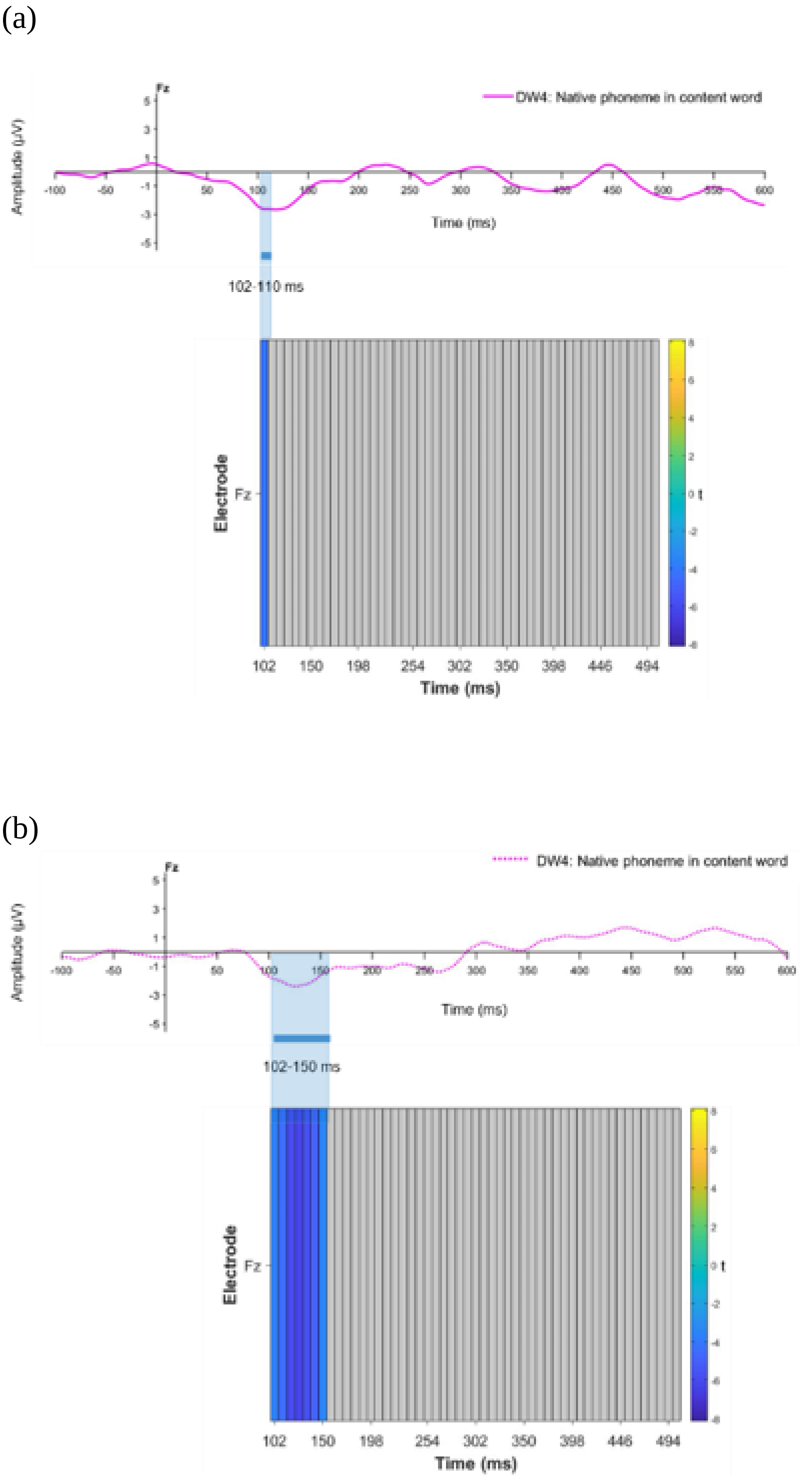
(b)



Note. MUA results for function words. (a) TLD group (continuous line); (b) DLD group (dotted line) stimuli. Time 0 = stimulus onset. Colourbar: t-scores for the MUA

Figure 3.7

Difference Waveforms per Group at Fz for DW4

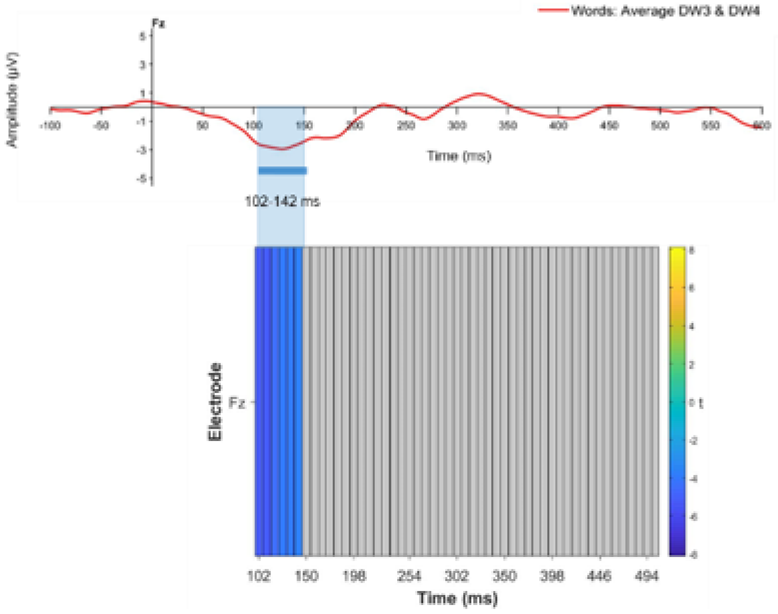


Note. MUA results for content words. (a) TLD group (continuous line); (b) DLD group (dotted line) stimuli. Time 0 = stimulus onset. Colourbar: t-scores for the MUA

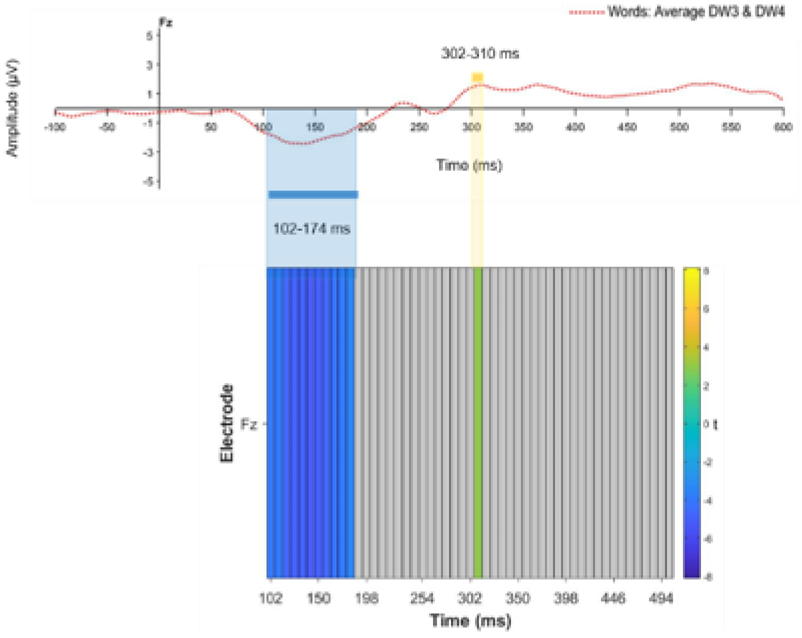
Figure 3.8

Difference Waveforms per Group at Fz for Words

(a)



(b)



Note. MUA for the average of content and function words. (a) TLD group (continuous line); (b) DLD group (dotted line) stimuli. Time 0 = stimulus onset. Colourbar: t-scores for the MUA

MMR differences between TLD and DLD children

The second analysis determined if there were any differences in the MMN/MMR amplitude between groups of children. Figure 3.9 contrasts the significant positive and negative responses in both groups for each DW type. Visual inspection of the temporal patterns suggests that onset latency for negative responses was similar between groups for words and non-words, but differed for positive responses in function words. In terms of duration, the negative responses were similar for DW3, but apparently shorter for DW4 earlier whereas the positive responses were longer for non-native nonwords (DW1) in the TLD group, and for native nonwords (DW2) in the DLD group.

Next, we compared the amplitude of the responses between both groups of children by performing MUA with FDR control procedure (Benjamini & Hochberg, 1995) on each DLD-TLD DW pair. Point-by-point t-tests (2-tailed, *q* level of critical t-scores= 0.05) indicated no between-group amplitude differences at electrode Fz, during the 100-250 ms or the 250-400 ms interval (Table 3.5).

Table 3.5

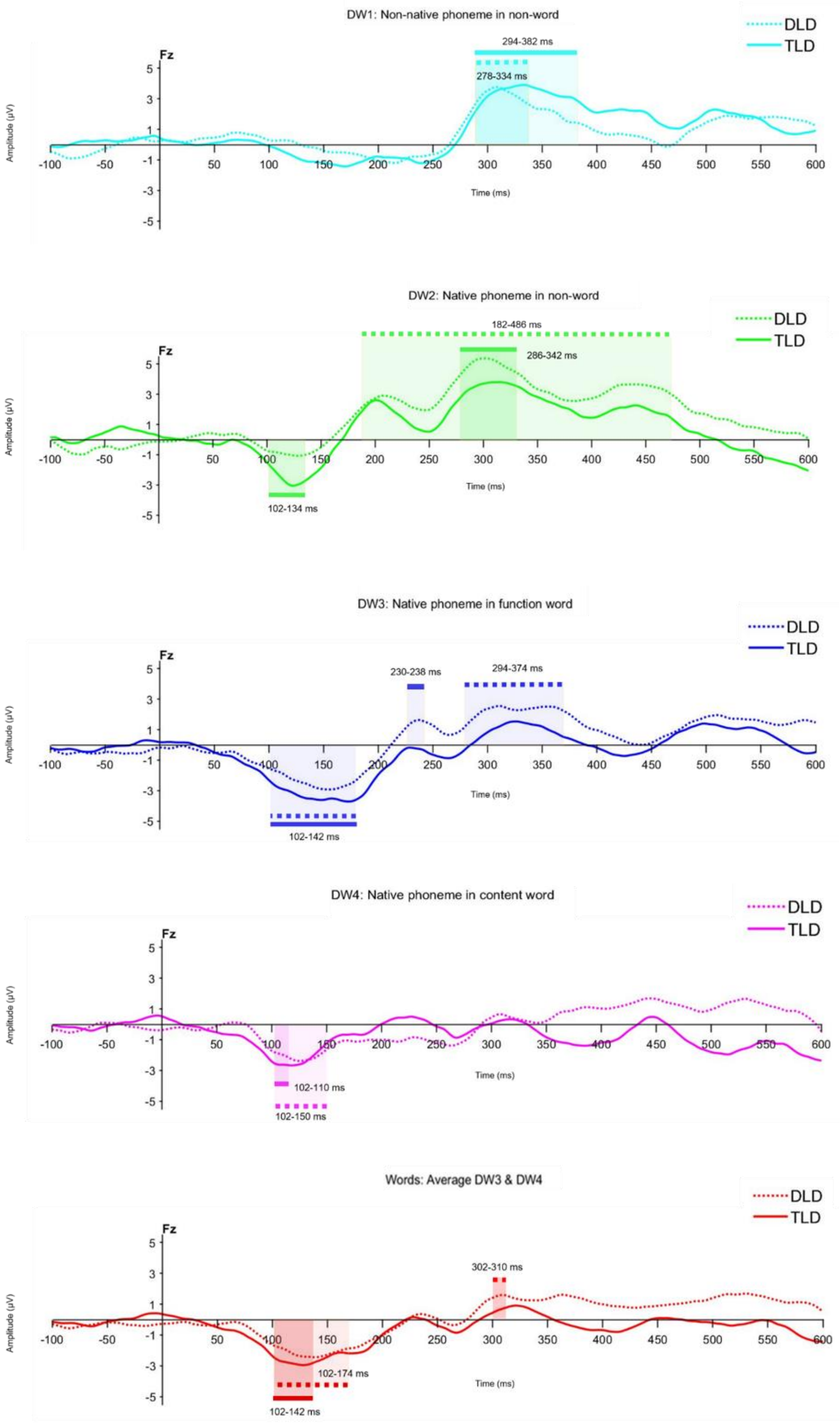
MUA Results for MMR Amplitude Comparisons between TLD and DLD Children

	100-250 ms	250-400 ms
	All FDR adjusted *p*-values ≥	All FDR adjusted *p*-values ≥
Non-native non-words	0.869	0.853
Native non-words	0.275	0.492
Function words	0.558	0.404
Content words	0.725	0.618
Words	0.978	0.478

Note. t-score degrees of freedom=25, total comparisons = 19 (number of time points, exact boundaries=102-246 and 246-398 ms)

Figure 3.9

Comparison of MMRs in both Groups of Children for each DW Type



Note. Difference waveforms at Fz electrode for all stimuli. Continuous line: TLD group; dotted line: DLD groups. Data low-passed filtered at 35 Hz for plotting.

Comparison between children and adult MMRs

The third ERP analysis compared the latency and amplitude of the MMRs between the groups of children, and with the adult's responses from the MMN validation study (Figure 3.10). Peak latency and mean amplitude (peak centred) were calculated as in Chapter 2 for TW1=100-250 and TW2=250-400 ms. Table 3.6 and 3.7 present the descriptive statistics for peak latency and mean amplitude for all groups, respectively.

Table 3.6

Descriptive Statistics for MMR Peak Latency, for all Groups in TW1 and TW2

	TW1					
	TLD		DLD		Adults	
	M	*SD*	*M*	*SD*	*M*	*SD*
Non-native non-words	184.6	50.71	197.1	37.9	178.5	29.8
Native non-words	136.6	38.5	127.9	22.2	167.4	22.5
Function words	145.1	23.2	160.1	28.5	202.5	23.2
Content words	137.1	38.9	161.3	51.0	157.0	21.3
Words	131.8	21.7	160.0	38.0	154.4	35.7
	TW2					
	TLD		DLD		Adults	
	M	*SD*	*M*	*SD*	*M*	*SD*
Non-native non-words	340.9	35.6	316.9	28.6	323.3	62.4
Native non-words	310.0	21.7	314.0	28.5	335.4	64.2
Function words	337.3	32.7	329.4	32.0	364.9	65.1
Content words	321.6	42.3	338.6	42.0	371.2	41.4
Words	326.6	32.9	330.4	34.2	400.1	24.1

Note. TLD, n=11; DLD, n=16; Adults, n=20.

In general, peak latency was longer in adults than children for TW1 and TW2. However, adult's peak latency was measured in significant MMN/LDN clusters, which was not possible in children. For children, peak latency values were extracted from negative deflections in TW1 and from positive deflections in TW2, regardless they were significant responses or not. Thus, no further analysis was performed on peak latency measures.

For mean amplitude, in TW1 children exhibited larger negative values than adults, and TLD children than DLD children. In TW2, adults showed larger negativities than children for all stimuli except content words, and TLD children showed more negative values than the DLD group for all stimulus types.

Table 3.7

Descriptive Statistics for MMR Peak-Centered Mean Amplitude, all Groups in TW1 and TW2

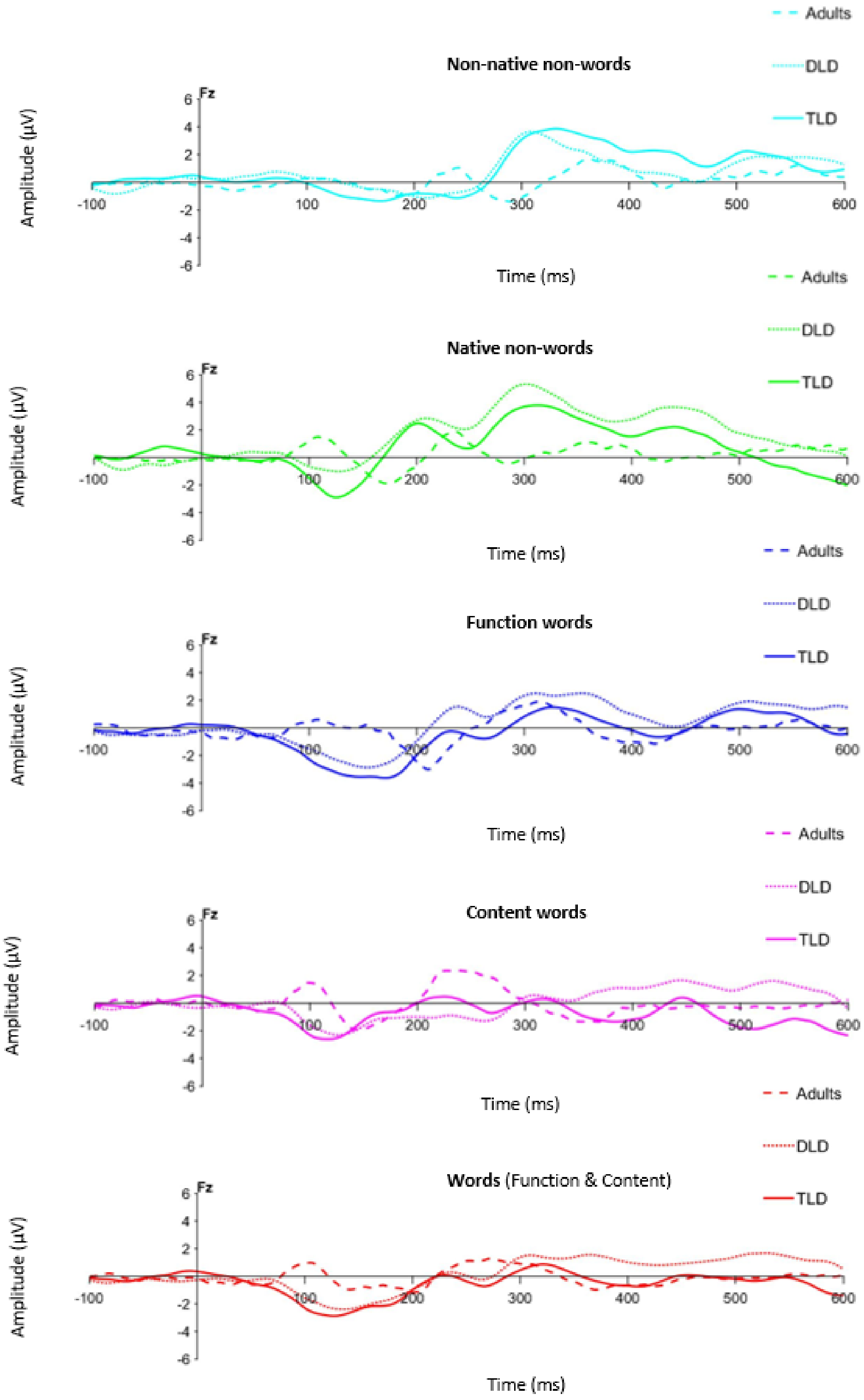
	TW1					
	TLD		DLD		Adults	
	M	*SD*	*M*	*SD*	*M*	*SD*
Non-native non-words	-2.35	2.73	-1.57	2.16	-0.76	1.13
Native non-words	-2.45	2.55	-1.19	2.02	-1.59	1.51
Function words	-3.97	3.22	-3.16	2.55	-2.08	0.92
Content words	-2.72	2.62	-2.60	1.68	-1.58	1.11
Words	-3.06	2.26	-2.63	1.78	-0.95	0.92

	TW2					
	TLD		DLD		Adults	
	M	*SD*	*M*	*SD*	*M*	*SD*
Non-native non-words	-0.81	2.80	-0.29	2.77	-1.45	1.48
Native non-words	0.85	3.56	1.78	3.08	- 0.81	1.01
Function words	-1.66	3.55	-0.03	2.17	-1.85	1.88
Content words	-2.27	3.07	-1.67	2.30	-1.56	1.55
Words	-1.58	2.50	-0.43	1.67	-1.72	1.68

Note. TLD, n=11; DLD, n=16; Adults, n=20.

Figure 3.10

Comparison of Difference Waveforms between Children and Adults for each Type



Note. Difference waveforms at Fz electrode for all stimuli. Continuous line: TLD group; dotted line: DLD group, dashed line: adults. Data low-passed filtered at 35 Hz for plotting.

For TW1 and TW2 Shapiro-Wilk test confirmed normal distribution (see Append 3.3) for all measures, except for DW2-TDL in TW1. Thus, we examined mean amplitude between-group differences for each TW using planned comparisons for each stimulus type using one-way ANOVA, adjusting the significance level for the number of stimulus types (0.05/ 5 comparisons, one per stimulus type=0.01). To account for unequal sample sizes and unequal variances (Appendix 3.2), we used Tamhane's post-hoc tests, with alpha= 0.01.

Table 3.8 presents the ANOVA results for peak-centred mean amplitude. Results indicates a significant amplitude difference only for Words (combined difference wave) in TW1 [$F(2,44)= 7.855$, $p= .001$], and only for non-native non-words in TW2 [$F(2,44)= 4.701$, $p= .014$], with a large effect size in both cases ($\eta^2 = 0.263$ and $\eta^2 =.176$, respectively). For TW1, post-hoc tests showed significantly larger negativities for Word stimuli in both groups of children (TLD children $M= -3.06$, $SD= 2.26$; DLD children $M= -2.63$ $SD=1.78$), than in adults ($M= -0.95$, $SD=0.92$). In TW2, native non-words showed less negative values in DLD children ($M= 1.78$, $SD= 3.08$) than in adults ($M= - 0.81$, $SD= 1.01$).

Table 3.8

Results of One-Way ANOVAs for Mean Amplitude Comparisons between Groups

TW1	*F*	*p*	η^2
Non-native non-words	2.441	.099	.100
Native non-words	1.368	.265	.059
Function words	2.277	.115	.094
Content words	2.139	.130	.089
Words	7.855	**.001 (*)**	.263
TW2	*F*	*p*	η^2
Non-native non-words	1.141	.329	.049
Native non-words	4.701	**.014 (*)**	.176
Function words	2.727	.076	.110
Content words	.382	.685	.017
Words	2.275	.115	.094

Note. For all tests, df = (2, 44). (*), significant at the 0.01 level.

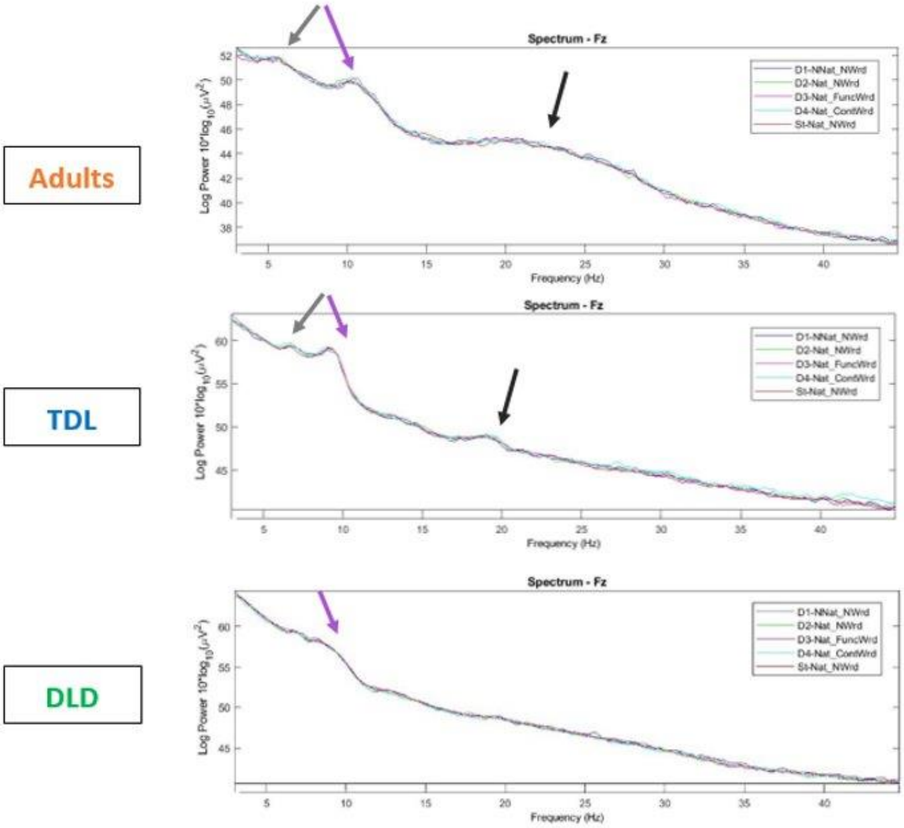
3.3.3 *Time frequency analysis of MMRs*

Spectral Power

As a data quality check, we first computed the spectrum of each stimulus type for each group, measured as normalized power (µV²). As can be observed in Figure 3.11, we could confirm that the 1/f pattern and typical peaks in the alpha band were present, indicating that our measures reflected cortical dynamics. All groups exhibited an increase in power around 10 Hz, consistent with alpha band activity. However, only the adults and TLD groups showed additional peaks around 5 Hz and 20 Hz, which was wider in adults (to 30 Hz).

Figure 3.11

Spectral Decomposition for Children and Adults Waveforms (all Stimuli)



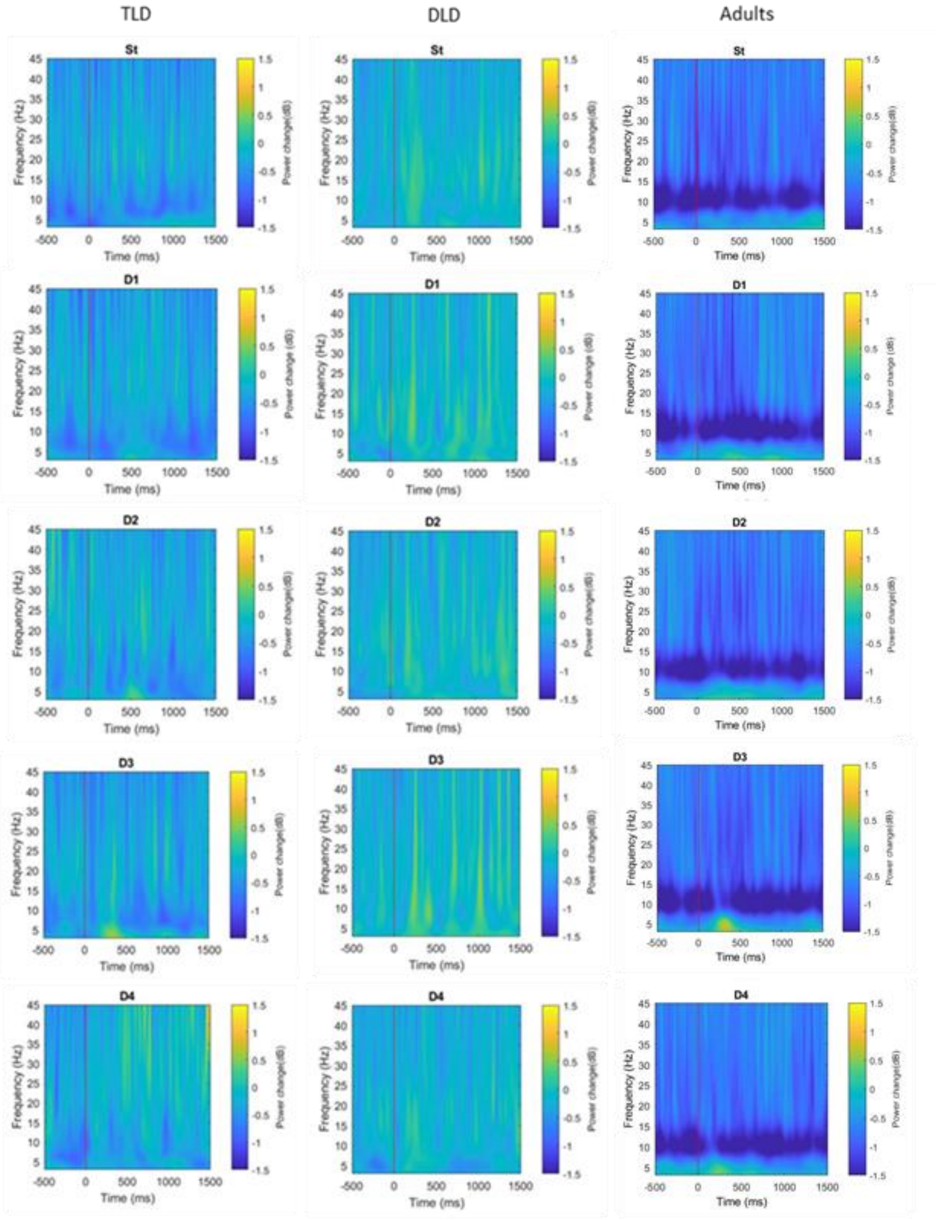
Note. Normalised power spectra for all stimulus types. Gray arrows: Peaks at or below 5 Hz; Purple arrows: Peaks around 10 Hz; Black arrows: Increases around or after 20 Hz.

Event-related spectral perturbation (ERSP)

The second TF analysis focused on determining if there were any between-group differences in spectral power over time for each stimulus type, as indexed by the ERSP. Figure 3.12 presents ERSP for each stimulus type for TLD and DLD children and the adult's group.

Figure 3.12

ERSP (Power Change over Time) for all Stimulus Types and Group

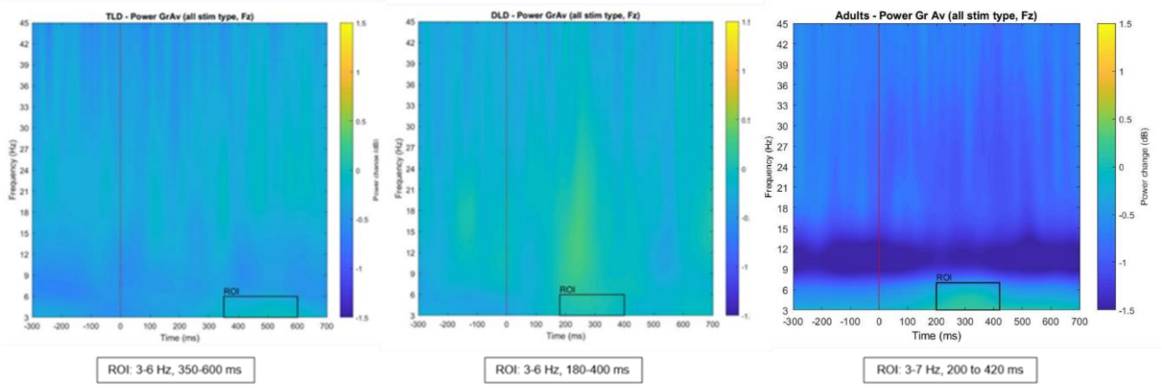


Note. ERSP plots indicate changes in dB power over time. Yellow and blue indicate power change toward positive and negative values, respectively. Baseline = -500 to -200 ms.

To avoid biased selection of the time windows and frequency ranges of interest for statistical analysis, we determined ROI by visual inspection of the plots containing the responses for all stimulus types on each group pooled together (Figure 3.13). This analysis identified one time range of increased activation (colour change towards yellow) in the theta band for each group; for the TLD group, between 350-600 ms (3-6 Hz); for the DLD group between 180-400 ms (3-6 Hz) and for the Adult group, between 200-420 ms (3-7 Hz). There is an earlier onset in adults (~200 ms) and DLD children (~180 ms) than in the TLD group (~350 ms). In the adults group though, there is a power decrease in the alpha range that spreads from the start of the baseline period to the post-stimulus interval, despite the baseline correction, suggesting this could be an artifact affecting this frequency range. For this reason, ERSP analysis focused on the theta ROI.

Figure 3.13

ROIs Selection on Total Average ERSP for each Group



Note. Total ERSP changes in *(a)* TLD children, (b) DLD children and, (c) Adult group. ROI 1: 3 to 6 Hz in children, 3-7 Hz in the adult group. Baseline correction from -500 to -200 ms.

To compare ERSP between groups, dB power was averaged across ROI time points, and collapsed across frequencies to get the average band power (theta band in this case).

Table 3.9 presents the descriptive statistics for ERSP, whereas mean ERSP values on each group for each stimulus type are compared in Figure 3.14.

Table 3.9

Descriptive Statistics for Average Theta Band ERSP (dB Power) for all Groups

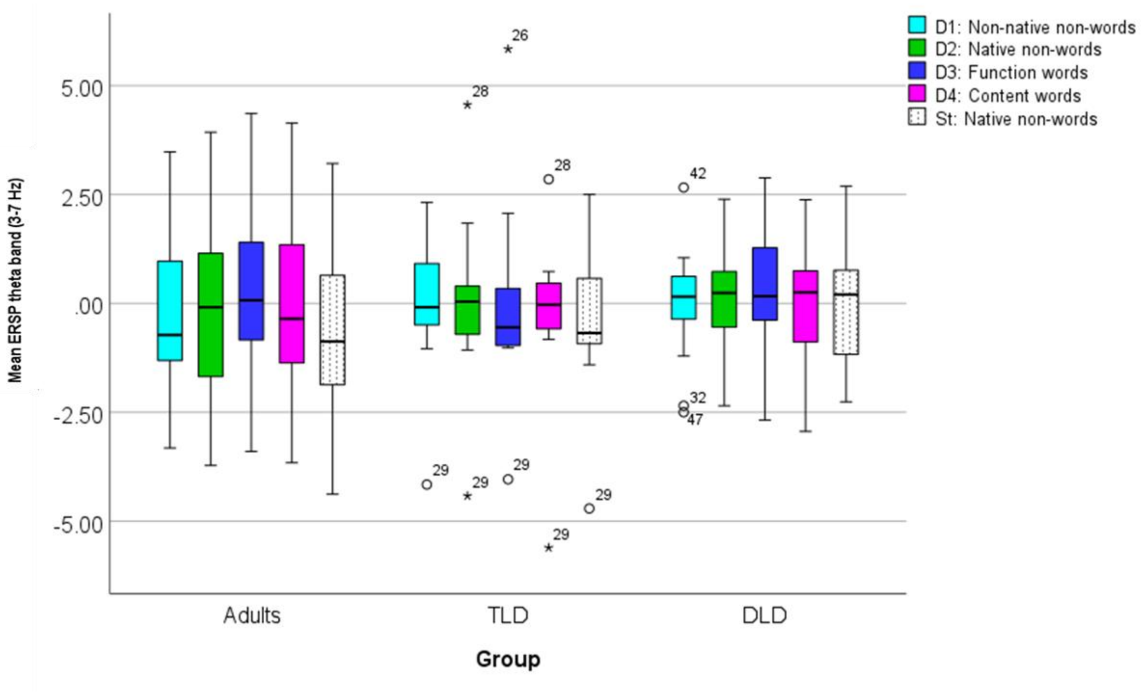
	TLD (n=11)		DLD (n=16)		Adults (n=20)	
	Mean	SD	Mean	SD	Mean	SD
Non-native non-words	-.109	1.65	.001	1.25	-.125	1.88
Native non-words	.039	2.15	.008	1.27	-.072	2.16
Function words	.032	2.43	.257	1.63	.267	2.01
Content words	-.326	2.03	-.021	1.39	-.063	2.07
St (native non-word)	-.428	1.81	-.041	1.34	-.471	1.97

Note. dB power averaged across ROI time points and theta range.

To examine differences in ERSP power for each stimulus type between the groups of children and adults we conducted a mixed repeated measures ANOVA with ‘Group’ as between-subject factor and ‘Stimulus Type’ as within-subject factor. After checking for data normality, and equality of variances, and of covariance matrices (Appendix 3.3), we used Greenhouse-Geisser correction for unmet sphericity (Mauchly’s W=.355, p<.001, df =9). The ANOVA revealed a significant effect of Stimulus Type [F(2.57,113)=3.358, p=.027], with a medium effect size (η_p^2 = .071) and adequate power= 0.70. Post-hoc pairwise tests on Stimulus Type effects indicated significantly larger power change for standards (M= -.313, SD= 1.71) than for non-native non-words (M= -.078, SD=1.60), native non-words (M= -.008, SD= 1.86), and function words (M= .185, SD= 1.95), but not for content words (M=-.136, SD=1.82). There was a non-significant effect of Group [F(1,44)= .048, p=.953], and a non-significant Group*Stimulus Type interaction, [F(5.14.,113)= .505, p=.774], with a small effect size (η_p^2 =.002 and η_p^2 =.022, respectively) and low statistical power (0.6% and 19%).

Figure 3.14

Box Plots for Theta ERSP (dB) Mean Values across ROI per Stimulus Type, all Groups



Note. ERSP baseline= -500 to -200 ms. Between-groups differences are non-significant for all stimulus types at the 0.05 level.

Inter-trial Phase Coherence (ITPC)

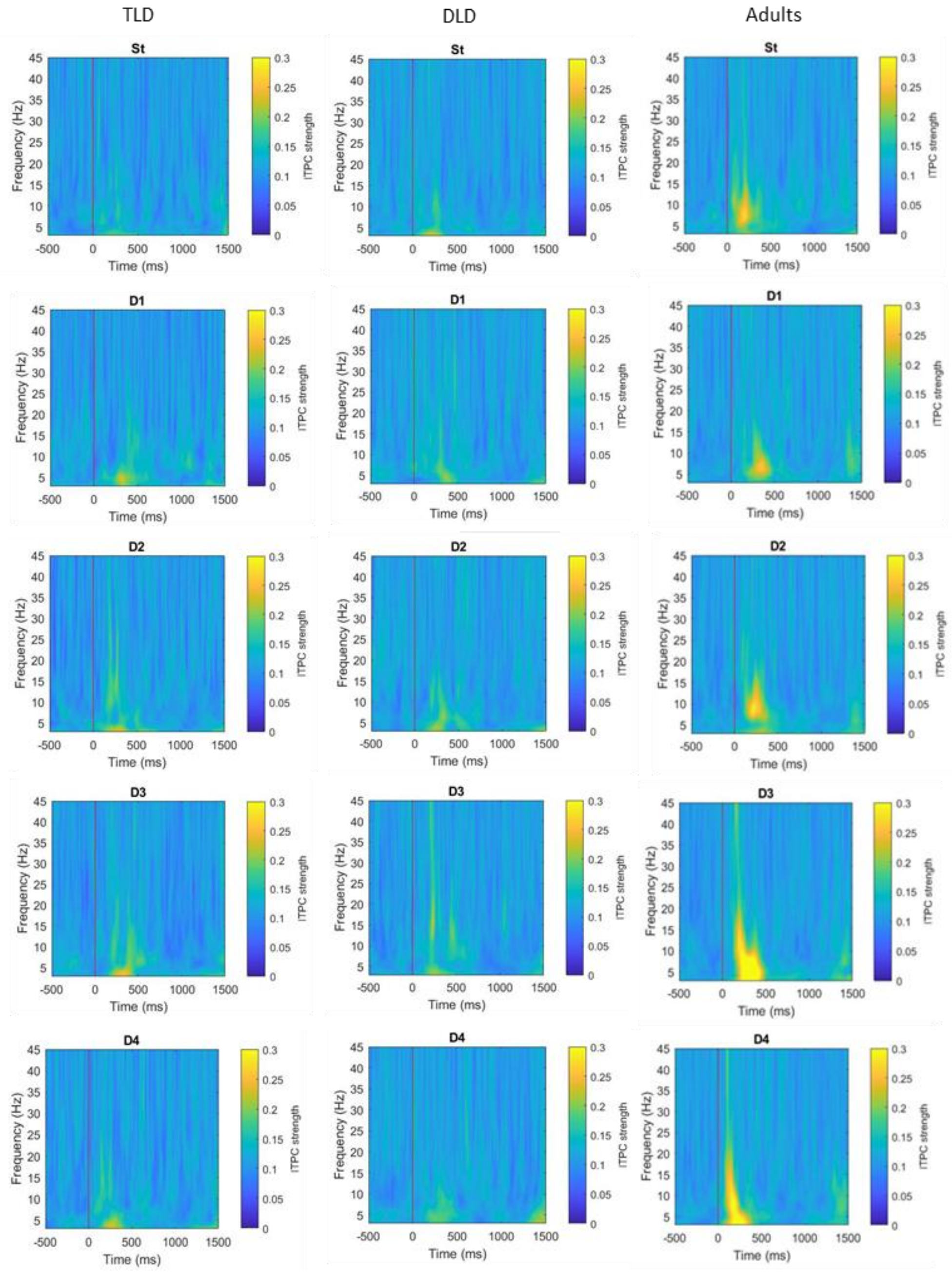
The final TF analysis focused on determining if there were any between-group differences in phase coherence over time for each stimulus type, as indexed by ITPC. Figure 3.15 presents ITPC values for each stimulus type for TLD, DLD, and adult group.

ROIs for ITPC statistical analysis were determined by visual inspection of the plots containing all stimulus types for each group (Figure 3.16). We identified ROI 1 in theta (3 to 7-8 Hz), with a similar onset and duration in TLD children and adults (150-400 ms) but slightly shorter in the DLD group (160-350 ms). We also identified ROI 2 in alpha (8 to 10-

12 Hz), with earlier onset and longer duration in adults (120-360) ms than in TLD (250-400) and DLD children (275-330), the latter showing the shortest alpha ITPC increase.

Figure 3.15

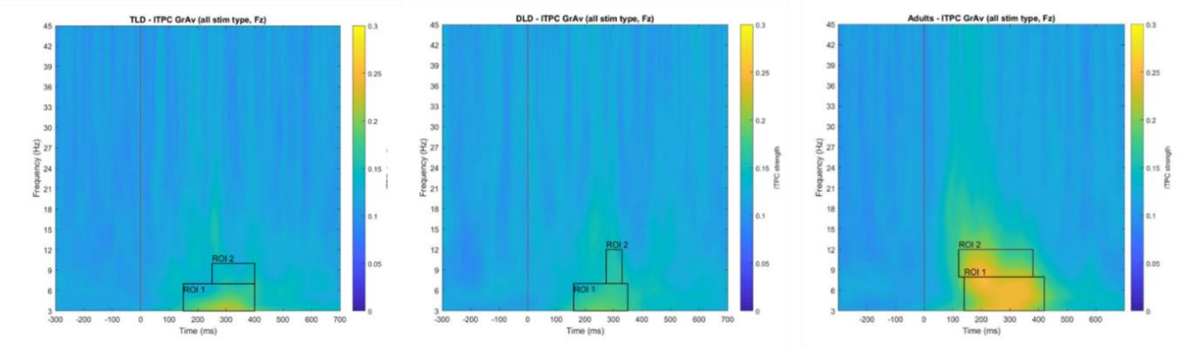
ITPC Strength over Time for each Stimulus Type, all Groups



Note. Colour changes towards yellow indicates ITPC increases over time, and blue indicate phase synchrony decrease.

Figure 3.16

ROIs Selection on Total Average ITPC for each Group



ROI 1: 3-8 Hz (theta), 150-400 ms
ROI 2, 8-10 Hz (alpha), 250 to 400 ms

ROI 1: 3-8 hz (theta), 160 - 350 ms
ROI 2: 8-12 (alpha), 275-330 ms

ROI 1: 3-8 Hz (theta), 150-400 ms
ROI 2: 8-12 Hz (alpha), 120-360 ms)

Note. (a) TLD children, (b) DLD children and, (c) Adults. In all groups, ROI 1: 3 to 8 Hz (theta band), ROI 2: 8-12 Hz (alpha band).

Table 3.10 presents the descriptive statistics for theta band (ROI 1). Adults showed higher ITPC for meaningful stimuli (words than non-words), but in general, with no difference for deviants and standard stimuli. In the TLD group, all deviants show higher ITPC than the Standards. No such standard-deviant distinction is present in the DLD group.

Table 3.10

Descriptive Statistics for Average Theta ITPC for all Groups (ROI 1)

	TLD		DLD		Adults	
	Mean	SD	Mean	SD	Mean	SD
Non-native non-words	.174	.027	.154	.047	.196	.049
Native non-words	.175	.052	.180	.046	.200	.050
Function words	.186	.062	.167	.046	.308	.082
Content words	.181	.040	.170	.051	.241	.076
St (native non-word)	.147	.043	.172	.067	.196	.046

Note. ITPC averaged across ROI time points and theta range

To compare theta ITPC (ROI 1), we conducted a mixed repeated measures ANOVA with Stimulus Type as within-subjects factor and Group as between-subjects factor, after confirming all the test assumptions were met (see Appendix 3.3). Results indicate a significant main effect of Stimulus Type [$F(4,176)= 6.75$, $p<.001$], with a large effect size ($\eta_p^2 = 0.133$) and adequate power (99%). Post-hoc comparisons showed higher theta ITPC for function ($M= .22$, $SD= .094$) and content words ($M=.19$, $SD= .069$), than for native non-words ($M=.18$, $SD= .049$).

There was also a significant main effect of Group [$F(2,44)=18.85$, $p< .001$], with a large effect size ($\eta_p^2 = 0.461$) and adequate power (100%), with larger theta ITPC for the Adult ($M=.23$, $SD=.061$) than for the TLD ($M=.173$, $SD=.093$) and DLD ($M=.17$, $SD=.051$) groups. Finally, there was a significant Stimulus Type*Group interaction [$F(8,176)=5.06$, $p<.001$], with a large effect size ($\eta_p^2 = 0.187$), and adequate statistical power (99%).

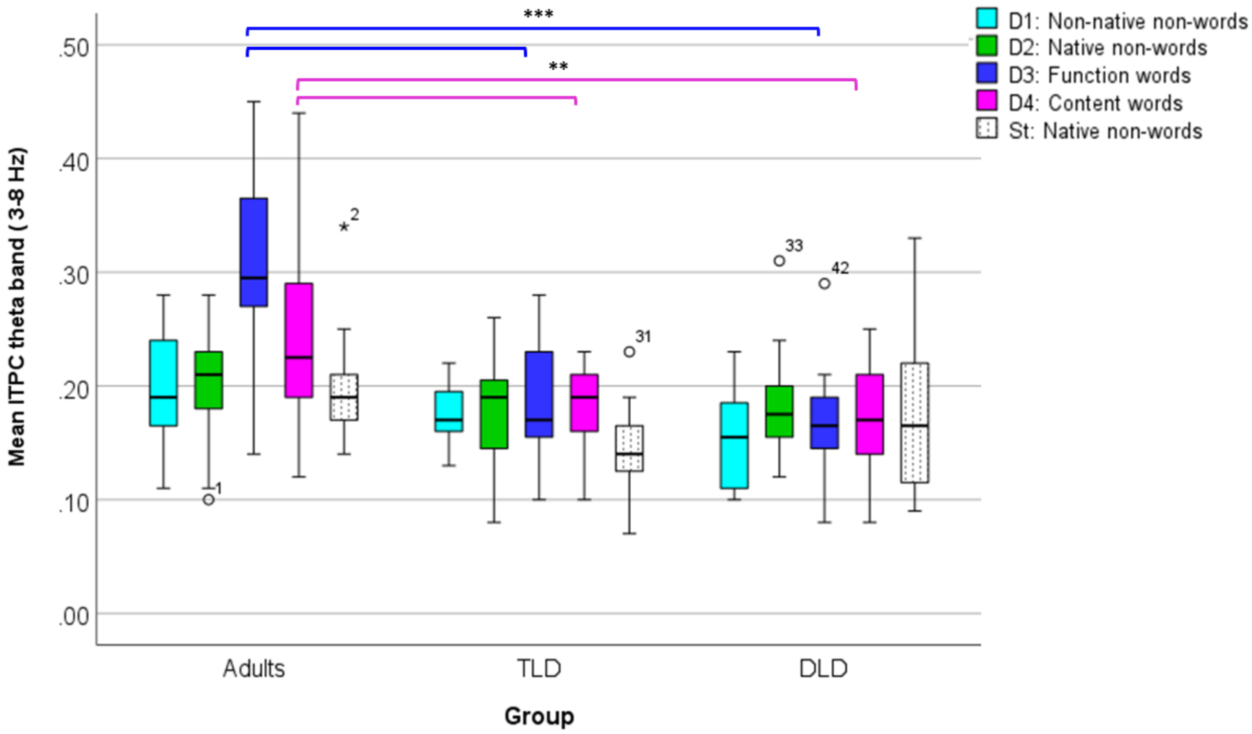
The interaction was followed-up with one-way ANOVAs (Bonferroni-corrected $p=.01$), comparing theta ITPC between groups for each Stimulus Type triad. For meaningless stimuli (non-words), theta ITPC showed no significant between-group differences for non-native non-words [$F(2,44)=4.003$, $p= .025$] or native non-words [$F(2,44)=1.194$, $p= .313$], as well as for standard stimuli [$F(2,44)=3.117$, $p= .054$].

On the contrary, theta ITPC for meaningful stimuli showed significant between-group differences. For function words, theta ITPC varied significantly between groups [$F(2,44)=23.129$, $p<.001$], with Tukey HSD post-hoc comparisons indicating higher phase coherence values in adults ($M= .310$, $SD= .082$) than in the TLD ($M=.186$, $SD=.062$) and DLD ($M=.167$, $SD= .047$) groups, but with no differences between both groups of children. Similarly, for content words, [$F(2,44)=6.901$, $p=.002$], Tukey HSD post-hoc test showed significantly higher values in adults ($M=. 241$, $SD= .076$) than in TLD ($M=.181$, $SD= .040$)

and DLD (*M*=.170, *SD*= .051) children, but no differences between children's groups. Figure 3.17 illustrates theta ITPC mean values in all groups for each stimulus type.

Figure 3.17

Box Plots for Theta Band ITPC (ROI 1) for Stimulus Type, all Groups



Note. ITPC range: 0-1. (***) significant at the 0.001 level. (**) significant at the 0.01 level.

The second statistical analysis of ITPC focused on the alpha band (ROI 2). Table 3.11, presents alpha ITPC descriptive statistics, indicating higher values for adults than for children, but no clear pattern for differences between children's groups.

Table 3.11

Descriptive Statistics for Average ITPC for all Groups for ROI 2 (Alpha Band, 8-12 Hz)

	TLD (n=11)		DLD (n=16)		Adults (n=20)	
	M	*SD*	*M*	*SD*	*M*	*SD*
Non-native non-words	.146	.043	.166	.065	.175	.047
Native non-words	.146	.053	.176	.061	.223	.075
Function words	.156	.054	.127	.040	.246	.082
Content words	.134	.034	.159	.065	.197	.052
St (native non-word)	.143	.065	.154	.074	.205	.065

Note: ITPC averaged across ROI 2 time points and collapsed over alpha range frequencies.

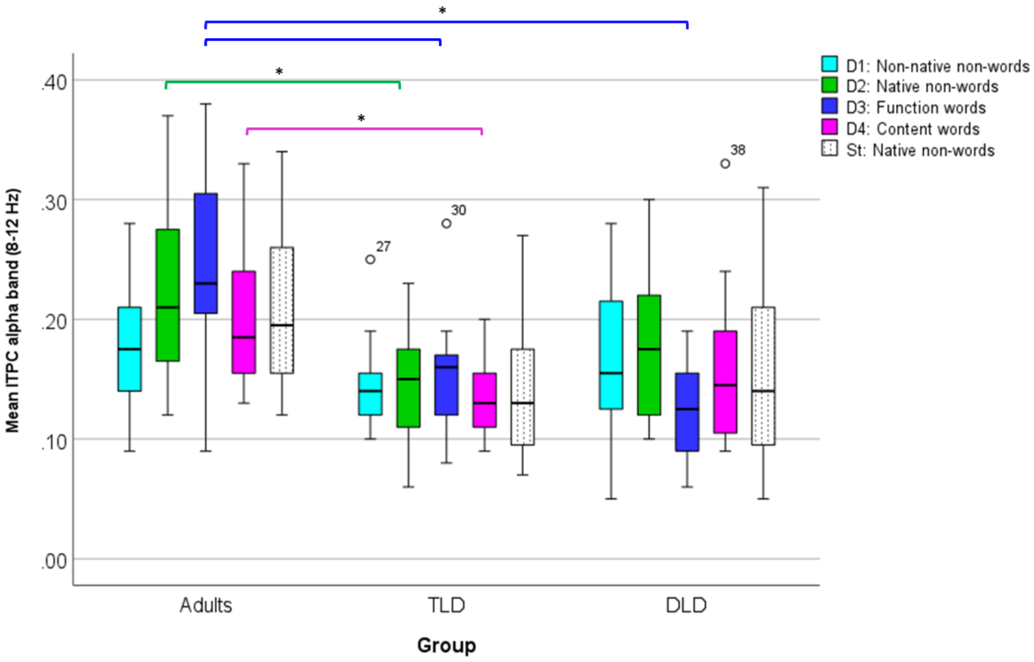
To compare alpha band ITPC (ROI 2) statistically, we conducted a mixed factorial ANOVA with the same factors as for theta, after confirming all the test assumptions were met (Append 3.3). Results indicate that the main effect of Stimulus Type was non-significant [*F*(4,176)= 1.073, *p*=.371], with a small effect size (η_p^2 = 0.024) and low statistical power (34%). There was a significant effect of Group, [*F*(2,44)=14.84, *p*<0.001],with a large effect size (η_p^2 = .401) and adequate power (99%), with Tamhane's post-hoc comparisons indicating significantly higher alpha ITPC in adults (*M*=.209, *SD*=.008) than the TLD (*M*=.144, *SD*=.011), and the DLD (*M*=.156, *SD*=.009) groups at the *p*<.001 level. A significant Group* Stimulus Type interaction was detected [*F*(8,176)=2.606, *p*=0.01], with a large effect size (η_p^2 = .106) and adequate power (92%).

The interaction was followed-up with one-way ANOVAs (Tamhane post-hoc, corrected *p*=0.01) to compare each Stimulus Type triads between groups. For function words, results indicate significant between-group differences in alpha ITPC [*F*(2,44)=16.902, *p*<.001] with a large effect size (η_p^2 = .434), with post-hoc pairwise comparisons indicating higher alpha ITPC in adults (*M*=.246, *SD*=.082) than in TLD (*M*=.156, *SD*=.056) and DLD

(*M*=.127, *SD*=.039) children. Alpha ITPC was significantly higher in adults for native non-words (*M*=.223, *SD*=.075, [*F*(2,44)=5.363, *p*=.008]), and content words (*M*=.197, *SD*=.051, [*F*(2,44)=5.431, *p*=.008]), than in the TLD group (*M*=.145, *SD*= .054 for native non-words, and *M*=.133, *SD*= .034, for content words), with a large effect size in both cases (η^2 = .196, and η^2 = .198, respectively), but there were no differences with the DLD group. Figure 3.18 presents mean alpha ITPC for all groups.

Figure 3.18

Box Plots for Alpha Band ITPC (ROI 2) for Stimulus Type, all Groups



Note. (*) indicates significant differences at .01 level.

Taken together, results from the TF analysis indicate an effect of the linguistic content involving meaning (words) on cortical synchrony with higher ITPC in the theta band, and to a less extent, in the alpha band. However, this effect was not detected for power change measures (ERSP) and was only present in adults, not in children.

3.3.4 Correlation between phonological awareness and EEG measures.

Finally, we determined whether there was an association between scores in the phonological awareness test (PECFO) and EEG measures. As we had compared the TLD and DLD groups in section 3.3.1, the current analysis pooled all children together, regardless their language status. Pearson correlation was calculated separately for mean amplitude (TW1 and TW2), ERPS and ITPC (ROI 1 and ROI 2) and phonological awareness scores (Table 3.12).

No significant correlations between mean amplitude, ERSP and ITPC ROI 2 and phonological awareness scores were observed on TW1 or TW2 for any stimulus type. For ITPC ROI 1 we only observed a significant negative correlation between theta ITPC for standards and PECFO scores [*r*=-.467, *p*=.028], but this was no longer significant after Bonferroni correction for multiple comparisons was applied to each measure (alpha=0.01).

Table 3.12

Correlation Analysis between Phonological Awareness Scores and EEG Measures

		ERP measures				
		Non-native non-words	Native non-words	Function words	Content words	Words (combined)
PECFO	Mean amplitude TW1					
	r	- .299	- .185	- .229	- .034	- .167
	p	.176	.409	.305	.879	.458
	Mean amplitude TW2					
	r	-.194	- .043	- .305	- .169	- .353
	p	.388	.851	.167	.451	.107
		Time-frequency measures				
PECFO		Non-native non-words	Native non-words	Function words	Content words	Standard (Nat-NW)
	ERSP theta					
	r	.082	- .321	- .271	- .283	- .319
	p	.716	.145	.223	.201	.147
	ITCP theta (ROI 1)					
	r	.206	- .183	- .112	.32	- .467
	p	.358	.415	.619	.146	.028
	ITCP alpha (ROI 2)					
	r	.039	- .368	.206	- .052	- .31
	p	.863	.092	.357	.818	.16

Note. *r*= Pearson's correlation coefficient; *p*= significance value. Corrected alpha=0.01.

3.4 Discussion

3.4.1 Summary of findings

This study aimed to compare cortical responses to speech with varying linguistic content under different language status; children with TLD and DLD, and adults using a range of ERP and time-frequency measures. As hypothesised, we detected significant MMRs for all speech stimuli in both groups of children, with different patterns than adults in terms of polarity, mean amplitude and ITPC. However, contrary to our expectations, we found no differences between TLD and DLD children on any EEG measure, nor correlation with behavioural tests, although their phonological awareness scores were significantly lower in the DLD group. The interactions between language status (‘Group’) and linguistic content (‘Stimulus type’) confirmed our hypothesis about greater top-down language effects for higher order linguistic content only in the adult group. These results suggest that language top-down modulations on speech perception are present in adulthood but either may not have developed yet in early childhood or may not be detectable with this EEG paradigm, for example because of excessive noise or variability in our data. Importantly, we found no evidence of impaired acoustic or speech processing in DLD, which suggests that speech perception in children with DLD and TLD could be similar, although such null results should be interpreted cautiously.

Specifically, our results confirm the presence of at least one significant negative or positive MMR for all stimulus types in both groups of children. However, a key difference with the adult group was the lack of significant early MMNs in children for most non-words, and of later LDNs for all stimulus types. These findings contradict previous literature reporting an early presence of the MMN (Cheour et al., 1998) and greater LDNs in children than adults (Bishop et al., 2011). For example, Kuuluvainen et al. (2016) reported that different speech and nonspeech contrasts elicited significant MMNs between 200-350 ms and

LDNs for the 350-500 interval. However, children in their study were 6–7-year-old, older than our participant and their speech stimuli did not include meaning. An alternative explanation for the lack of MMN/LDNs relates to a possible attenuation effect of an extended ISI duration. In young children, the MMR reflects sensory memory capacity which has been reported to increase between the ages of 2 and 6 years resulting in progressively better discrimination of memory traces at longer delays, this is ISIs over 500 ms (Glass, Sachse & von Suchodoletz, 2008). In our experiment, we used an ISI of 1000 ms to avoid neural refractoriness (Morr et al., 2002), however, this could have had a detrimental effect in eliciting the MMN/LDN.

As predicted, we observed that both groups of children exhibited immature responses when compared to adults as indicated by positive MMRs during the MMN and LDN intervals. Previous literature have described a positive polarity for the MMR for infants (Cheour, 2007) and, for children, until the age of 7 years in response to complex stimuli (Maurer et al., 2003). On the contrary, other studies in pre-schoolers (Kuuluvainen et al., 2016; Strotseva-Feinschmidt et al., 2015) indicate one could expect a typical, adult-resembling MMN/LDN patterns, even if occurring at longer latencies. However, we observed positive polarity only for non-words, indicating that meaningless word forms elicited more immature responses than words, maybe because the lack of meaning makes them more complex to perceive. This interpretation contradicts the possible lack of top-down language effects discussed earlier, but could be explained by the fact that point-by-point analysis reveals differences that are no longer detectable when averaging values across a time-window (e.g. because they cancel out) giving a clear example of the methodological issues in this field. In addition, scalp patterns in children showed broad distributions, especially for TW2, instead of the more focalised responses often seen in adults (Shafer et al., 2010) also indicating less mature MMRs.

Another indicator of immaturity is that MMRs in children exhibited greater latency and longer duration (for example, a 164-ms-long MMR for native non-words in the DLD group), making it hard to differentiate early and late MMRs for some stimuli and to compare latencies between groups, particularly, for non-words. In the literature, responses in 3-year-olds for monosyllabic function words differing in their final consonant peaked at 262 ms after deviance (Maurer et al., 2003). Strotseva-Feinschmidt et al., (2015), reported that children between 5–8 years, showed latencies between 180 and 350 ms, whereas Paquette et al, (2013) showed that MMRs for phonemic contrasts in 3-7 year-old children peaked at 272 ms. These findings are consistent with the latencies and MMR duration we observed for non-words but occur much later than the responses we detected for function and content words. Again, this could indicate easier and faster cortical processing of meaningful stimuli. For phoneme or word deviants, Strotseva-Feinschmidt et al. (2015), who used similar stimuli as in our study (contrasts between monosyllabic function words) in the same age group, reported overall latencies of 400 ms for the MMN and 700 ms for the LDN, which are much longer. However, the use of peak measures for ERPs may be sub-optimal (Bishop et al., 2011) as they are sensitive to noise level (Luck, 2014), which can be high in paediatric EEG (Trainor, 2012).

Regarding the MMR mean amplitude, our findings are partially consistent with previous literature. For example, Paquette et al, (2013) reported an amplitude of - .067 µV at Fz for phonemic contrasts in 3–7-year-old children, which agrees with our results for non-words in TW2 but not in TW1, in which children showed much larger negative values. The lack of amplitude differences between children's groups is consistent with multiple studies failing to differentiate TLD and DLD groups based on speech-elicited MMRs (for a review see Kujala & Leminem, 2017). When comparing children versus adults, our findings support our prediction of significantly smaller amplitude in adults than children, but this occurred only for Words in TW1. Contrary to our hypothesis, mean amplitude was smaller in children than adults, but only for the DLD group in TW2 for native non-words. This resembles previous findings of smaller MMN amplitudes for 6-year-old children (Lovio, et al., 2009).

In terms of TF analysis, we confirmed less synchronized activity in children than adults but only for words and when measured by ITPC but not by ERSP. Theta ERSP was affected by the linguistic content (stimulus type), with reduced power change for standards than for most deviants (except function words), which is consistent with the idea of increased theta synchronysation for novel stimuli. Larger ERSP for deviants is consistent with findings reported by Fuentemilla et al., (2008) and Hsiao et al., (2009; 2010). The lack of power differences we observed between standards and function words could be explained by a larger ERP negativity, thus, the lack of significant effect may result from acoustic differences. However, if this is the case, we would expect to see a consistent pattern for function words along all measures that was not present, for example, increased amplitude with higher ERSP and ITPC. Importantly, there were no ERSP differences between groups of children, or between children and adults contradicting our predictions, but in line with findings reported by Bishop and Hardiman (2010). Also, it is worth considering some methodological issues in our ERSP analysis: (i) Using visual inspection of the condition average plots to determine ROIs was suboptimal, as despite performing baseline correction in the adult plot, we observed unexplained negative alpha power before stimulus onset suggesting a possible artifact and (ii) The effect size was small, except for ITPC, meaning that some between-group differences may have gone undetected.

On the contrary, ITPC in the theta band (and to a less extent in alpha) showed a main effect of linguistic content and language status, with a significant interaction between them, all with large effect size. This is a key finding as it indicates higher synchrony in adults than children but only for meaningful stimuli (function and content words), consistent with our hypothesis of greater top-down language modulations for higher order linguistic representations in participants with more advanced language skills. Previous research has linked increased theta ITPC to syllable encoding and discrimination (Ortiz-Mantilla et al., 2022) whereas alpha ITPC is thought to reflect automatic allocation of attentional resources for speech sounds and inhibition of task-irrelevant stimuli (Strauß et al., 2014).

The presence of robust ITPC differences indicates more efficient responses to speech in adults than children, which is in line with previous studies. This aligns with Skeide & Friederici's (2016) proposal of greater bottom-up and slow emergence of top-down modulations after the age of six years. However, as there is no difference between TLD and DLD children, it could be argued that our results come from brain maturational changes (effect of age) rather than language top-down influences. If this were the case, we would not have observed the interaction of language status and linguistic content in the Adult group.

Finally, phonological awareness test scores did not correlate with any EEG measure, even though significantly lower scores were observed in the DLD than in the TLD group. This contradicts previous evidence of better phonological skills associated with larger MMNs for phonemic changes in 5-6 year-old children (Linnavalli, et,al., 2017), but is consistent with many studies that report no clear links between ERPs and behavioural measures.

3.4.2 Strengths, limitations, and future research

To our knowledge, this is the first study to use a multifeature paradigm in Spanish-speaking preschoolers with DLD diagnosis and to compare their responses to age-matched TLD controls and adults. Moreover, few MMR studies in children have used not only syllables or non-words but also words and validated the experiment in a previous study to obtain reference adult response patterns.

One contribution of this study is that we confirmed that our multifeature experiment was able to elicit robust MMR in young children presenting multiple speech deviants while reducing the EEG testing time. In less than 20 minutes (plus set-up times), it was possible to collect enough clean data for all the children that underwent the EEG session, as demonstrated by noise levels under 35% for all participants and stimulus type. Combining artifact rejection and correction procedures, we were able to include the data of all the participants, with a minimum of 42 trials per stimulus type which is well above the standard threshold for paediatric studies (10 trials, according to Bell & Cuevas, 2012). This highlights the importance of combining manual and automatic data cleaning procedures to improve data quality (Cohen, 2017), helping to reduce data loss and sampling bias due to participant's exclusion (Bell & Cuevas, 2012).

Retaining all the participants was especially important for this study, as one of the main limitations was the small sample size for each group, which was a consequence of the COVID-19 pandemic restrictions for data collection. Although small samples are not uncommon in children EEG studies because of difficult recruitment and high drop-out rates (Bell & Cuevas, 2012), especially for including clinical groups, is worth noting that the reduced number of children participants may have affected the statistical power of our results. This is a relevant aspect to consider in paediatric EEG studies, as even children with typical development show high inter-individual variability, which makes it harder to detect differences between TLD and DLD children.

Importantly, differences in the language and cognitive skills within the DLD group could have influenced the MMR results. Although all language-impaired children in this study had an expressive-receptive disorder diagnosis, it was impossible to determine the exact level of homogeneity in their language development and cognitive profiles. This could have introduced higher variability in their MMR difficulting a distinction between the DLD and TLD groups based on their cortical dynamics. Moreover, a large body of evidence indicates that the language symptoms in DLD are dynamic over time (Bishop et al., 2016;

2017), suggesting that identifying neural markers of language outcomes at the group level could be more challenging than expected.

A second limitation is that, as mentioned in Chapter 2, our stimuli differed in their acoustic structure. Acoustical matching of the initial phonemes for non-words was considerably easier than for word stimuli, as they should also be matched in their age of acquisition and oral frequency. Thus, larger acoustic differences rather than effects of language knowledge or linguistic content may have driven some of our results, as in Lee et al. (2012), who reported negative, adult-like MMRs for larger syllabic deviants and positive MMRs for small deviants. However, if this were the case, we would expect a consistency between the different EEG measures; for example, greater MMR amplitude should coincide with greater ERSP and ITPC for the same type of stimulus, which we did not found.

An important remaining question is what EEG analysis and statistical methods are more suitable when comparing cortical speech perception responses between groups of children, and children versus adults, given the high diversity of latencies and amplitude values, electrodes and time windows reported in the previous literature. This complicates the a priori selection of time windows and electrodes for analysis, as findings vary substantially across studies. A possible approach to reduce bias in our ERP analysis to follow the same steps used in the TF analysis for determining ROIs for amplitude and latency, for example, using global field power from the total group average as in (François et al., 2020).

Nevertheless, an important contribution of this study is that it confirms that ITPC is a robust measure, probably a more suitable one for comparing children and adults, chiefly, because ITPC results showed large effect sizes, which was not the case for the ERSP and ERP measures. Moreover, the detected theta ITPC increases were independent of changes in amplitude or power, as the MMN amplitude was not larger for adults than children, and the ERSP showed no between-group differences. Thus, our findings corroborate the value of TF analysis, as a relevant complement to ERP measures, encouraging its use in further speech perception development studies. However, it is important to note that ITPC distortions may also occur, due to effects of noise or ERP amplitude (van Diepen & Mazaheri, 2018)

Future research in TLD/DLD groups could explore other EEG measures related with speech perception, as resting-state analysis or linear modelling of continuous speech tracking, helping to increase the ecological validity of the experiments. Another possibility is to replicate this study in older children, ideally by a longitudinal, follow-up study to re-test these same children at later age or a new group of older participants. Likewise, other statistical methods could be more informative than MUA or ANOVA as these assume independence of observations, which contradicts the multivariate nature of the EEG (Volpert-Esmond et al., 2021). For example, multivariate pattern analysis (MVPA) could determine if children can be correctly classified into groups based on individual EEG measures (Petit et al., 2020).

3.4.3 Conclusions

Taken together, these findings confirm that the adult group showed more consistent speech processing responses than children, but in children this was not determined by their typical or atypical language developmental status. Importantly, the fact that adults showed greater ITPC in theta (and alpha) bands for function and content words, indicates that they may detect phonemic changes better than children, but they do so when these contrasts are contained in meaningful word forms and not in non-words. The lack of that top-down language effects on the TLD/DLD groups suggest these emerge at some point in childhood although later than the age range we studied, although it could also be explained by the carachteristics of our sample and stimuli. Thus, future studies could explore language modulations on speech processing in TLD/DLD children at older ages, for example, late childhood or adolescence.

Chapter 4. Resting-state oscillations and speech perception in children with typical language development and DLD.

4.1 Introduction

Speech perception involves task-dependent changes in neural oscillations and also, in resting-state (RS) rhythms; these corresponds to the spontaneous activation of cortical networks when the brain is awake but not engaged in a task. The patterns of endogenous RS activity in the EEG have been associated with different cognitive functions, including speech and language processing, and show developmental changes that may predict language skills at later stages. Thus, characterizing RS activity during early childhood could improve our understanding of typical and atypical language development.

RS measures have enormous potential as clinical indices of cognitive development because they require no response or stimuli, making data collection easier than for speech perception experiments and much shorter (usually 3 -5 min of data). However, there is still little research on the implications of RS EEG changes for speech perception and language development during early childhood.

The primary aim of this chapter was to examine the relationship between RS oscillations and language status in young children. We compared EEG resting-state power and lateralization measures between Spanish-speaking children with TLD and DLD and adults. A second aim was to relate children’s EEG RS measures to their performance in speech perception tests. This study contributes to understanding oscillatory dynamics during early childhood in TLD and DLD, comparing RS EEG patterns between children and adults.

4.1.1 Speech perception development and resting state oscillations

In the brain, synchronised neural activity underlies a wide range of cognitive processes, such as language and speech processing, even without a task. The changes in RS neural dynamics can be quantified as variations in the spectral energy at different frequency bands (for example, as spectral power) and reflect baseline excitability in neural networks involved in different cognitive processes, such as speech perception (Houweling et al., 2020). Thus, characterising the brain's intrinsic patterns in the EEG signal and their change along development is valuable for understanding how the brain processes external stimuli and determining how RS brain activity relates to speech perception skills and interacts with language knowledge across the lifespan.

Previous research in adults has shown that (RS) brain activity predicts both neural dynamics and behavioural performance during speech perception. For example, gamma oscillations are involved in local and global scale synchrony (Buzsaki & Draguhn, 2004), playing a key role in phonological processing (Meyer, 2018).

Breshears et al. (2018) recorded RS cortical local field potentials in the STG of eight brain-surgery patients. They found that RS high gamma power (70-150 Hz) in the STG (both hemispheres) correlated with the perception of speech (sentences) but not of acoustically matched non-speech (rotated stimuli), indicating that 'tuning' of RS activity and phonemic processing were task-dependent (Morillon et al., 2010). A MEG study by Houweling et al. (2020) investigated the relationship between inter-individual differences (n=88 adults) in RS power and speech perception under varying background noise levels. They found positive associations between words-in-noise test performance and RS power (mainly in the superior temporal gyrus) for high beta (21–29 Hz) in the LH and for low gamma oscillations (30-40 Hz) in the RH. These findings suggest that baseline neural activity in different bands provides an optimal neural context for speech perception, facilitating processing under adverse listening conditions. However, these findings have not been systematically replicated in children; although RS patterns change shows evident changes during development, it is unknown what they involve for speech perception or how they might be influenced by age or language abilities.

Developmental changes in power measures

On the EEG, it is possible to observe typical age-related changes in the RS rhythmic (periodic) activity and background neural noise. The neural activity becomes more consistent (coherent) with age and more spatially focalized because of cortical maturation and cognitive changes (Eggermont & Ponton, 2003). This is observed in the EEG as a reduction in broadband (absolute) power, a power redistribution, and changes in the topography and boundaries of different frequency bands (Uhlhaas et al., 2009; 2010; Miskovic et al., 2015; Rodriguez-Martinez et al., 2017). Thus, canonical adult bands are not necessarily equivalent to children's ones (Ostlund, 2022), which seem to be lower (Saby & Marshall, 2012) but still present the characteristic EEG structure (1/f, power decrease as a function of frequency). In addition, neural background noise decreases from childhood to adolescence (Bishop et al., 2012; Hämmerer et al., 2013) and adulthood (Vanvooren et al., 2015), also reflected in the RS EEG patterns.

In general, developmental changes in the RS EEG involve an age-related decrease in spectral power for low frequencies and an increase for high frequencies (Lum et al., 2022; Meng et al., 2021; Rodriguez-Martinez et al., 2015; Saby & Marshall, 2012). For example, Yordanova & Kolev (2008) and Perone et al. (2018) described a decrease in theta (4-7 Hz) and an increase in alpha (~7-13 Hz) power with age (n=50 children, 6-11 years old) with a continuous decrease in power below 8 Hz during adolescence. According to Uhlhaas et al. (2010), gamma-band oscillations emerge during early childhood and show developmental changes until adulthood, but the direction of these changes is unclear. A large-scale study (n=707, age 3-12 years) by Takano and Ogawa (1998) reported a steep increase in RS gamma power (35–45 Hz) in younger children between the ages of 3 (n=71) and 4 (n=65) years, which was more pronounced for frontal and central channels, and become stable in older children (4-12 years). On the contrary, another large study (n=156) by Tierney et al. (2013) demonstrated less gamma power (31 to 50 Hz) in older participants than in young children (n=35, 3-5 years), with strong negative correlations between gamma power and age from early childhood to adulthood.

Notably, some evidence indicates that the patterns of RS power at different ages relate to different brain maturational and cognitive changes. For example, power decrease is associated with the grey matter reduction due to synaptic pruning (Tierney et al., 2013), cortico-cortical myelination and changes in neurotransmission (Uhlhaas et al., 2009; 2010), whereas high levels of theta power in infants and young children could reflect a developmental state of optimal synaptic plasticity (Stroganova & Orekhova, 2007).

Speech perception development and RS power

Despite the apparent links between spectral power age-related changes and cognitive development, very few studies have investigated the relationship between endogenous neural activity and language and speech perception development in young children. However, behavioural evidence consistently shows that their speech perception skills improve with age (see Chapter 1). For example, Bradlow and Bent (2002) reported that children as young as three years demonstrated speech perception difficulties in the presence of multi-talker noise, although their performance improved with age. Thompson et al. (2016) reported an association between age and speech in noise tests in children 3.0- to 4.9-year-olds. Similarly, a study in school-aged children by Nittrouer et al. (2013) reported that their speech-in-babble test scores improved with age and language experience. These findings indicate that older children perform better in speech in noise tests than younger ones during early childhood, although it is difficult to separate the effects of age, attention and language skills.

However, there is less evidence about how speech perception in children is related to RS EEG changes. Some studies indicate that resting-state EEG measures predict speech perception development at later stages. Other studies have found a positive correlation between greater high-frequency (HF) and low-frequency (LF) spectral power and better speech perception and language abilities. Gou et al. (2011) found that frontal resting gamma power (31-50 Hz) at 16, 24 and 36 months old significantly correlated with later performance in language tests at the ages of 4 and 5 years (non-word repetition, PLS-3 and CELF-P sentence structure scores). The authors proposed that higher RS frontal gamma power predicts later language development because it entails better attentional and working memory processing (Gou et al., 2011). Likewise, a longitudinal study by Cantiani et al. (2019) reported that increased left gamma power measured at the age of 6 months (n=84) correlated with better language outcomes at the age of 24 months For the alpha band (7-10 Hz), Kwok et al., (2019) found that alpha power inversely correlated with children's (TLD, 4-6 years, n=41) performance in a battery of language tests (CELF-5), interpreting these findings as greater neural inhibition and less excitability related to attentional control.

In older TLD children (n=52 children, ~10-year-old), a study by Lum et al. (2022) reported that RS theta power negatively correlated with sentence repetition. Similarly, a longitudinal study by Meng et al. (2021) reported that theta power decreased predicted expressive vocabulary at ages 9 and 11 years (n=53). In contrast, beta power increase from 7 to 9 years predicted receptive vocabulary at age 11. These changes suggest that RS oscillatory patterns reflect typical brain development, although none of these studies have distinguished what specific networks generate each type of RS pattern (e.g. attentional or language).

Although it seems clear that spontaneous brain activity plays an essential role in speech perception and language development, there is strikingly little research about RS EEG patterns in children with DLD. In other neurodevelopmental disorders, research suggests that atypical RS oscillatory patterns may underlie cognitive and behavioural deficits (e.g., see Bosl et al., 2011 and S for a study in children with ASD, and dyslexia, respectively), for example, because of differences in cortical maturation or imbalances between neural excitatory and inhibitory control (Donoghue et al., 2020). Thus, it is reasonable to think that atypical RS patterns could occur in DLD. Nevertheless, some studies have already proposed that, as RS gamma oscillations may predict later language development, they could be used as a clinical index for screening infants at risk of language deficits (Cantiani et al., 2019). However, to our knowledge, Benasich et al. (2008) is the only study examining the relationship between the maturation of brain oscillations (gamma band) and the development of language abilities in infants at higher risk of DLD.

Benasich et al. (2008) studied infants with a family history of DLD in a first-degree relative (FH+, n= 22) and age-matched controls (FH−, n= 41), testing them longitudinally at the ages of 16 (n=22), 24 (n=23), and 36 (n=18) months. They found that the FH+ group showed consistently lower gamma power over frontal regions than the FH- controls and that gamma power strongly correlated with language and cognitive skills at all ages. Specifically, children with higher gamma power showed better inhibitory control and more mature attention-shifting skills. Benasich et al. (2008) thus concluded that the emergence of high-frequency neural synchrony might be critical for cognitive and linguistic development. However, it is unclear what happens at later ages in children, for example, during early childhood in children affected by DLD.

Overall, previous research suggests that RS EEG power measures can provide valuable insights into the development of speech perception abilities and that children at risk for language impairments may present alterations in this process (Benasich et al., 2008). However, there is a need for considerably more research and replication to corroborate or disprove these findings.

4.1.2 Oscillatory hemispheric asymmetries and speech perception

Plenty of evidence indicates that lateralisation in neural oscillations is involved in speech perception. The asymmetry (or significant lateralisation) of neural oscillations refers to the differences in the activity patterns of neural oscillations at different frequencies between the two cerebral hemispheres. This is a crucial feature of the brain's functional organisation, and it is especially relevant for speech perception. In adults, a large body of evidence indicates that both speech-evoked and resting state (endogenous) oscillations are asymmetrical (see Meyer, 2018 for a review).

A predominant explanation of the role of oscillatory lateralisation in speech processing is the Asymmetric Sampling in Time (AST) Hypothesis (Poeppel, 2001; 2003). According to the AST theory, speech processing in non-primary auditory areas shows functional asymmetries between hemispheres. These biases are related to differences in the distribution of the centre frequency at which neuronal ensembles synchronise spontaneously (at rest). In the right hemisphere (RH), neural ensembles are more skewed towards synchronising at a theta rate (3–7 Hz), and in the left hemisphere (LH), they are skewed towards low-gamma (20–50 Hz) frequencies (Giraud et al., 2007). During speech perception, this RS asymmetry would "prime" the brain for sampling different features on each hemisphere. The LH would be primed for extracting information over shorter intervals (20–50 ms), processing fast acoustic changes, such as the transitions between consonant and vowel sounds, whereas the RH would be primed for sampling speech over longer time windows (~150–300 ms), required for prosodic processing (Giraud et al., 2007; Giraud &

Poeppel, 2012). However, there is less clarity about the exact developmental trajectories of these RS oscillatory asymmetries.

During language acquisition, an important landmark is the establishment of left-lateralised neural activity to support speech processing. Studies have shown that infants as young as newborns exhibit left-lateralised neural responses to speech sounds (Peña et al., 2003), suggesting that the basic neural mechanisms for speech perception are present early in life. A consistent leftward asymmetry for low gamma oscillations (20-55 Hz) seems to be in place at the age of 3 years along, but contrary to adults, young children show no rightward asymmetrical activity for the theta band (3-7 Hz), suggesting that the right auditory cortex oscillatory specialisation develops later than in the LH (Thompson et al., 2016). However, although it is established that RS oscillations and their lateralisation continue to develop throughout childhood and adolescence, clear age-related patterns have not been described for young children and children affected by DLD.

In TLD children, leftward lateralisation of RS oscillations in the gamma range (20-50 Hz) is present in early childhood and appears to be related to speech perception skills. One of the few studies in this field was conducted by Thompson et al., 2016 on 65 children between 3 and 4.9 years old. The authors reported that RS gamma left lateralisation was more pronounced in children with better speech in noise test performance. This suggests that a greater asymmetry in RS HF activity facilitates speech sampling under challenging conditions, which is consistent with the AST theory.

Previously, a popular theory of DLD indicated a crucial role of atypical brain lateralisation and lack of language leftward asymmetry as neural correlates of this disorder (see Mayes et al., 2015, for a review). However, most of the findings about language lateralisation in DLD come from haemodynamic studies (e.g., fMRI, as in de Guibert et al., 2011), and have not been linked to neural oscillations. For example, it has not been determined whether there is a lack of oscillatory priming on each hemisphere in DLD, as could be expected from the AST hypothesis. Moreover, many studies have used handedness as a behavioural proxy of language lateralisation, which may lack reliability, providing contradictory and inconsistent evidence about the role of atypical hemispheric dominance in DLD. An important a large-scale replication study (n=263 twins) by Wilson and Bishop (2018) using fMRI-fTCD found no evidence of greater prevalence of atypical laterality in DLD-affected participants; even more, an important percentage of their TLD participants showed no clear lateralisation, concluding that the lack of a functional asymmetry in the brain may not necessarily involve poor language development.

To summarise, RS neural activity and lateralisation of oscillations are key aspects of the brain's functional organisation, and their maturation is likely to play an essential role in speech perception and language abilities in children. Understanding the factors that influence this process can provide insights into the mechanisms underlying language acquisition and lead to potential clinical uses of RS EEG, such as biomarkers or predictors of typical and atypical speech and language development.

4.1.3 The current study

Despite the advantages of EEG in neurodevelopmental research, few studies have investigated RS oscillations in speech perception and language development. To this day, there is no evidence about how the RS patterns change with age or how they are related to the maturation of brain language networks. There is no clarity about the link between RS patterns and the maturation the ventral and dorsal language tracts, about role of oscillatory lateralisation in language development and whether RS measures are related to behavioural indices of speech perception, such as speech-in-noise or filtered speech tests. For example, most of the evidence supporting the AST hypothesis comes from adult studies, but it has not been tested yet in young children with typical and atypical language skills.

In contrast with research in other neurodevelopmental disorders such as dyslexia or autism, only one study links DLD and RS oscillations. However, it was conducted more than a decade ago and in infants, not in children, and who did not have a diagnosis of DLD but were at family risk of presenting it (Benasich et al., 2008). After a thorough literature search, we confirmed that, to this date, no study had explored the role of atypical RS oscillatory power or lateralisation in young children with DLD. So far, we do not know whether DLD-affected children exhibit delayed, altered, or typical RS activity patterns and their role in DLD behavioural symptoms. Understanding these aspects is extremely important given the current need for objective clinical markers that could help to improve the identification of children at risk of DLD at early ages.

Considering this knowledge gap, we conducted an RS EEG study to determine if some previous findings could be replicated in DLD children. Namely, we looked at an association between frontal gamma power and language skills (Gou et al., 2011) and between HF leftward asymmetry and speech in noise performance (Thompson et al., 2016) or language status (Benasich et al., 2008). However, as the amplitude of gamma oscillations is small because of the 1/f spectral power distribution and has low SNR, we were aware it was probably hard to study in young children. For this reason, we examined gamma oscillations and activity for the theta, alpha and beta bands.

The first goal of this study was to characterise RS band power at lateralisation of oscillations at different frequencies in young children with TLD and DLD and to compare their responses to those observed in adults. A second goal was to compare the performance of both groups of children in speech perception tests and determine whether there was a relationship between behavioural and RS EEG measures.

Thus, this study addressed the following research questions:

(i) What are the patterns of RS power and lateralisation of oscillations at different bands for each group of participants?

(ii) Are there any differences between the TLD, DLD and adult groups in RS average band power and lateralisation indices at different frequency bands?

(iii) In TLD/DLD children, is any of the EEG variables associated with performance in speech perception tests?

Considering that the literature on RS oscillations in TLD at this age is scarce and almost inexistent for children with DLD, our hypotheses were exploratory and aimed to replicate previous findings even though they represented different populations or age groups.

The primary hypothesis was that RS measures and developmental language status at the group level would be positively associated. Thus, we predicted that TLD children would exhibit (i) greater frontal resting gamma power and (ii) stronger HF asymmetry than children with DLD. Between adults and children, we expected (i) reduced gamma power because of brain maturational changes (e.g., Uhlhaas et al. 2009; 2010), and (ii) no differences in the strength of the asymmetry, as this should be already established by the age of our sample (Weiss-Croft & Baldeweg, 2015; Thompson et al., 2016).

The secondary hypothesis was that speech perception skills would show differences based on children's language status (TLD/DLD) but also an association with EEG lateralisation measures, as reported by Thompson et al. (2016). Thus, we expected TLD children to perform significantly better than the DLD group in behavioural speech perception tests. These test scores would be associated with all children's RS gamma band power HF lateralisation indices. Finally, although we had no a priori hypothesis for the theta, alpha and beta bands, we expected the typical 1/f structure in all groups but with a smaller amplitude in adults**,** because of the age-related power decrease (Saby & Marshall, 2012).

4.2 Methods

4.2.1 Participants

All demographics and recruitment procedures were the same as those used in Chapter 3, except by fewer adult participants in the current study (n=18, *M*age= 33.7 years, *SD*=4.9, age range=24.8-44.9, 11 female).

4.2.2 Speech perception measures

Speech perception tests inform about the ability to extract meaningful speech cues from complex acoustic environments. For this study, we considered two low-redundancy monoaural subtests (ASHA, 1996); a speech in babble and a filtered speech test obtained from the "Santiago Auditory Processing Battery" (Fuente, 2006). Each subtest consists of fifty Spanish monosyllabic words divided into two lists of 20 stimuli (one list for each ear) plus two practice items delivered via headphones. All stimulus in this battery were balanced in their linguistic frequency and age of acquisition for Chilean Spanish (Appendices 4.1- 4.2)

The speech-in-babble subtest consists in recognising words embedded in multi-talker babble, both presented in the same ear at 40 dB SL with a non-adaptive, fixed SNR equal to 0. This test simulates real-world listening scenarios and assesses an individual's ability to segregate target speech in the presence of competing talk. The filtered speech subtest consists of recognising low-pass-filtered monosyllables, in this case at 1500 Hz presented at 50 dB SL. These tests manipulate the acoustic characteristics of speech to assess the ability to process spoken stimuli with degraded spectral or temporal cues.

For each speech perception subtest, children were asked to repeat what they heard (target word) vocally. Each correct answer scored 5%, with an age-expected values over 60%

in TLD children, according to Chilean preliminar studies (e.g. Balmaceda et al., 2008). The order of the subtests and starting ear were randomly determined to avoid the potential effects of the presentation order. Before the tests, children received a Chilean articulatory screening test (TAR, Barrios et al., 1987, see Appendix 4.3), to check their phonemic repertoire and avoid confounds when scoring the speech perception tests.

4.2.3 Procedures

Children sat still in a quiet room next to their parents or carers. RS EEG was recorded continuously for three minutes with eyes open (EO) according to previous studies, while children fixed their gaze in a black tablet (8.7 inch screen) placed in front of them (distance=100 cm) at eye level. All the other procedures were the same as those in Chapter 3.

4.2.4 EEG preprocessing

EEG analysis was performed with Matlab 2016-2022a, EEG Lab (Delorme & Makeig, 2004) and Fieldtrip (Oostenvald et al., 2011). The continuous EEG was downsampled to 500 Hz and referenced to electrode Cz; to improve the data quality, allowing us to retain more epochs than the average reference. A high-pass Butterworth IIR filter with a cut-off of 1 Hz was applied to reduce slow drifts and improve the ICA decomposition. The continuous EEG was visually inspected to remove bad channels and data portions contaminated with large artifacts. ICA was performed to eliminate activity from eye blinks, eye movements, and muscular artifacts, according to the criteria described in Chapter 2. The removed channels were interpolated, and data was re-referenced to the average.

The preprocessed EEG was segmented into fifty-seven 2-second epochs (1000 samples) with 50% overlap, windowed with a Hanning taper to attenuate the edges and to avoid ridge artifacts. This epoch length was chosen to ensure that low-frequency activity would not be affected, as discussed by Thompson et al. (2017). For each epoch, the frequency spectrum was computed between 2-60 Hz in steps of 0.5 Hz, using a Fast Fourier Transform, resulting in 116 linearly spaced frequencies with a 0.5 Hz frequency resolution.

To get a general impression of the data, we computed global power at each channel for all participants and averaged the spectral energy between 2-60 Hz for each group. To avoid distortions resulting from the filter cut-off and line noise artefacts, a global power analysis was restricted to the 2-45 Hz range (92 frequencies) and calculated across the following frontal and central channels: Fp1-2, AF3-4, F7-8, F3-4, FC1-2, FC5-6, and Fz. Then, power was binned into the theta (3-7 Hz), alpha (8-12 Hz), beta (13-25 Hz) and gamma (25-45 Hz) bands and averaged within each band (e.g., as in Giraud et al., 2007).

The lateralisation of oscillations was calculated as in previous studies (e.g., Thompson et al., 2016), dividing the EEG channels into two sets: left (FP1, AF3, F3, F7, FC1, FC5, T7, C3, CP1, CP5, P3, P7, PO3, O1), and right (FP2, AF4, F4, F8, FC2, FC6, C4, T8, CP2, CP6, P4, P8, PO4, O2), excluding the midline electrodes. Spectral power was averaged within each electrode set between 2-45 Hz, and a "laterality index" (LI) was calculated at each frequency with the following formula: LI= Absolute Power (Right − Left)/Absolute Power (Right + Left). A number less than zero indicated a bias of oscillations towards the left hemisphere, and higher than zero towards the right hemisphere. For each participant, the laterality indices were averaged into a low-frequency bin (LF, 3–7 Hz) for the theta range and a high-frequency bin (HF, 20–45 Hz), corresponding to high beta and low gamma oscillations.

4.2.5 Study design

This study was observational and involved within and between-group analysis. The independent variable was language status, operationalized as the “Group” category, with three levels: TLD, DLD and Adults. The dependent variables were all continuous and included EEG measures of: (i) average band power (in μV^2) at the theta, alpha, beta and gamma bands, (ii) oscillatory lateralization (positive, negative, or neutral indices), and (iii) the percentage of correct responses for the speech in noise and filtered speech tests.

4.2.6 Statistical Analysis

Statistical analyses were performed with Matlab 2016-2022a and SPSS 22-29. We first checked the data distributions for all the dependent variables to determine whether each variable showed normality and linearity, so the appropriate statistical methods were applied to test our hypotheses. When the assumptions for linear methods were not met, non-parametric tests were preferred over Bootstrapping or permutations methods, as the former perform better with small sample sizes.

We conducted planned comparisons between the three groups for the different RS measures to test our primary hypothesis. We expected inherent differences between frequencies for the average band power because of the 1/f spectral structure. However, our focus of interest was determining between-group differences at each frequency range. Thus, between-group comparisons were conducted separately for each band or laterality measure using one-way analysis of variance ANOVA or Kruskar-Wallis tests if the normality or linearity assumptions were unmet (see Appendix 4.4). To avoid inflating the family-wise error because of running multiple tests, we used Bonferroni-corrected alpha even though it was not strictly necessary, as this study is exploratory.

To test the secondary hypothesis, we compared the performance for each speech perception test only between the groups of children, as these tests were not conducted in the adult group due to practical reasons (permission to use the adult APD test battery was not granted at the time of testing). Firstly, we examined the between-group differences in the test scores using independent samples t-tests or Mann-Whitney's U if parametric assumptions were unmet. Secondly, we explored the association between speech perception and EEG measures (gamma power and HF asymmetry) using Pearson's correlation or Spearman's rank if parametric and linear assumptions were unmet. When corresponding, all alpha levels were Bonferroni-corrected for multiple comparisons.

Importantly, it was not possible to control for age and non-verbal test scores because these screening variables (reported in Chapter 3) did not meet the required assumptions to be used as covariates. Their distribution was not normal in the children's groups, and there was no linearity between the covariates and any of the DVs (see Appendix 4.4). Thus, age and non-verbal scores were not adequate covariates and would have invalidated the results of any analysis, including them as such (e.g., Analysis of Covariance, ANCOVA).

Finally, effect sizes were measured with eta squared (η^2) considering large effect ≥ 0.14, medium effects ≥ 0.06, small effects ≥ 0.01 and Cohen's d (large effect = 0.8; medium effect= 0.5; small effect= 0.2). The strength of associations was measured with Pearson's (r) or Spearman's rank (ρ) correlation coefficients, considering 0.01-.019=negligible, 0.20-0.29=weak, 0.30-0.39=moderate, 0.40-0.69=strong and 0.70 ≥ very strong relationship between the variables (Field, 2013).

4.3 Results

4.3.1 Behavioural Measures

To determine behavioural differences in speech perception between the groups of children, we assessed their speech in babble and filtered speech perception skills. Table 4.1 presents the descriptive statistics for speech perception tests in the TLD and DLD groups.

Table 4.1

Descriptive Statistics for Speech Perception Tests, in the TLD and DLD Groups

	TLD		DLD	
Test	*M*	*SD*	*M*	*SD*
Speech in Babble	62.50	13.43	55.54	14.18
Filtered speech	61.56	11.33	46.79	11.16

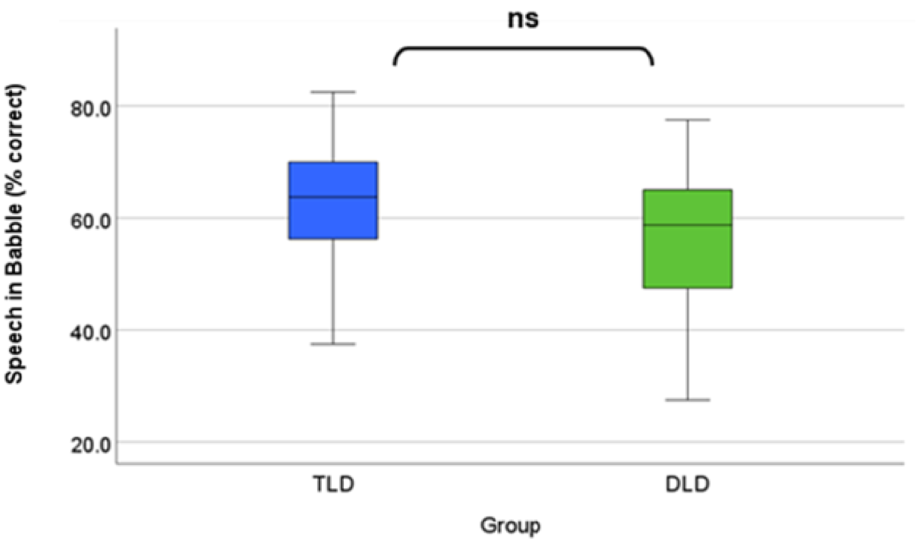
Note. Missing values excluded. TLD n=8, DLD, n=11.

Data was normally distributed in both groups for the speech in babble test (Appendix 4.4).Thus we compared the groups using independent samples t-tests. The TLD group showed a higher percentage of correct responses (*M*=62.5, *SD*=13.43) than the DLD group (*M*=55.54, *SD*=14.18), but this difference was non-significant, *t*(20)=1.13, *p*=0.272, with a medium effect size (Cohen's d=0.5). Figure 4.1 displays the mean values of each group.

For the filtered speech test, Mann-Whitney's U indicated that the median percent correct score was significantly higher in the TLD (*Mdn*=16.13) than in the DLD group (*Mdn*=8.86), *U* =19, *z* =-2.56, *p* = .01, using an exact sampling distribution for U (Dineen & Blakesley, 1973). Figure 4.2 displays the mean ranks for the groups of children.

Figure 4.1

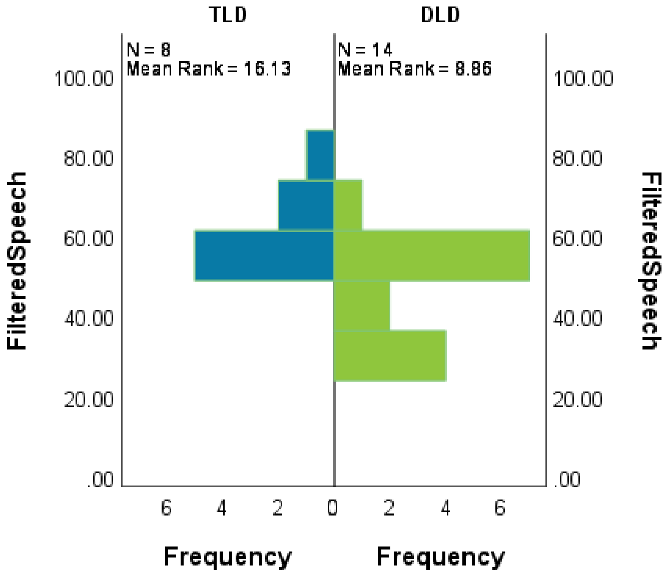
Box Plot for Mean Percent Correct Responses for the Speech in Babble Test in Children



Note. Blue box: TLD (n=8), green box: DLD (n=11). Ns= non-significant at the 0.05 level.

Figure 4.2

Pyramid Plot for Mean Ranks, Filtered Speech Percent Correct Responses in Children



Note. Blue bars: TLD (n=8), green bars: DLD (n=11). Differences are significant at α= 0.05.

4.3.2 Resting-state EEG Measures

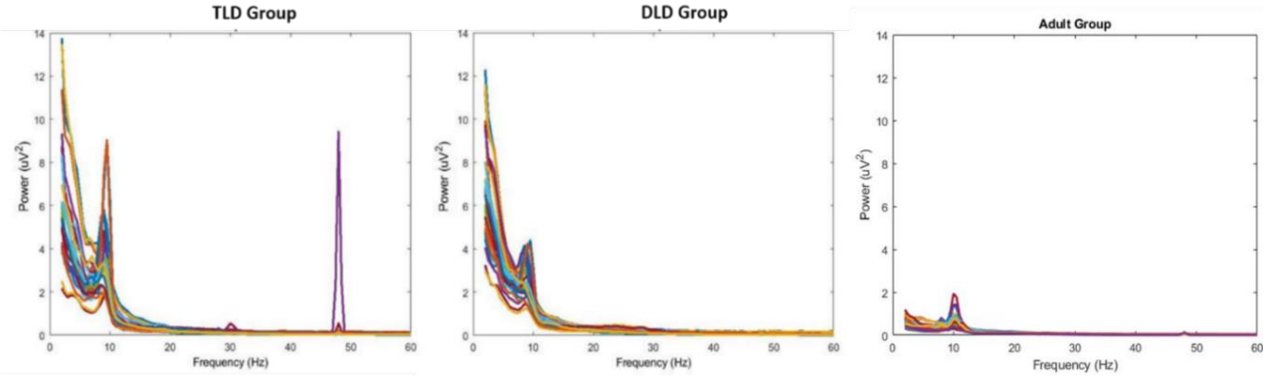
4.3.2.1 Spectral power analysis

Global power

As a data check, our first step was to compute the power spectra for each channel, averaged across participants for each group (Figure 4.3). In all groups, the spectrum for all electrodes shows the typical 1/f gradual decrease in power and the expected alpha peaks at approximately 10 Hz, as expected in a typical resting state EEG. In addition, one of the electrodes in the TLD group presents a peak at approximately 48 Hz, which is consistent with remaining electric line noise.

Figure 4.3

Global Power for all Channels on each Group, 2-60 Hz

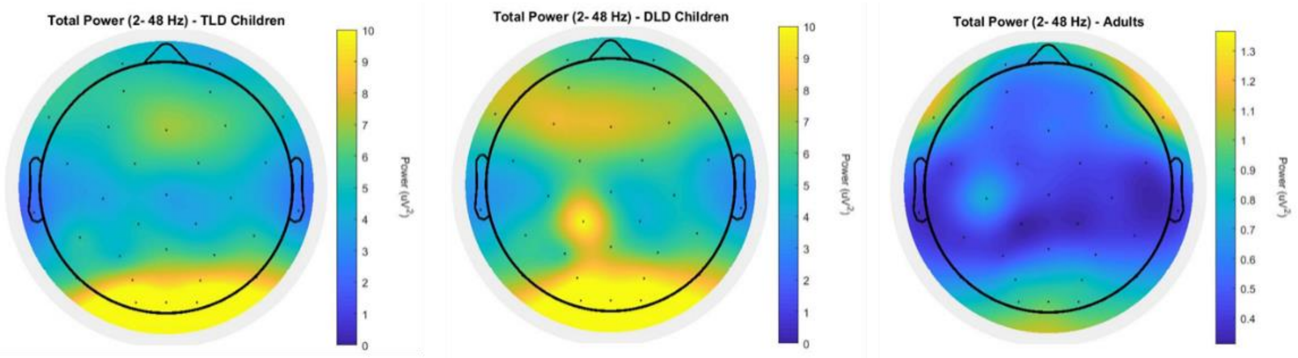


Note. Left: TLD group (n=11); middle: DLD group (n=16); right: Adult group (n=18).

To avoid the effects of the line noise peak at 50 Hz and the filter cut-off at 1 Hz, we reduced the range of frequencies for analysis to 2-45 Hz. Figure 4.4 presents the power scalp distribution for all groups, indicating a posterior positivity in children, and frontal-central negativities in adults. The isolated centroparietal activation in the DLD group is likely to represent a remaining artifact.

Figure 4.4

Scalp Distribution of Spectral Power between 2-45 Hz, all Groups

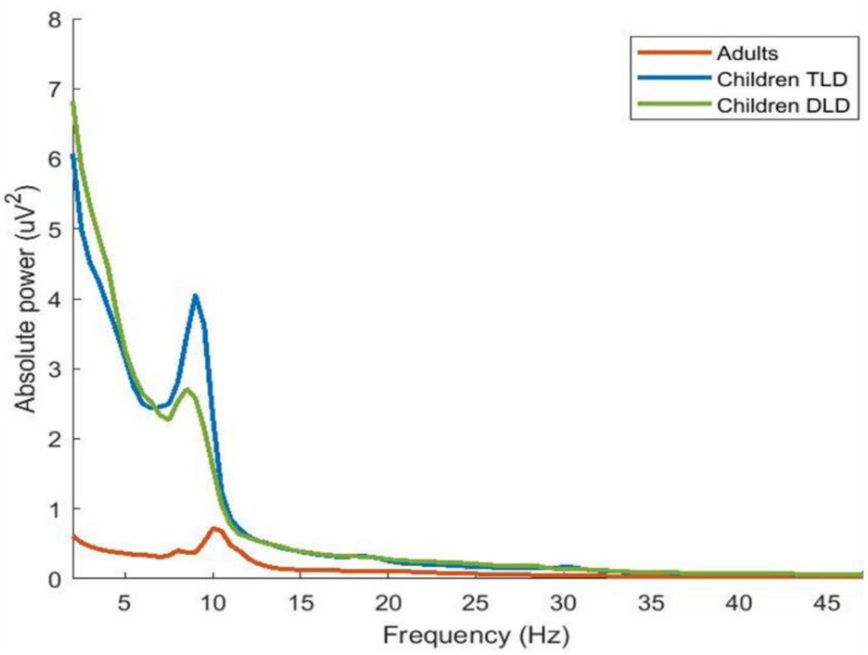


Note. Resting global power is displayed topographically for the TLD group (left, n=11) DLD group (middle, n=16) and adult group (right, n=18).

Next, spectral power was averaged across all electrodes for each group (Figure 4.5). The magnitude seems smaller in the adult than the children's groups, ranging from 0.3 to 1.3 µV², whereas in the TLD (0-10 µV²), and the DLD group (0-10 µV²) the responses were similar, except in the alpha band. All groups show a peak in the alpha band (larger for the TLD group), followed by an energy decrease. In the TLD/DLD groups, the alpha peak appears slightly below 10 Hz, whereas in adults looks at 10 Hz.

Figure 4.5

Global Power Spectrum Collapsed across all Electrodes



Note. Global power spectrum (0-45 Hz) averaged across all electrodes for each group.

Average band power

The first analysis examined between–group differences in average power at each frequency band, calculated across electrodes Fp1-2, AF3-4, F7-8, F3-4, FC1-2, FC5-6, and Fz. Table 4.2 displays the descriptive statistics at all frequency bands for each group.

Table 4.2

Descriptive Statistics for Average Band Power (µV²) per Frequency Band

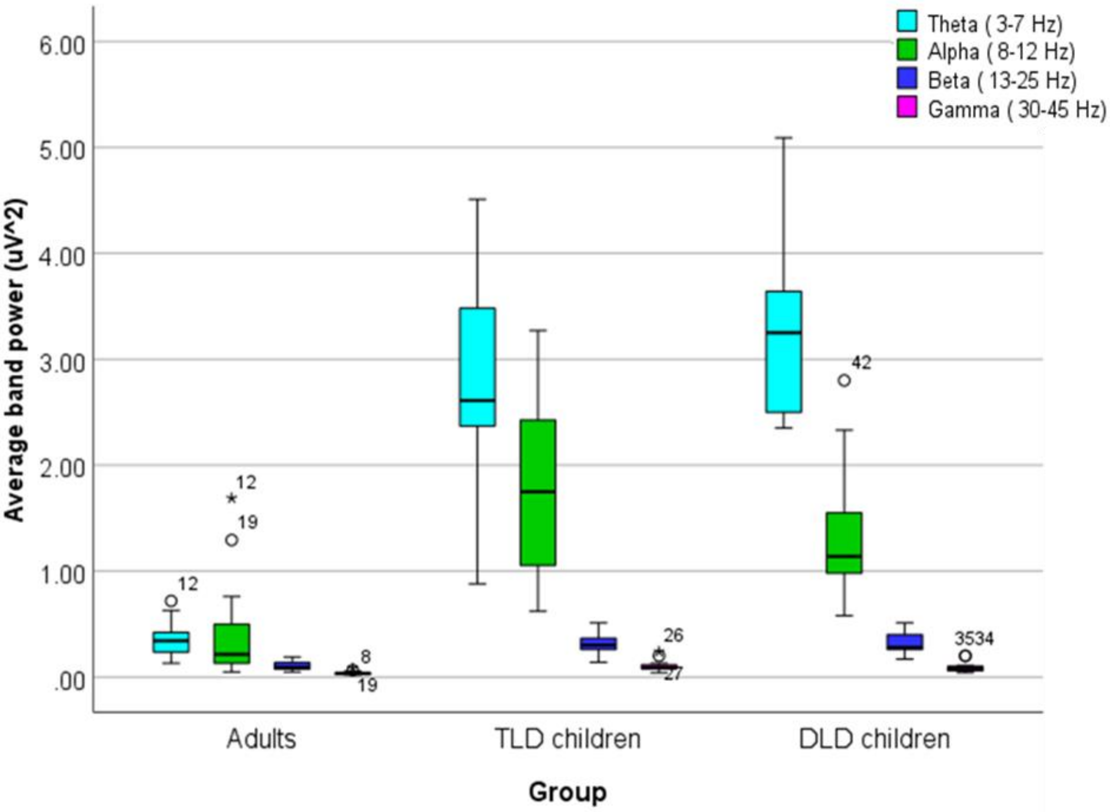
		TLD		DLD		Adults	
	Hz	*M*	*SD*	*M*	*SD*	*M*	*SD*
Theta	3-7	2.85	1.02	3.36	.88	.37	.17
Alpha	8-12	1.73	.86	1.32	.57	.41	.44
Beta	13-25	.32	.11	.32	.10	.11	.04
Gamma	25-45	.11	.06	.09	.05	.04	.12

Note. Adults=18, TLD n=11, DLD n=16.

Figure 4.6 illustrates the average band power for each group, evidencing two relevant features; (i) adults show smaller power than children at all frequencies, and (ii) the ratio between theta and alpha seems smaller in adults than in children. Next, we performed planned between-group comparisons for average power at each frequency band (see Appendix 4.4 for data normality and variance homogeneity tests).

Figure 4.6

Box Plots for Average Band Power at each Frequency for all Groups

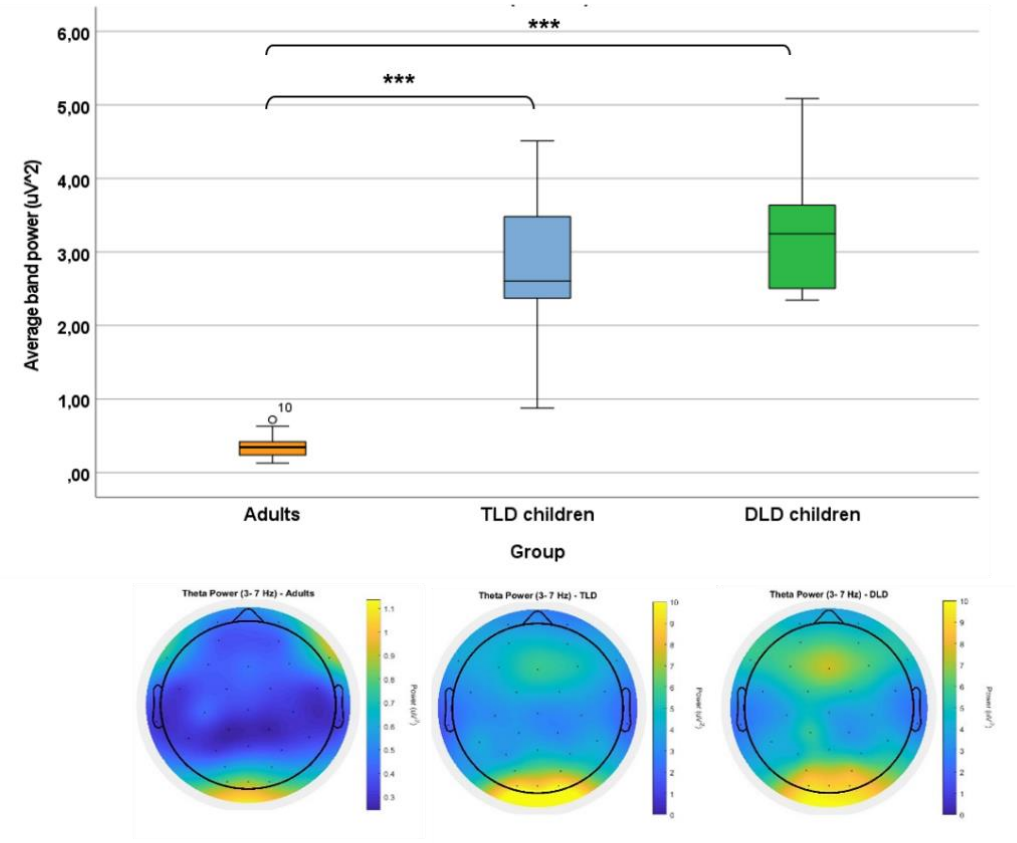


Note. Adults (left, n=18), TLD (centre, n=11), and DLD (right, n=16) group.

Average theta band power and scalp distributions are displayed in Figure 4.7, showing a posterior scalp distribution and stronger activation in children than adults. One-way ANOVA indicated a significant effect of Group [$F(2,44)=80.434$, $p<.001$] with a large effect size $\eta^2 = .793$. Multiple comparisons with Tamhane's correction for unequal variances (see Appendix 4.4) indicated significantly lower theta power in adults (*M*= .37, *SD*= .17) than in the TLD (*M*= 2.85, *SD*= 1.02) and the DLD (*M*=3.36, *SD*= .88) groups, at the $p<.001$ level, but no significant differences between the TLD and DLD groups.

Figure 4.7

Boxplots and Scalp Maps for Average Theta Band Power (3-7 Hz), all Groups

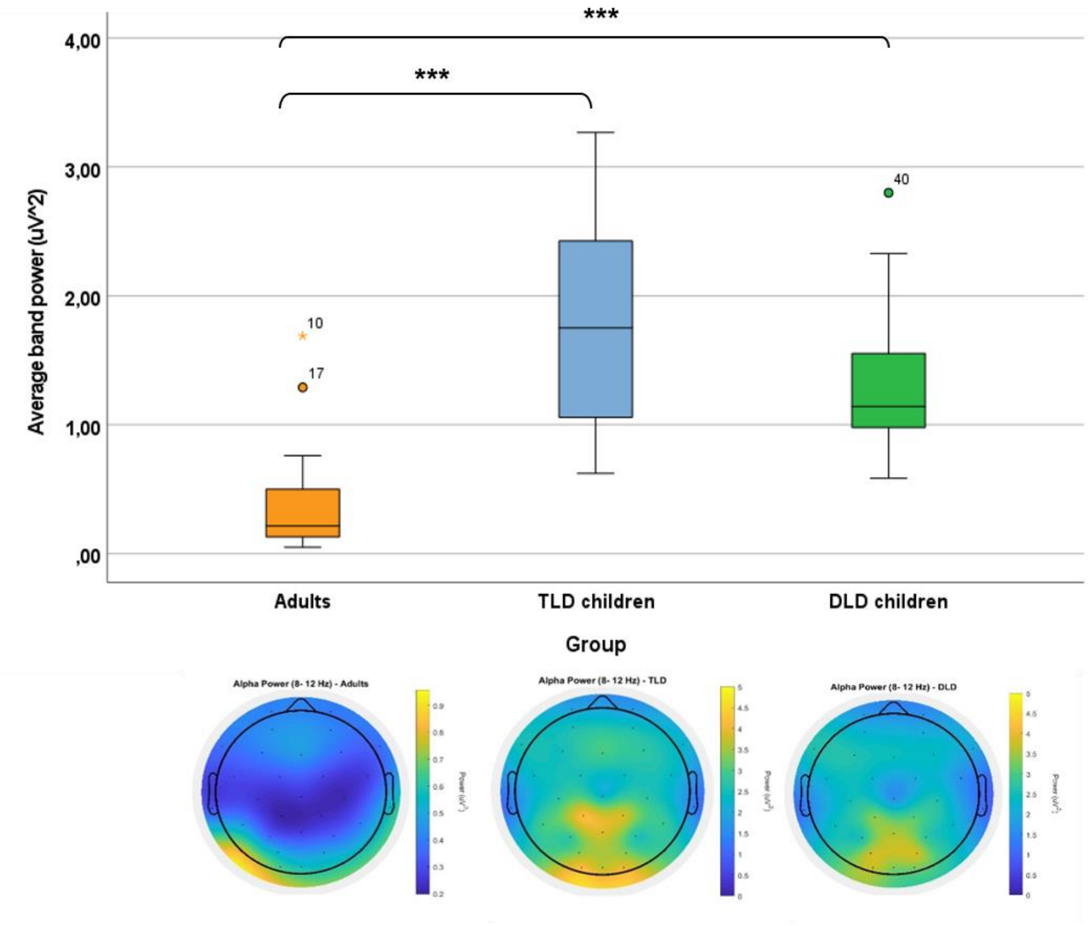


Note. Boxplots (top) and scalp distribution (bottom) for average theta power for the Adult (left, n=18), TLD (center, n=11), and DLD (right, n=16) groups. Colourbar scale for adults is smaller for visualization. (***) = significant at the $p<.001$ level.

Figure 4.8 illustrates mean values and scalp topography for average alpha power, showing broader central and occipital activation in children than in adults. Independent-samples Kruskal-Wallis test (Bonferroni-corrected alpha=. 017) indicated significant between-groups differences, *H* (2,45) = 23.59, *p* <.001. Pairwise comparisons indicated significantly smaller alpha power in adults (mean rank=11.50) than in the TLD (mean rank=33.00) and DLD (mean rank=29.0) group at *p*<.001, but no differences between the children groups.

Figure 4.8

Box Plots and Scalp Maps for Average Alpha Band Power (8-12 Hz), all Groups

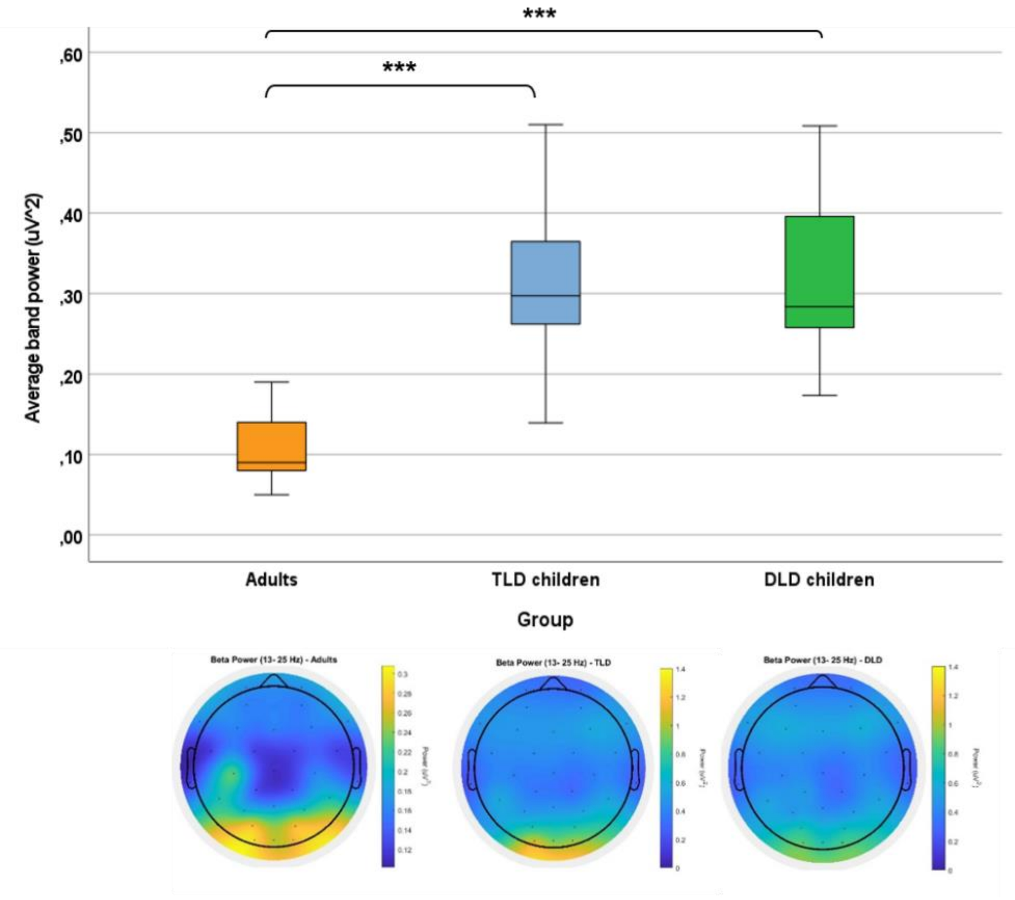


Note. Boxplots (top and scalp distribution (bottom) for average alpha power for the Adult (left, n=18), TLD (centre, n=11), and DLD (right, n=16) group. Colourbar scale for adults is smaller for visualization. (***) =significant at the *p* <.001 level.

Beta band average power and scalp distribution are presented in Figure 4.9, showing comparatively greater posterior activation in adults than children, although in a smaller power scale. One-way ANOVA indicates between-group differences *F*(2,44)=32.65, *p*<.001, with a large effect size η^2 =.61. Multiple comparisons with Tamhane's correction for unequal variances indicated significantly smaller beta power in adults (*M*= .11, *SD*= .044) than in the TLD (*M*=.32, *SD*=.11) and the DLD group (*M*= .32, *SD*=10) at the *p*<.001 level, but with no differences between the children's groups.

Figure 4.9

Box Plots and Scalp Maps for Average Beta Band Power (13-25 Hz), all Groups

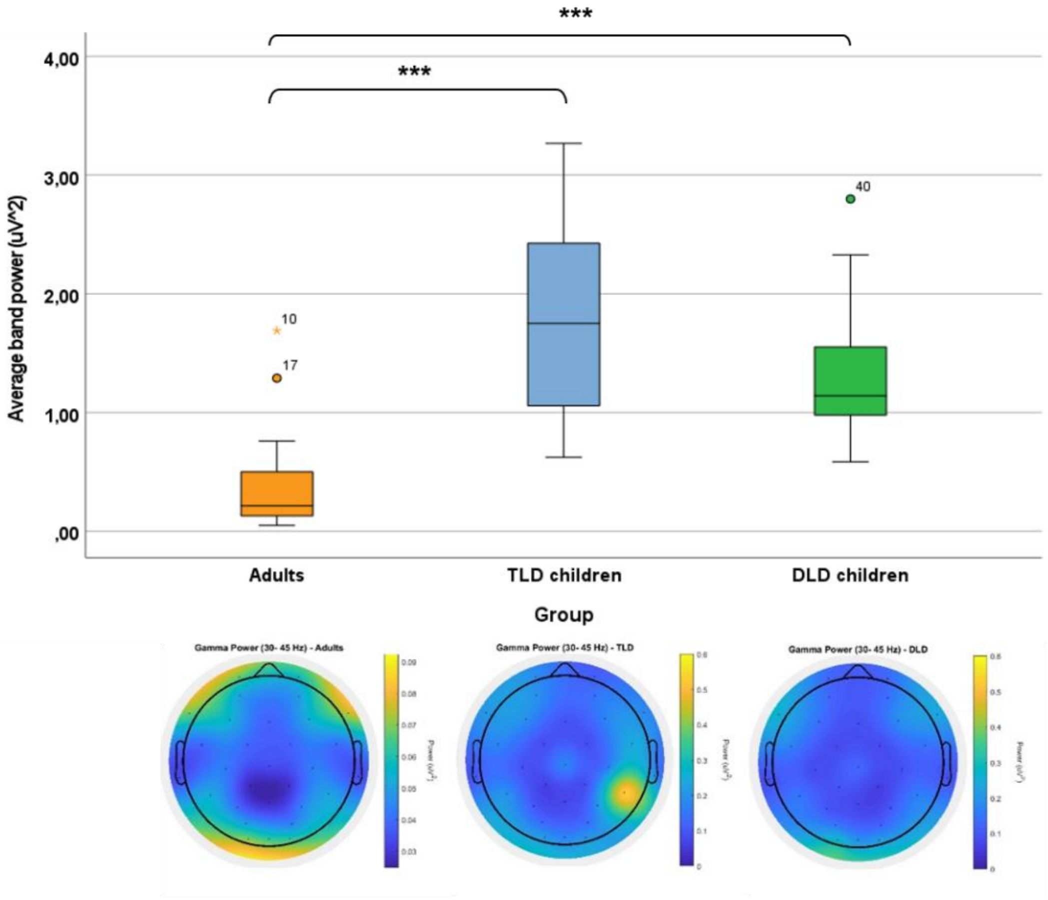


Note. Boxplots (top) and scalp distribution (bottom) for average beta power for the Adult (left, n=18), TLD (centre, n=11), and DLD (right, n=16) group. Colourbar scale for adults is smaller for visualization. (***) is significant at the *p* <.001 level.

Figure 4.10 displays the mean values and topography of gamma-band power, suggesting frontal and posterior activation in adults and broadly distributed effects in children, with a right parietal focus of activation in the TLD group. Independent samples Kruskal-Wallis test indicates significant differences between the mean ranks for the adults (10.84), TLD (32.41) and DLD (30.09) group, *H* (2, 45) =25.57, *p* <.001. Pairwise comparisons indicated significantly smaller gamma power in adults than in the TLD and DLD group at the *p*<.001 level, but again, with no differences between children groups.

Figure 4.10

Box Plots and Scalp Maps for Average Gamma Band Power (30-45 Hz), all Groups



Note. Boxplots (top) and scalp distribution (bottom) for average gamma power for the Adult (left, n=18), TLD (centre, n=11), and DLD (right, n=16) group. Colourbar scale for adults is smaller for visualization. (***) is significant at the *p* <.001 level.

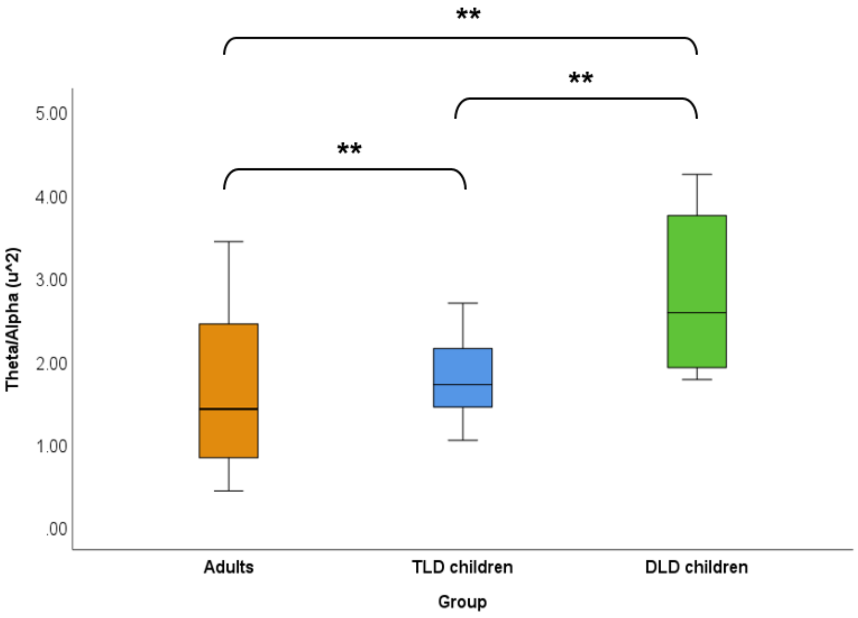
Band ratio analysis

To account for the apparent differences between the frequency band's power ratios between the groups, we compared theta/alpha and theta/beta power ratios using independent-samples Kruskal-Wallis tests (see Appendix 4.4). As this is an exploratory analysis, no alpha correction was used. Figures 4.11 and 4.12 display the average rank of each group for theta/alpha and theta/beta power ratios, respectively.

For the theta/alpha ratio, we detected significant differences between the mean ranks for the Adult (17.5), TLD (19.5) and DLD (31.63) groups, *H* (2, 45) =10.86, *p* =.004. Pairwise comparisons indicated a significantly smaller theta/alpha power ratio in adults (*M*=1.63, *SD*=.97) than in the DLD group (*M*=2.82, *SD*=.96), and in TLD (*M*=1.81, *SD*=.55) than in DLD children, with no differences between the adult and TLD group. These results indicate that those groups with better language skills presented significant smaller theta/alpha ratio.

Figure 4.11

Box Plots for Theta/Alpha Ratio Mean Ranks, *all Groups*

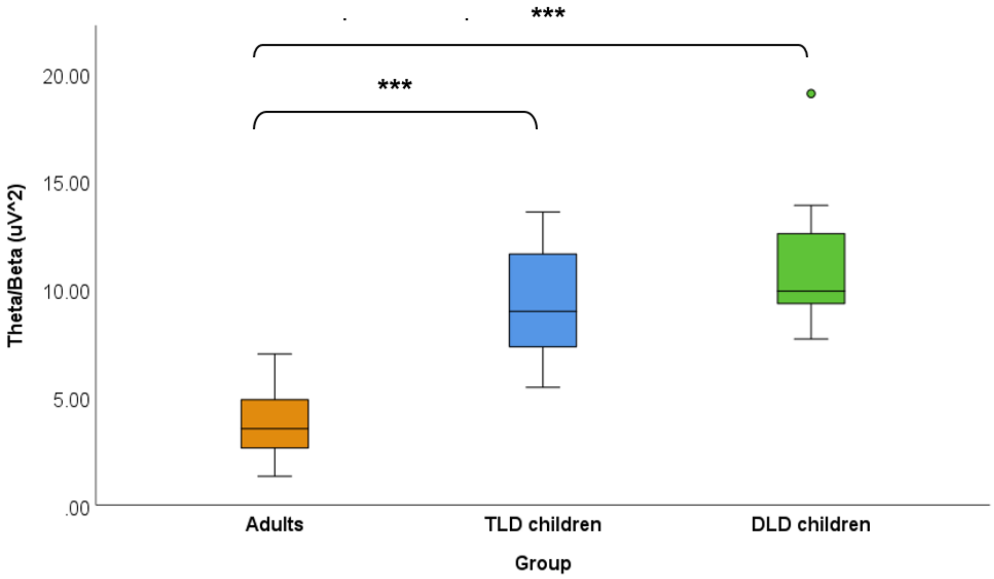


Note. Boxplots for theta/alpha mean ranks for the Adult (left, n=18), TLD (centre, n=11), and DLD (right, n=16) group. (**) is significant at the *p* <.01 level.

For the theta/beta power ratio, there were significant between-groups differences in the mean ranks for adults (9.67), TLD (28.73) and DLD (34.06) children, *H* (2, 45) = 31.99, *p* < 001. Pairwise comparisons indicated a significantly smaller theta/alpha power ratio in adults (*M*=1.63, *SD*=.97) than in both groups of children at the *p*<.001 level, but no differences between the TLD (*M*=2.82, SD=.96) and the DLD group (*M*=1.81, *SD*=.55). These results indicate that smaller theta/beta ratio was related to the participant's age, but not to their language skills.

Figure 4.12

Box Plots for Theta/Beta Ratio Mean Ranks, *all Groups*



Note. Boxplots for theta/beta mean ranks for the Adult (left, n=18), TLD (centre, n=11), and DLD (right, n=16) group. (***) is significant at the *p* <.001 level.

4.3.2.2 Hemispheric lateralization

Average laterality indices per group

To determine any differences in the lateralisation of oscillations, we first computed the laterality indices at each frequency for all participants. Figure 4.13 illustrates the lateralisation indices at each frequency in each group. In the TLD group (plot a), oscillations are left-lateralised from approximately 10 to 28 Hz and over 32 Hz, with no lateralisation between 2 and 8 Hz. In the DLD group (plot b), oscillations are right-lateralised from approximately 12 Hz and higher, with no lateralisation between 2-12 Hz. In the Adult group (plot c), oscillations below 25 Hz are right-lateralised and left-lateralised over 25 Hz, but the magnitude of this lateralisation seems smaller than in the TLD group. This indicates that lateralisation patterns are similar between adults and TLD children but not DLD children.

Asymmetry of oscillations

Each participant's laterality indices were averaged into a low-frequency bin (LF, 3–7 Hz) corresponding to the theta range and a high-frequency bin (HF, 20–45 Hz) corresponding to high beta and low gamma oscillations. Table 4.3 presents the descriptive statistics for laterality indices for each group. Mean values for LF and HF oscillations appear close to zero in all groups, meaning there is no lateralization.

Table 4.3

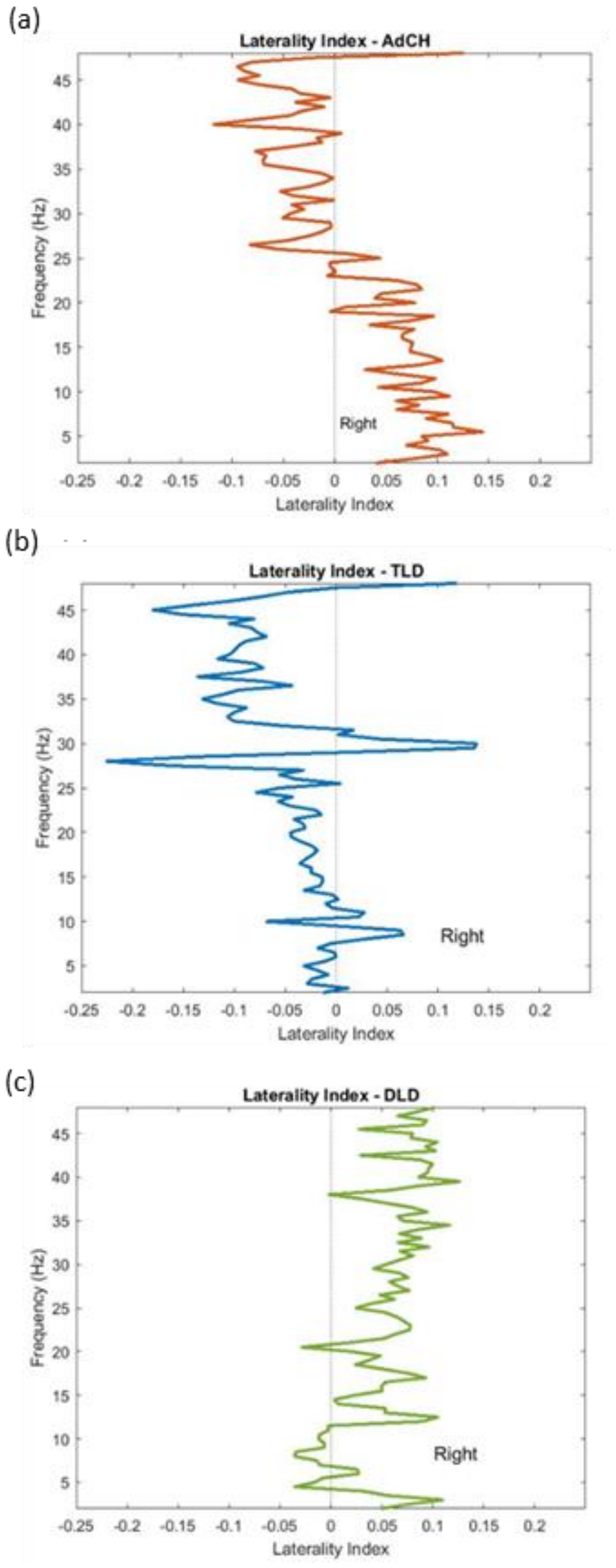
Descriptive Statistics for Laterality Indices

		TLD		DLD		Adults	
	Hz	*M*	*SD*	*M*	*SD*	*M*	*SD*
LF	3-7	.01	.07	-.02	.06	.03	.06
HF	20-45	.001	.06	.013	.11	-.002	.09

Note: TLD, n=11; DLD, n=16; Adults, n=18.

Figure 4.13

HF and LF Lateralisation Indices for all Groups



Note. (a) Adult group, (b) TLD group, (c) DLD group.

After confirming a normal distribution for LF and HF oscillations in both groups (Appendix 4.4), within-group analyses were conducted using one-sample t-tests (one-sided) to determine if LF and HF laterality indices differed significantly from zero A significant difference from zero would indicate a hemispheric asymmetry for a given frequency range. We also compared LF and HF lateralization indices within each group using paired sample t-tests to determine any differences in the degree of lateralization between both ranges. For each analysis, alpha was adjusted to 0.17 to correct for multiple comparisons (0.05/3).

Table 4.4 displays the results of the within-group analysis for each group. Results showed that neither the LF (3-7 Hz) nor the HF (20-45 Hz) laterality indices differed significantly from zero. Likewise, the differences in lateralization between LF and HF oscillations were non-significant for all groups. These findings indicate no asymmetry was detected in any group, with a small effect size in all the tests (below 0.5).

Table 4.4

Within-Subjects Analysis for Laterality/Asymmetry Measures

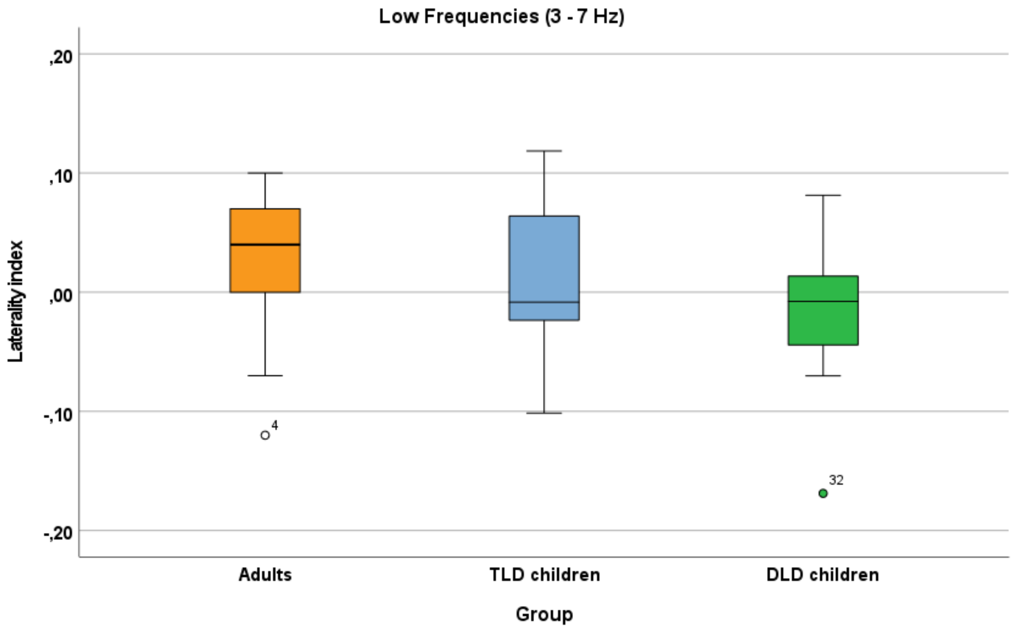
Group	Asymmetry measure	t-test type (one sided)	df	t	p	Cohen’s d
TLD	LF vs zero	One sample	10	.501	.314	.151
	HF vs zero	One sample	10	.048	.481	.015
	LF vs HF	Paired sample	10	.491	.317	.148
DLD	LF vs zero	One sample	15	-1.17	.130	-.292
	HF vs zero	One sample	15	.459	.326	.115
	LF vs HF	Paired sample	15	-1.233	.118	-.308
Adults	LF vs zero	One sample	17	1.84	.04	.43
	HF vs zero	One sample	17	-.09	.46	.09
	LF vs HF	Paired sample	17	1.15	.133	.11

Note. LF: Low-frequency oscillations; HF: High-frequency oscillations. TLD, n=11; DLD, n=16; Adults n=18. Bonferroni- corrected alpha= 0.017. All tests non-significant (ns).

Next, we compared the lateralisation indices for LF (Figure 4.14) and HF oscillations (Figure 4.15) between the TLD, DLD and Adult groups. Separate one-way ANOVA with Bonferroni-corrected alpha (0.17) indicated no between-group differences for LF [$F(2,44)=2.01$, $p=.147$, $\eta^2=.087$] or HF [$F(2,44)=.122$, $p=.885$, $\eta^2=.006$] with small effect sizes in both cases.

Figure 4.14

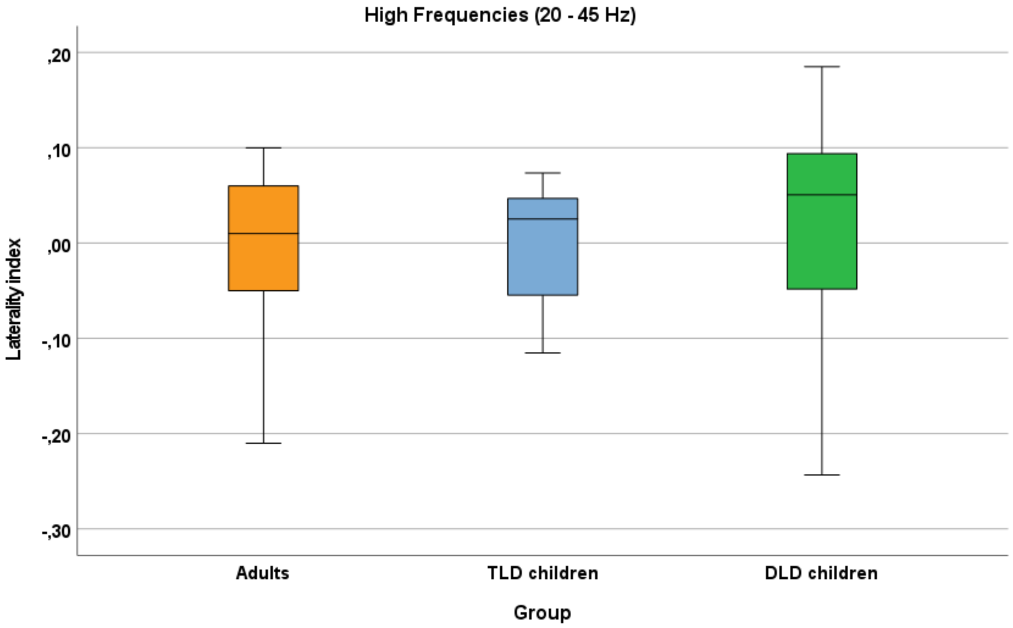
Box Plots s for LF Lateralisation Indices, all Groups



Note. LF lateralisation mean values for the Adult (orange, n=18), TLD (blue, n=11), and DLD (green, n=16) group. Results are non-significant at alpha= 0.17.

Figure 4.15

Box Plots for HF Lateralisation Indices, all Groups



Note. HF lateralisation mean values for the Adult (orange, n=18), TLD (blue, n=11), and DLD (green, n=16) group. Results are non-significant at alpha= 0.17.

4.3.3 EEG versus Behavioural Measures

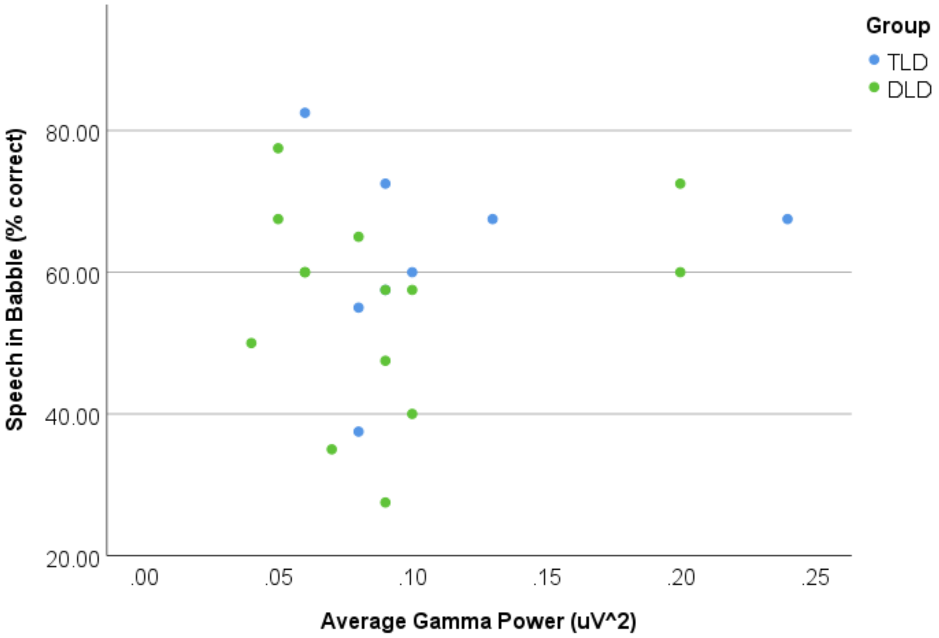
To test the secondary hypothesis, we examined if there was an association between children's performance in speech perception tests and RS measures (gamma-band power and HF lateralization indices). As we had previously compared behavioural results between groups, this time we pooled all children together (n=22), addressing the possibility of equivalent cognitive mechanisms regardless of the children's language status. Planned correlation analysis comprised gamma-band power and HF oscillatory lateralisation versus speech perception tests and was Bonferroni-corrected for multiple comparisons (corrected alpha= 0.05/4= .013). In addition, a complementary correlation analysis was conducted between theta-band power ratio and speech perception measures, although without correcting for multiple comparisons, as this was an exploratory analysis.

4.3.3.1 Gamma power versus speech tests

For the speech in noise test, Spearman's analysis indicated no significant correlation (*r*(20)= .145 *p* =.519) between the percentage of correct answers and average gamma-band power (Figure 4.16). Similarly, there was no significant correlation between the percentage of correct answers for the filtered speech test and the average gamma power at frontal-central electrodes (*r* = -.086, *p* = .703), as can be observed in the scatter plot in Figure 4.17.

Figure 4.16

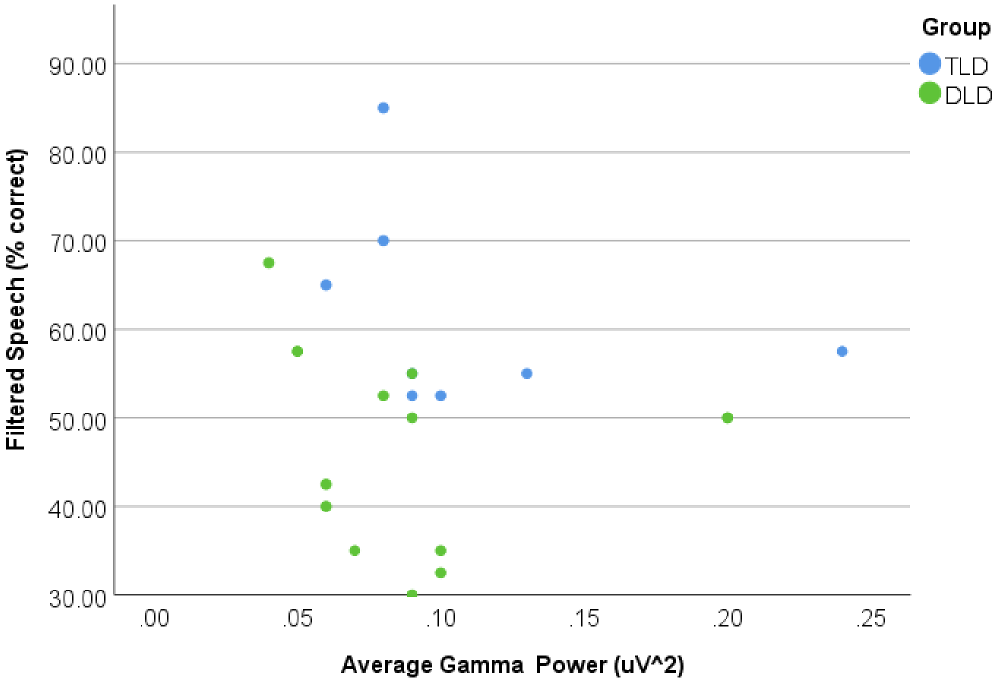
A Scatter Plot Illustrating Speech in Babble Performance versus Gamma Band Power



Note. Blue dots: TLD group (n=8), green dots: DLD group (n=16). Correlation is non-significant at the .013 level.

Figure 4.17

A Scatter Plot Illustrating Filtered Speech Performance versus Gamma Band Power



Note. Blue dots: TLD group (n=8), green dots: DLD group (n=16). Correlation is non-significant at the .013 level.

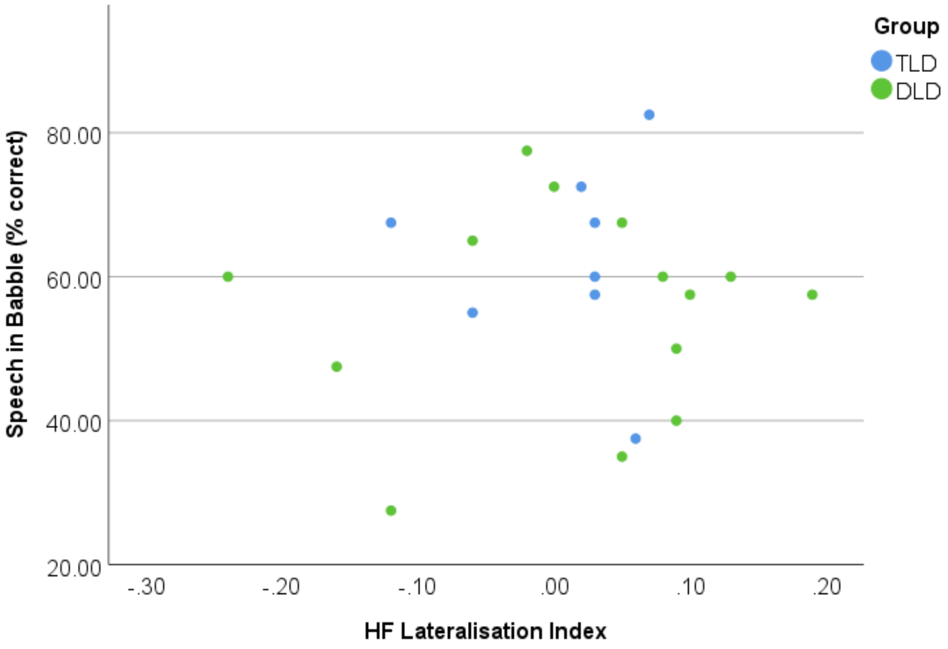
4.3.3.2 Asymmetry vs Behavioural measures

Finally, we assessed the relationship between the lateralisation of cortical oscillatory activity at high frequencies and speech perception performance via correlation analysis on the pool of all children (n=22).

Pearson's analysis showed no significant correlation (*r*= .039 *p* =.863) between the speech in babble test and the laterality indices for high frequency oscillations, illustrated in Figure 4.18. For the filtered speech test, Spearman's test indicates no significant correlation (r (20) = -.119, *p* =.598) between the percentage of correct answers in the filtered speech test and the laterality indices for high frequency oscillations. The relationship between both variables is displayed in Figure 4.19.

Figure 4.18

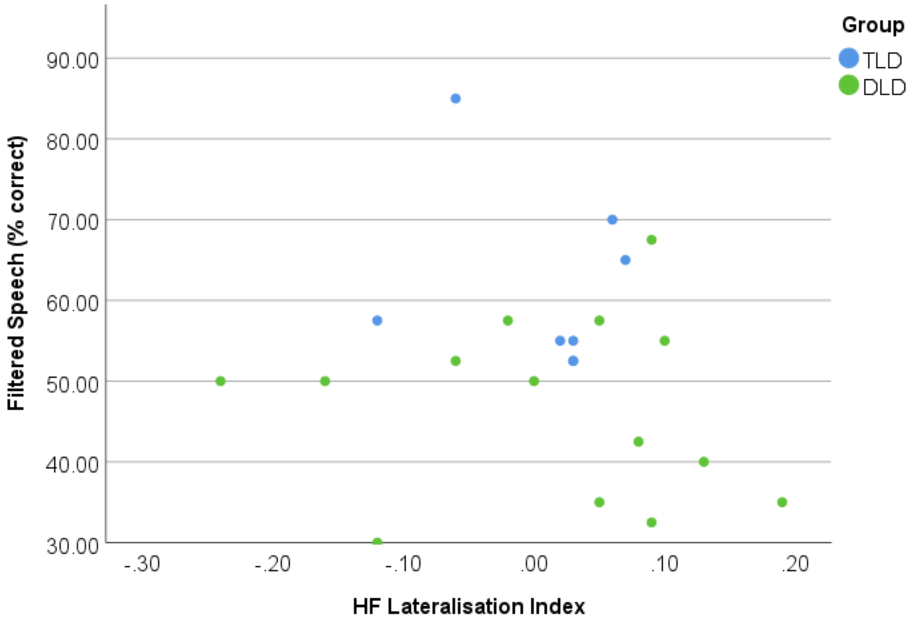
A Scatter Plot Illustrating Speech in Babble Performance versus HF Lateralisation Indices



Note. Blue dots: TLD group (n=8), green dots: DLD group (n=16). Correlation is non-significant at the .013 level.

Figure 4.19

A Scatter Plot Illustrating Filtered Speech Performance versus HF Lateralisation Indices



Note. Blue dots: TLD group (n=8), green dots: DLD group (n=16). Correlation is non-significant at the .013 level.

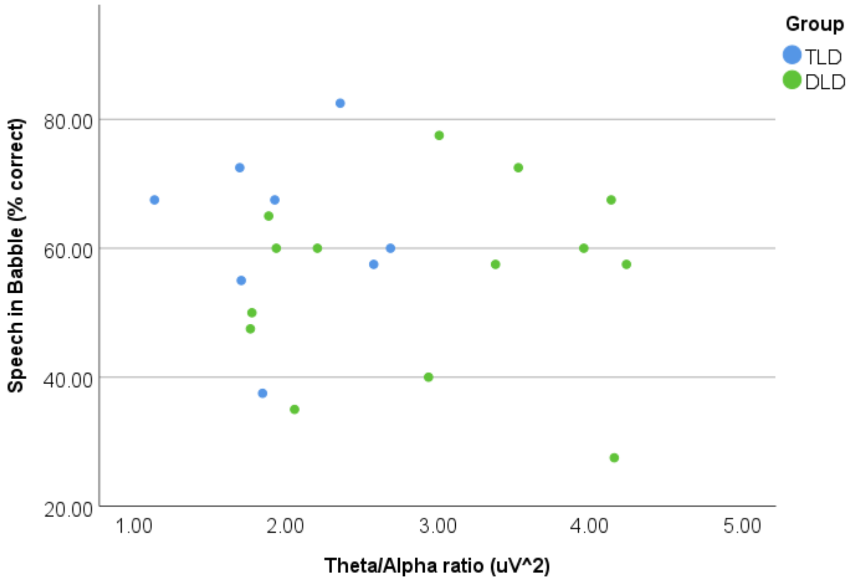
4.3.3.3 Theta/Alpha ratio versus Behavioural Measures

To further explore the findings about theta/alpha ratio differences between all groups, we investigated the association between this EEG measure and the speech in babble (Figure 4.20) and filtered speech (Figure 4.21) test results using Spearman’s correlation analysis.

For the speech in babble test, results indicated no correlation with the theta/alpha power ratio values, (*r*(20)= -.00, *p*=.996, 95% CI [-.433 .432]). On the contrary, there was a significant, strong negative correlation between filtered speech test scores and theta/alpha ratio, (*r* (20) = -.49, *p*=.022, CI 95% [-.759 -.068]), indicating that detection of filtered speech is higher when the ratio between theta and alpha power is smaller.

Figure 4.20

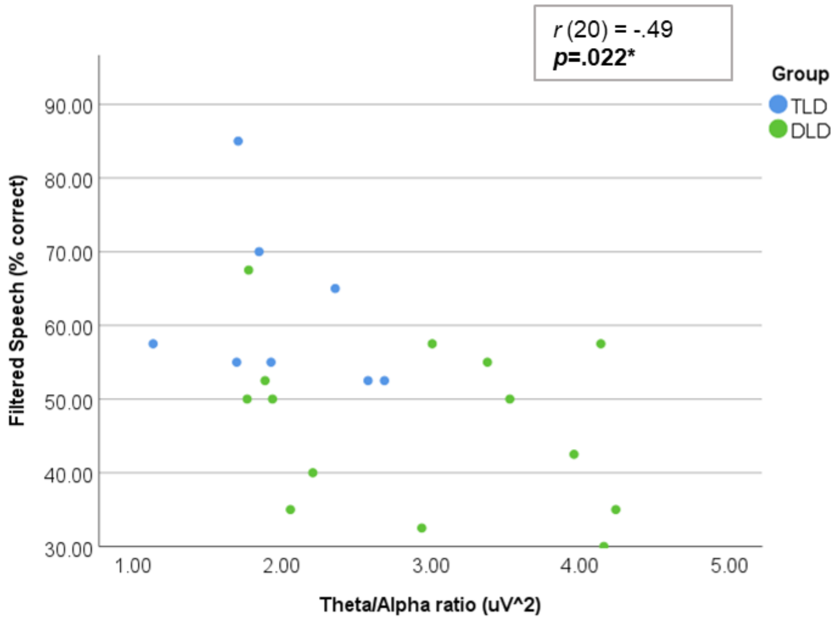
A Scatter Plot Illustrating Speech in Babble Performance versus Theta/Alpha Ratio



Note. Blue: TLD group (n=8), green: DLD group (n=16). Non-significant at α= 0.05.

Figure 4.21

A Scatter Plot Illustrating Filtered Speech Performance versus Theta/Alpha Ratio



Note. Blue: TLD group (n=8), green: DLD group (n=16). (*) Significant at α= 0.05.

4.4 Discussion

4.4.1 Summary of findings

The aims of this study were twofold: (i) to examine differences in RS EEG measures in children with TLD, DLD, and adults, and (ii) to investigate children's performance in speech perception tests and their association with HF oscillations. As expected, we confirmed that adults showed significantly lower band average power than children for all the frequency ranges. However, the results do not support our primary hypothesis, as none of the average power or lateralisation measures differed between children with DLD and their TLD peers. Moreover, there was no evidence of significant LF or HF asymmetry, which does not support the idea of RS oscillation priming.

Our secondary hypothesis was only partially supported, as children with TLD showed significantly better speech perception performance. However, this was only for one of the two tests, and, contrary to what we expected from the previous literature, there was no correlation between behavioural and high-frequency EEG measures (gamma power and HF lateralisation). As RS measures were similar in the TLD and DLD groups, the differences in band power between children and adults likely reflect brain maturation (age) and not an influence of language typical/atypical status.

Finally, there were significant differences in the theta-alpha ratio between all our groups (adults<TLD<DLD) and an inverse correlation between the theta-alpha ratio and filtered speech scores in children, suggesting that these measures could be more sensitive to pick-up differences between the TLD and DLD group. However, such differences may not necessarily originate in between-group language differences but in other factors, for example, non-verbal skills.

Multiple previous studies have described the difference we detected between children and adults in spectral energy. We observed similar patterns in theta, alpha, beta and gamma bands as those described by Perone et al. (2018), Tierney et al. (2013), and Yordanova and Kolev (2008). However, we could not confirm the increase in gamma power reported by Takano and Ogawa (1998). In addition, a visual inspection of our data's global spectrum indicates that the alpha peak in children occurs at slightly lower frequencies (~8 Hz) than in adults (10 Hz), which aligns with previous studies such as Kwok et al. (2019). Thus, the patterns for RS global and average band power observed in our groups are consistent with the developmental trajectories described in the previous literature, showing an evident flattening of spectral power between early childhood and adulthood.

However, our study could not replicate previous findings about positive associations between frontal resting gamma power and language development, as Benasich et al. (2008) and Gou et al. (2011) reported in infants aged 6 to 36 months. We expected higher frontal gamma power in the TLD group associated with their better language skills; however, this was refuted by the absence of power differences between our children groups and lack of correlation between EEG and speech perception measures. This result could be explained by the fact that participants in previous studies were younger than in ours and their age range was considerably broader. Thus, such differences may have disappeared by the age of our samples (early childhood). A feasible way to further examine this point would be to re-test our children's groups in the future and see whether the gamma power recorded in this study predicts their later language skills. Another possible explanation is that our study could not detect the effects of language skills on oscillatory lateralisation, for example, because of the high variability of linguistic profiles between children and small effect size. In the future, we could replicate this experiment in a more homogeneous sample of children with DLD.

A key aspect is that we found no evidence of significant hemispheric RS lateralisation (asymmetry) for the frequency ranges related to phonemic (HF) or syllabic processing (LF) in any group, meaning that our findings do not support the AST hypothesis. For the LF range, we replicated Thompson et al.'s (2016) findings of centrally distributed LF oscillations with similar mean group indices -0.002) and effect sizes. However, we did not observe the HF leftward bias reported in their study, which we would have expected, at least in the adult group, according to the AST hypothesis. A possible alternative explanation is that in our study, the effect sizes for lateralisation (less than d=0.5) are smaller than in Thompson's (d= 1.14), which could have prevented us from detecting potential asymmetry in our groups. Indeed, visual inspection of the lateralisation plots in Figure 4.13 suggests language-related differences in the laterality indices between groups, although they were non-significant.

Importantly, EEG methodological aspects must be considered when interpreting the laterality results. For example, to determine asymmetry, performing point-by-point t-tests or permutation tests instead of conventional t-tests could improve the sensitivity to detect clusters of significantly lateralised oscillations. Secondly, to avoid an electric line noise peak in the TLD group, we defined the HF range between 25-45 Hz, whereas Benasich et al. (2008), Gou et al. (2011) and Thompson et al. (2017) used 30-51 Hz. This shift in HF boundaries could have affected our results by introducing more high-beta and less high-gamma band activity in our HF range. In addition, it is worth noting that lateralisation indices are a power-based measure; thus, if spectral power shows age-related reduction, it may not be appropriate to directly compare adult indices to children's ones without some scaling or normalisation procedure.

An unexpected finding of this study was the significant difference in the theta/alpha and theta/beta power band ratios between groups. Theta/alpha band ratios were smaller in adults than children and in TLD than in DLD children. We also observed that theta/alpha ratios were inversely correlated with filtered speech test scores in children. This supports previous findings by Kwok et al. (2019) of an inverse correlation between alpha power and language skills in children at similar ages. However, although the differences in theta/alpha ratio that were consistent with our group's language status, we should not consider them a confirmation of the RS-language skills relationship without controlling for the effect of non-verbal abilities. This also applies to the differences we observed in theta/beta ratio, which was significantly smaller in adults than children but with no difference between the TLD and DLD groups. Although our results suggest that the theta/beta ratio is sensitive to age differences but not language status, it is essential to interpret these findings cautiously.

That being said, band ratio results in this study indicate not only a developmental decrease in global power but also a relative decrease in theta band power and an increase in alpha and beta power. However, the functional significance of EEG band power ratios has not been fully established yet. On the one hand, there are studies considering them a reliable measure of cognitive performance or even as clinical biomarkers of cognitive dysfunction in different types of neuropsychiatric disorders such as dementia, Attention Deficit Hyperactivity Disorder (ADHD) and Parkinson's Disease (e.g. Azami et al., 2023; Donoghue et al., 2020; Picken et al., 2019; Schmidt et al., 2013). On the other hand, some studies indicate that band ratio measures reflect periodic and aperiodic spectral activity, potentially conflating power measures and leading to incorrect interpretations (Donoghue et al., 2020).

In RS EEG, greater alpha and beta power has been associated with increased arousal and top-down attentional control (Klimesch, 2012), which in our study could indicate greater alertness and wakefulness in adults than children. Although the functional interpretation of RS theta power is less clear, recent studies suggest that it reflects cognitive control processes and may increase during excessive monitoring, shifting or updating operations (Clements et al., 2021). Another possible speculation is that age-related reduction in theta power could reflect brain maturational changes and also increases in network synchronization, resulting in more efficient local and long-range theta connectivity through more consistent phases rather than amplitude signalling.

More recently, the beta/theta ratio has been proposed as a marker of cognitive processing capacity, which could be altered in individuals with cognitive disorders. For example, a study by Picken et al. (2019) in 41 adults with ADHD found an elevated theta/beta ratio in this clinical group. Similarly, a study by Tramell et al. (2017) showed that theta/alpha ratio was related to cognitive abilities modulated by age in both young (below 30 years) and older (over 70 years) neurotypical adults (n=16 and n=20, respectively). However, the question about the origin of band ratio differences remains open and needs to be addressed in future studies to determine the functional significance and define their developmental trajectories.

For our secondary hypothesis, we partially confirmed previous findings, as children with better language skills (TLD) outperformed those with DLD only for the Filtered Speech and not for the Speech-in-Babble test. In addition, we did not find any evidence of an association between speech perception performance and RS EEG measures, except for a negative correlation between theta/alpha ratio and filtered speech scores. This contradicts findings by Benasich et al. (2008), Gou et al. (2011) and Thompson et al. (2017), indicating that the vast majority of our RS measures of cortical activity do not reflect our participant's language status (adult-like, TLD or DLD), or the children's speech perception skills.

Regarding the behavioural results, better performance in speech perception tests in children with TLD than DLD group is consistent with previous studies (e.g. Goswami et al., 2015). However, we did not observe this difference for the speech in the noise test, although it has been previously reported (e.g. Ziegler et al., 2011). These results could not be explained by differences between the group's hearing levels as they were equal. However, they may have to do with the difference in phonological processing skills between the TLD and DLD groups (see screening and PECFO results in Chapter 3) or more general cognitive skills, as arousal or attention levels. Importantly, these tests evaluate different aspects of speech processing; speech in babble assesses the ability to separate a target from the background, and filtered speech requires the brain to complete a degraded signal. Speech-processing skills could develop differently in children with TLD and DLD, explaining the difference in performance and the negative correlation with theta/alpha band power ratio. Future research could explore the association between speech perception skills and RS measures in young children with and without DLD.

4.4.2 Strengths, limitations, and future research

This study's main contribution is that it quantifies RS EEG activity during early childhood, characterizing the RS oscillatory patterns in young children with typical and atypical language development. So far, we are unaware of any research examining spectral power and lateralization measures in these groups and investigating their relationship with speech perception measures. Pursuing this line of research is especially important in language neurodevelopmental research, as by understanding and monitoring children's RS EEG activity, researchers and clinicians may be able to identify those who are at risk for neurodevelopmental disorders (e.g. DLD) and provide early intervention to support them.

However, there are several limitations to the present study. As discussed in Chapter 3, the first limitation is the small sample size, which was further reduced as some children did not attend the third study session (behavioural tests). The final sample size of 8 subjects in the TLD group and 14 in the DLD groups limits the strengths of our findings, in particular those about behavioural tests. In the future, more studies must confirm these results in a larger, more representative sample of children.

A second limitation is that due to the particular characteristics of our data, we could not perform some statistical analysis that could have been more informative than the current ones. We were not able to use the participant's age and non-verbal scores as covariates because these variables did not meet the required assumptions (e.g. normality and linearity between the covariate and DV, for an ANCOVA) even after attempting to transform them (e.g. RMS, log or exponentially). Although linear mixed-effects models would have been a good option to deal with missing data in the speech perception tests, our data did not meet the required assumptions for these models, which could have invalidated their results (Heise et al., 2022). Importantly, this indicates that linear methods may not always be optimal for detecting developmental patterns in RS EEG data, as pointed out by Bosl et al. (2011). They investigated the non-linear complexity of the RS EEG signal using modified entropy at multiple scales (MMSE), a measure that has shown age-related increases. Using machine-learning algorithms, they were able to classify infants at risk of ASD (n=46) and controls (n=33) at different ages with high accuracy based on this measure. Thus, future research could surpass this limitation by implementing non-parametric, non-linear analysis methods.

In terms of the EEG methods, a third limitation is that the band power and laterality measures used in this study are both based on the amplitude of the spectral energy, which, as discussed in Chapter 1, is affected by individual variation in EEG, neural noise, small samples, and small effect sizes, especially when using group averages. Thus, future research could investigate other RS EEG measures less reliant on spectral power. For example, functional connectivity analysis could inform about the degree of synchronization of neural populations at rest. Notably, there is growing research interest in the role of aperiodic (arrhythmic) electrophysiological activity, which is abundant in children's EEG measures and reflects excitatory and inhibitory balance in cortical networks (see Ostlund et al., 2020 toolbox and tutorial). Including aperiodic measures in the parameterization of the neural power spectra (e.g. aperiodic offsets and exponents) and functional connectivity measures could contribute to more accurate descriptions of cognitive and language development (Donoghue et al., 2020).

Finally, another limitation is that the behavioural tests in this study may not have reflected children's speech perception performance in their daily life. As with many clinical measures, the APD battery tests consist only of isolated words, so it could be argued that they primarily reflect auditory than speech perception skills, as at the single word level, speech processing cannot be modulated by linguistic processing or language skills (e.g. as predictive processing or use of linguistic context). In addition, we cannot rule out that fatigue, boredom or inattention may have hindered children's performance in the speech perception tests, as usually happens when testing preschoolers. Future studies could use more ecological behavioural measures, such as the perception of sentences or continuous speech.

4.4.3 Conclusions

Together these findings confirm that EEG resting state activity is stronger in children than adults, but do not support the idea of differences in spectral power between the TLD and DLD group. This is consistent with our findings from Chapter 3, that top-down language effects emerge at some point in childhood although later than the age range we studied. Importantly, the lack of significant oscillatory asymmetry in all our groups, and correlation between speech perception measures and gamma oscillatory activity does not replicate previous findings and does not provide any evidence to support previous theories of atypical brain lateralisation in DLD, such as the AST hypothesis. An unexpected result, though was that the ratio between theta and alpha band power was significantly different between all groups and inversely correlated to filtered speech performance, suggesting that future studies could further explore the functional significance of this ratio.

Chapter 5. Neural tracking of continuous speech in young children with typical and atypical language development

5.1 Introduction

In daily life, speech perception is a complex task that frequently occurs in challenging listening conditions. Although young children can understand continuous speech fairly well, the mechanisms and neural circuits that support adult-like speech perception are still to be refined over time through neuromaturation, experience and language development. In adults, multiple studies have shown that cortical tracking of acoustic and linguistic speech features is a crucial brain mechanism for natural speech processing. However, the developmental trajectories of cortical speech tracking and its relationship with language acquisition remain unknown.

Although plenty of studies have investigated speech perception development at the brain level, a persistent criticism is that highly controlled paradigms (e.g., ERPs) lack ecological validity, as they do not reflect the full complexity of speech perception in natural settings (Hamilton & Huth, 2020). Thus, there has been growing interest in investigating neural speech tracking in children, its relationship with language skills and its potential role in neurodevelopmental disorders, although no study has yet focused on DLD.

This chapter investigates the perception of continuous speech in young children with TLD and DLD, focusing on characterising their patterns of neural tracking of acoustic and lexical speech features. This study aims to shed light on the neural processes involved in continuous speech perception and their relationship with language skills during early childhood.

5.1.1 Neural tracking of speech

Cortical encoding of speech features

One crucial aspect of speech processing is extracting relevant information from the continuous speech stream to be encoded as neural activity. Cortical tracking[5] of speech refers to the brain's ability to align its neural activity with different features in the speech signal (Brodbeck & Simon, 2020), allowing the brain to compute the speech information at multiple timescales and levels of representation. In the last two decades, cortical speech tracking has emerged as an essential mechanism to explain how the brain encodes and processes continuous speech and has been actively investigated in adults.

At the acoustic level, an important source of information for the brain is the temporal envelope of speech, which represents slow amplitude modulations of the speech signal over time. During speech perception, the temporal modulations convey important information about speech cues like phonemes (manner of articulation, voicing or vowel identity), syllables, and prosodic contours (Rosen, 1992). In adults, extensive research has shown that neural responses in the auditory cortex align with the amplitude envelope of continuous speech (Ding & Simon, 2014). When represented in the frequency domain, multiple studies report phase synchronisation between cortical responses (EEG) and the speech envelope at low frequencies (<10 Hz) but also in the gamma band (for a review, see Alexandrou et al., 2018). This synchronisation is usually referred to in the literature as 'coherence', a measure of cross-correlation between spectral densities. However, neural tracking is not restricted to low-level acoustics (Gillis et al., 2021) but extends to higher-order linguistic representations (Kösem & Van Wassenhove, 2017).

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[5] This study will consider speech 'tracking' as time-synchronised and ''entrainment' as phase-synchronised activity (for a review, see Gillis et al., 2022).

Cortical tracking of abstract, linguistic features present in the continuous speech signal has been demonstrated in several experiments, for example, for phonemic categories, lexical information, syntax and meaning (see Gillis et al., 2022, for a review), reflecting an internal, hierarchical organisation in the brain. It also implies that neural coupling with speech features occurs beyond primary cortical areas (e.g., A1), suggesting that linguistic neural tracking could be used as an objective measure of higher-order speech comprehension. For example, a MEG study by Ding et al. (2016) in 47 adults demonstrated that cortical tracking of abstract linguistic structures (words, phrases, and sentences) could be dissociated from acoustic processing, reflecting internal language knowledge (Ding et al., 2016). Similarly, an EEG study in 29 adults by Gillis et al. (2021) demonstrated that information about word frequency and the amount of phoneme/word surprise in the speech input were tracked beyond the speech acoustic properties.

Other studies focused on semantic processing have investigated how the brain tracks the amount of novelty in the speech input, for example, measuring a word's level of predictability according to their context. Several studies have reported that words with greater surprisal or dissimilarity elicit negative deflections like an ERP N400 response (Broderick et al., 2018). In addition, there is also evidence of neural tracking of the speech syntactic structure (Niesen et al., 2023). Overall, previous findings support the idea that speech tracking reflects a processing hierarchy (Heilbron et al., 2022).

Importantly, multiple studies demonstrate that speech tracking is driven by input properties and strongly modulated by top-down mechanisms such as attention and prior language knowledge (Di Liberto et al., 2015; Reetzke et al., 2021). For example, there is robust evidence of an enhancement of neural tracking for attended than non-attended speech (Alexandrou et al., 2018), for speech in a native than in non-native languages (Pena & Melloni, 2012), and when the language content is known to the listener, for example by semantic priming of previously unintelligible sentences (e,g, Baltzell et al., 2017), suggesting that bottom-up/top-down interactions consistently modulate speech tracking.

Measures of speech cortical tracking

Previous studies have used different measures of speech cortical tracking, making it possible to extract EEG components related to different speech features (Crosse & Lalor, 2016). A straightforward method is to quantify direct cross-correlations between the speech envelope and the EEG responses at different time lags, like on ERP analysis (see Abrahams et al., 2009; Rios-Lopez et al., 2020). This type of analysis can be performed in the frequency domain, for example, converting both signals into spectral representations and determining the degree of coherence (phase synchrony) at a given oscillatory band. Despite this approach is computationally simple, it is suboptimal because it results in significant noise being introduced by the high correlation between speech and acoustic features (Crosse et al., 2016).

More recently, linear modelling methods have sorted out this issue using regularised regression to predict the relationship between cortical responses and speech stimuli while controlling for correlated features. These methods estimate Temporal Response Functions (TRFs) that describe how the response variable (e.g., the neural component in the EEG) depends linearly on the explanatory variables over time at a given time lag (Crosse et al., 2015). Univariate TRFs are used in encoding (or 'forward') models to independently predict a neural response from a presented speech stimulus at each EEG channel. In contrast, multivariate TRFs are used in decoding (or 'backward') models to reconstruct the speech stimuli using information from all the EEG channels. In both cases, the predictive accuracy between the actual and predicted data is assessed by the degree of correlation between signals, for example, using Pearson's r coefficient, with greater correlation values representing more robust neural tracking (Crosse et al., 2015; 2021).

Importantly, encoding and decoding models have different advantages and disadvantages and can complement each other to address different research questions. As Jessen et al. (2021) pointed out, encoding models are easy to interpret regarding neural activity because the TRF weights represent brain activation patterns calculated independently for each channel. However, they require a priori selection of the channels for analysis. On the contrary, decoding models combine the cortical responses at different EEG channels for reconstructing the speech stimulus, weighting them according to how much information they provide, which has two advantages: (i) it improves the signal-to-noise ratio by cancelling noise out, and (ii) it makes unnecessary to select the EEG channels beforehand. This makes backward models more sensitive than forward ones, thus more suitable for use in populations with noisy data, such as children or clinical groups. However, decoding models cannot be directly interpreted or related to scalp patterns because their weights represent the filters used to extract the information from the EEG and not necessarily each channel's activation (Gillis et al. (2022). To sort this issue, Haufe et al. (2014) proposed a method to forward-transform backward models, allowing their neurophysiological interpretation.

Notably, forward and backward linear modelling are well-validated methods to investigate neural tracking of the speech envelope and different linguistic features, either as continuous or categorical inputs (Broderick & Simon, 2020). For example, Sassenhagen (2019) describes how to model EEG responses to linguistic features in continuous speech (e.g., phonemes, word type, or lexical frequency) by coding them into a multivariate design matrix and using them as regressors for the EEG. Other authors recommend backward models for continuous speech features (e.g., amplitude envelope or spectrogram) and forward models for discrete ones (e.g., phonemic or lexical information) because decoding these features may require non-linear data transformations (Crosse et al., 2021; Gillis et al., 2022). Then, it is possible to compare the reconstruction accuracy values for different speech features to determine how well each type of linguistic information uniquely reflects in the EEG (Di Liberto et al., 2015).

Moreover, speech acoustic and linguistic features can be combined in mTRFs models to represent the EEG content more accurately, considering that EEG signal results from overlapping neural responses to different speech features that occur at different latencies. For example, Di Liberto et al. (2015) demonstrated that mTRF models perform better when including the speech acoustic envelope and linguistic information (phonetic features) are combined in the same encoding model.

5.1.2 Functional Implications of Speech Tracking

So far, there is agreement about the key role of speech cortical tracking for spoken language comprehension. However, previous studies have yielded mixed results about the functional role of neural tracking. Nevertheless, although there is no evidence of a 1:1 correspondence between cortical tracking and speech comprehension, some brain-speech associations have been established, mainly for envelope entrainment.

Firstly, from the perspective of the speaker's physical features, cortical tracking of the envelope is critical for speech intelligibility. Previous studies indicate that manipulations of the speech envelope severely affect phoneme and sentence recognition, and, on the contrary, some findings suggest that when the envelope is preserved, frequency degradations do not deteriorate too much the speech intelligibility (Kubanek et al., 2013). This could be explained because the speech envelope contains energy changes important for speech intelligibility, for example, informing about phonemic and syllabic transitions. However, it does not imply that envelope tracking is sufficient for successful speech comprehension. Indeed, there is evidence that the spectro-temporal fine structure is also necessary for speech comprehension (Ding & S, 2014).

Secondly, a substantial amount of research indicates a relationship between speech perception performance and envelope neural tracking, although the interpretation of this link is not straightforward. Some evidence indicates that individuals who show stronger envelope tracking (e.g., a greater correlation between the EEG and speech signals) perform better in speech perception tasks, especially under challenging listening conditions (Ding & Simon, 2014). On the other hand, older and hearing-impaired people exhibit enhanced envelope tracking, despite speech perception deficits common in these populations, meaning that an over-represented envelope may accompany poor speech comprehension (Brodbeck & Simon, 2020; Palana et al., 2022). These mixed results make it hard to determine if more robust entrainment facilitates speech comprehension or whether it indexes greater listening effort or attention (Song & Iverson, 2018).

Finally, the degree of cortical entrainment is determined by the task demands and experimental contrasts being studied. As summarised by Alexandrou's review (2018), research in this field has used a variety of paradigms to study speech neural tracking, with evidence of greater envelope tracking for intelligible than for unintelligible sentences, normal-rate than time-compressed speech, for attended than unattended speech or when perceiving clear speech versus speech in noise. Other studies indicate that envelope tracking is robust to background noise, at least until the noise doubles the signal (Ding & Simon, 2013). This indicates that the degree of neural tracking depends on the listening conditions, for example, if they involve active or passively listening or simultaneous tasks. Nevertheless, it is possible that semantic processing still happens under unattended listening to speech (Brodbeck et al., 2018).

In sum, although there is agreement about the importance of speech neural tracking for speech comprehension, there is less clarity about its functional significance; so far, it seems to be related to the stimulus intelligibility but also to attention and listening effort, individual and task characteristics, most likely involving a mixture of acoustic, cognitive, and linguistic factors.

5.1.3 Age-related differences in cortical speech tracking

Across developmental stages, there are age-related changes in how auditory and language information is weighted in the brain for speech processing, resulting from the neuromaturation of cognitive and language networks and the accumulation of language knowledge. From infancy to adolescence, perceptual reliance on acoustic cues decreases, whereas linguistic knowledge increases as children become more proficient language users (Skeide & Frederici, 2016). This means that sensitivity to acoustic and linguistic information is different between infants, children, and adults. Consequently, it will likely involve developmental changes in cortical tracking of speech features at different language acquisition stages.

Importantly, it has been established that acoustically driven entrainment is already present at early stages, although its strength seems to change across age groups and frequency bands. For example, early findings showed that theta synchronisation between the EEG and slow/fast amplitude modulations in non-speech stimuli was present in newborns (Telkemeyer et al., 2009). For speech, studies using encoding models indicate robust low-frequency (1-8 Hz) envelope tracking is present in 7-months infants (Jessen et al., 2019; Kalashnikova et al., 2018). A longitudinal study in young children by Rios-Lopez et al. (2020) demonstrated that envelope tracking was present at four years old but only for the delta range. Notably, they reported age-related increases in delta entrainment between the ages of 4-5 (n= 32), 5-6 (n= 34), and 6-7 years (n= 33). These initial results suggest developmental changes in how the information in the speech envelope is represented in the EEG at different frequency bands. However, some studies used direct cross-correlation and not regularised regression measures.

As in adults, envelope tracking in children is modulated by top-down factors, especially in adverse listening conditions. A MEG study by Vander Ghinst et al. (2019) compared cortical responses in children (6- to 9-year-old) and adults when perceiving attended speech in different levels of multi-talker noise (noiseless, and SNRs= 5, 0, and 5 dB). They found significant cross-coherence between the EEG and attended speech stimuli in the delta (<1–4 Hz) and theta range (4–8 Hz) in all SNR conditions in adults, but for children, values were adult-like only below 4 Hz. Importantly, disruption of neural tracking in the theta band for increasing noise was more significant in children than adults, suggesting that cortical tracking at the syllabic rate is not mature during late childhood and may be related to children's poorer speech in noise performance.

One aspect in which neural envelope tracking seems functionally relevant is acoustic-phonological mapping. According to Leong & Goswami (2014, 2015), there is a relationship between phonological development and sensitivity to changes in speech spectro-temporal patterns. Envelope tracking would allow the representation in the brain of phonological units as phonemes, syllables, and stress patterns, supporting the acquisition of phonology in young children. This is confirmed by a recent MEG study by Bertels et al. (2023) that demonstrated maturational changes in cortical tracking of phrases and syllables presented with different background noise levels (n=144, ages 5 to 27 years). Their results indicate that whereas tracking of slower linguistic elements (e.g., prosodic cues) is in place since infancy, access to fine-grained information at the syllable level matures later, with marked improvements around the age of 9 years old that are associated with better speech comprehension performance, especially in noisy conditions.

In addition, age-related improvements in higher-order linguistic tracking may support the development of other speech comprehension skills, such as word recognition or syntactic processing. Niesen et al., 2023, studied cortical tracking of syntactic structures using sentences with removed prosodic cues and found similar left-dominant patterns in adults (n=20) and children (n=20, 7–9 years), although children showed less tracking accuracy. When multi-talker background noise was added to the sentences, children and adults showed reduced tracking of the syntactic structure. However, only adults showed increased neural tracking for monosyllabic words, suggesting that syntactic tracking was absent in children.

Together, these findings suggest that cortical tracking shows differences for acoustic and linguistic speech components and age-related changes, although the patterns have not been described yet. So far, it seems that acoustic tracking is present at birth and develops during childhood, especially for the syllabic rate (theta band). However, there is little research about lexical tracking in children, indicating a need of more studies to determine the role of speech tracking in language acquisition.

Language disorders and atypical speech tracking

Considering the evidence of a critical role of cortical entrainment in speech, clinical populations affected by speech processing deficits could exhibit atypical neural speech tracking. This makes it especially important to characterise cortical responses during continuous speech processing to determine whether different patterns can be identified between typical and atypical populations. As many studies have pointed out (e.g., Gillis et al., 2022; Molinaro et al., 2016) neural tracking analysis have enormous potential as clinical tools for diagnosis and treatment.

For example, a recent systematic review by Palana et al. (2022) examined cortical entrainment in speech processing deficits, confirming that older people and individuals with hearing impairments exhibit a cortical overrepresentation of the speech envelope. However, recent evidence shows that both acoustic and linguistic speech tracking declines in older adults (Gillis et al., 2023). In adults and adolescents with autism spectrum disorder (ASD), there is evidence of reduced left-lateralised tracking of envelope modulations and atypical theta-gamma interactions, which predicted the severity of language deficits. Moreover, although this confirms that speech perception deficits are associated with cortical tracking abnormalities, there is little evidence in children with and without neurodevelopmental disorders. This is exemplified in Palana's (2022) review, which shows that very few studies have investigated speech tracking in children; by July 2020, only 5 of the 25 papers they reviewed included underage participants, and only one of them (Di Liberto et al., 2018) included children younger than seven years.

Nevertheless, some evidence indicates reduced or atypical envelope tracking in older children and adolescents with speech processing disorders. Di Liberto et al. (2018) showed significantly smaller envelope tracking in the delta-theta range in children with dyslexia (n=10, age 9-13 years) than TLD controls (n=10, age 9-13 years) and adults (n=10, 25-40 years). The strength of neural tracking also correlated with phonological and reading skills in all the groups. Despite the small sample size study, their results are consistent with previous findings showing atypical patterns of entrainment between hemispheres in older poor readers (Abrams et al., 2009) and reduced speech envelope tracking in low frequencies in dyslexic children (Leong & Goswami, 2014, 2015; Power et al., 2016). Recently, Goswami (2022) has proposed that impaired neural alignment with the speech envelope in DLD could be linked to phonological processing deficits in this disorder (Temporal Sampling hypothesis, see chapter 1), although this has not been experimentally tested.

To summarise, previous evidence shows that cortical speech tracking is necessary to efficiently map sensory information into higher-level linguistic representations at multiple levels (Jochaut et al., 2015). However, there is a great need for replication and further research to determine the developmental trajectories and role of speech tracking in DLD and other neurodevelopmental disorders. Importantly, many previous studies do not provide average and dispersion values for their measures, making it difficult to establish a trajectory for neural tracking development in typical and atypically developing children and compare findings between studies.

5.1.4 The current study

This study investigates the patterns of speech cortical tracking in natural listening conditions during early childhood to deepen our understanding of speech perception development and its relationship to typical and atypical language acquisition. We aimed to investigate cortical responses to continuous speech in two groups of Spanish-speaking children between 4.7 and 5.7 years old; a group with DLD diagnosis (n=17), and a TLD group (n=12), comparing their responses to those observed in neurotypical adults (n=17).

EEG responses were recorded during unattended listening of 18 short stories (average data per participant= 12.5 minutes) to estimate individual Multivariate Temporal Response Functions (mTRFs) using backward linear modelling. This allowed us to predict the speech acoustic and lexical frequency envelopes from the EEG and compare these models at the group level (Crosse et al., 2016) to determine how acoustic and linguistic features in the speech signal are represented in children's cortical responses.

Thus, in this experiment, we were interested in characterising the mTRFs decoding patterns for speech low-level acoustic features and higher-order lexical information as a neural component in the EEG signal reflecting speech cortical tracking.

Specifically, in this study, we asked:

(i) Are there any differences in neural tracking of speech between children and adults? And if so, for what speech components?

(ii) Do children with DLD show differences from TLD children in the patterns of speech neural tracking? If so, in what speech features?

Since, to our knowledge, this was the first study investigating neural tracking of speech in children with DLD, our hypotheses were exploratory and based on previous findings for other age groups and clinical populations (e.g., ASD or dyslexia). Firstly, considering that neural speech tracking is present at early ages and increases from childhood to adulthood, we hypothesised that both children's and adults' mTRFs would show a significant correlation with the speech stimuli but expected a greater cortical synchronisation (stronger responses) in adults, indicating more efficient speech representation.

Secondly, as speech tracking is modulated by language abilities (i.e., word knowledge), we expected more efficient tracking in those participants with better language skills, this is, in adults than children and TLD than DLD children because of greater top-down language modulations, even under unattended conditions because of more automatic acoustic and lexical speech processing. Finally, we hypothesised the effects of language differences to be larger for lexical than acoustic tracking measures, varying according to the linguistic properties of each word (lexical frequency) rather than due to acoustic processing.

By utilising advanced EEG modelling methods in ecologically valid conditions, we sought to shed light on the neural mechanisms underlying speech processing in natural settings during early childhood and their relationship to language skills. They might have important clinical implications for developing new diagnostic tools and interventions for speech perception deficits or language disorders in young children.

5.2 Methods

5.2.1 Participants

All recruitment procedures were the same as those described in Chapter 3. The total number of participants for this experiment was 46, including 12 children with TLD (Mage= 5.05, *SD*=0.48), 17 children with DLD (Mage=5.13, SD=0.35), and 17 adults (*M*age=33.4, *SD*=4.3). As expected, the age of the adults was significantly higher than that of the children [$F(2,45)=617.247$, $p<.001$, $\eta p^2=.966$], but with no differences between the TLD/DLD groups.

5.2.2 Stimuli

The stimuli consisted of 18 short stories in Spanish, extracted from '*Cuentos programa Chile Crece'*, a website of the Chilean government with resources for 2-4 year-olds (http://www.crececontigo.gob.cl/actividades-para-compartir/cuentos/4/?filtroetapa=ninos-y-ninas-de-2-a-4-anos) (Appendix 5.1). The stories were narrated by a native Chilean Spanish female speaker and recorded in an anechoic chamber at 44.1 kHz into separate audio files (.wav). A 50 ms ramp-on/off segment was added at the beginning and end of each track, respectively, using Praat software (Boersma & Weenink, 2018). The stimulus duration ranged from 46.99 to 56.22 sec ($M = 50.94$; $SD = 2.66$). Next, we extracted the acoustic and lexical information in the speech signals.

Acoustic envelope

The broadband amplitude envelope was extracted for each audio file by applying a Hilbert transform and then high and low-pass-filtered at 2 Hz and 38 Hz, respectively, with a zero-phase Butterworth filter to keep the frequencies of interest for the EEG. Then, the envelope was normalised, dividing it by the root-mean-squared of its amplitude and downsampled to 64 Hz to speed up computations.

Lexical features

To study the neural processing of the lexical information in the speech stimuli, we extracted the parameters for each word in all the stories according to their lexical frequency, onset and offset times, duration, and word class (function or content word). Function words occur with high frequency in a given language but produce little lexical activity in the brain. In contrast, content words are less frequent but produce higher brain activation, which is dependent on their contextual predictability (the less predictable, the higher activity).

For each story, the corresponding audio file and text transcript were aligned using WebMAUS, an online forced alignment tool (Kisler et al., 2017) that allows words to be segmented and annotated into separate layers (phonemes, syllables, words). Audio-text alignment was manually corrected using Praat, and the resulting vectors with the onset/offset times for each word were extracted to an Excel spreadsheet. The duration of each word was calculated as word Offset – word Onset, in seconds. Figure 5.1 exemplifies the audio/text alignment and different levels of representation of an 8-sec speech segment.

The lexical database for this study comprised 801 unique words extracted from all 18 stories. Each word was classified according to its grammatical class into function or content (lexical) words[6], consistent with the ERP analysis in Chapter 3. The linguistic information for determining the word classes was extracted from the database by Sadowsky et al. (2012, https://sadowsky.cl/lifcach.html). In addition, word frequency values, normalised per million words (pmw), were assigned to each word according to the latest update of the Reference Corpus of the Current Spanish (CREA) https://corpus.rae.es/lfrecuencias.html).

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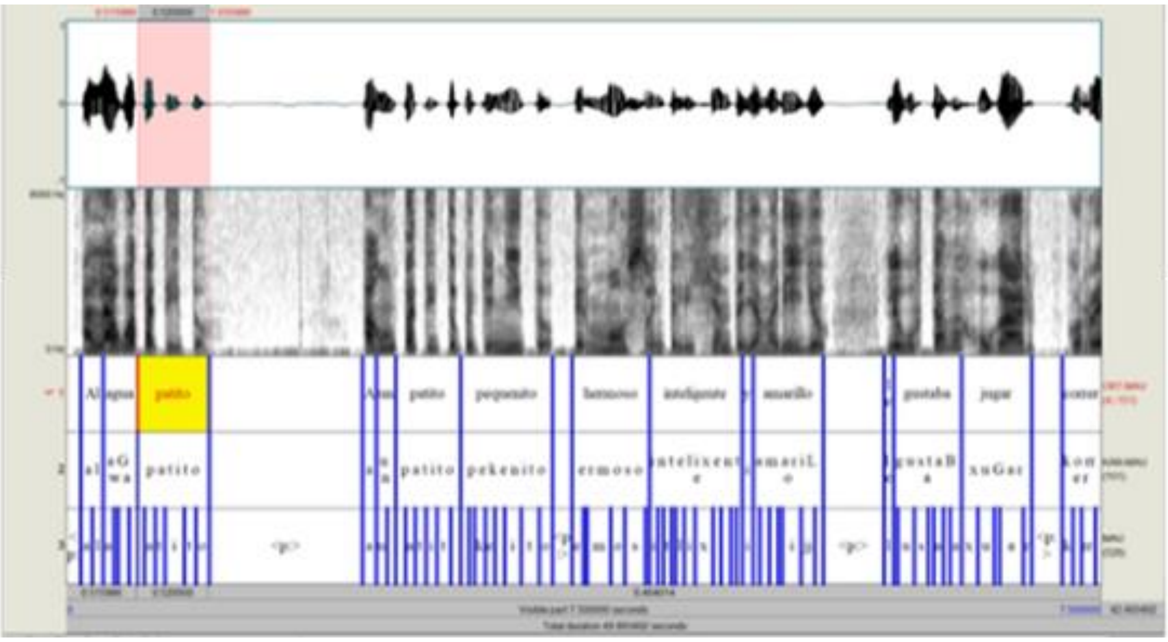
[6] Function words are those with structural (grammatical) use, including conjunctions (C), determiners (D), interjections (I), pronouns (PN) and prepositions (PP). Content words are those that convey meaning, including adjectives (AJ), adverbs (AV), nouns (N) and verbs (V).

Figure 5.1

Extraction of Different Speech Features for an Example Waveform



Note. First eight seconds of story 2. First row: Audio waveform at 44.1 kHz; Second row: Spectrogram; Third row; Word segmentation; Fourth row; ortographic output from WebMaus; Fifth row: Phonemic segmentation.

The final database consisted of a matrix of the following dimensions: 801 unique words x 7 speech features; amplitude envelope, word onset, word offset, content word, function word, word duration, and word frequency. All the words on each story were assigned their corresponding values from the database and converted into vectors at the same sampling rate as the EEG data (64 Hz) for later alignment, coded as follows for each sample: word onset (1=true 0=false), word offset (1=true 0=false), word type=function words (1=true 0=false, categorical), word type=content words (1=true 0=false, categorical), word duration (numeric, in ms), and oral word frequency, normalised per million words (numeric, continuous).

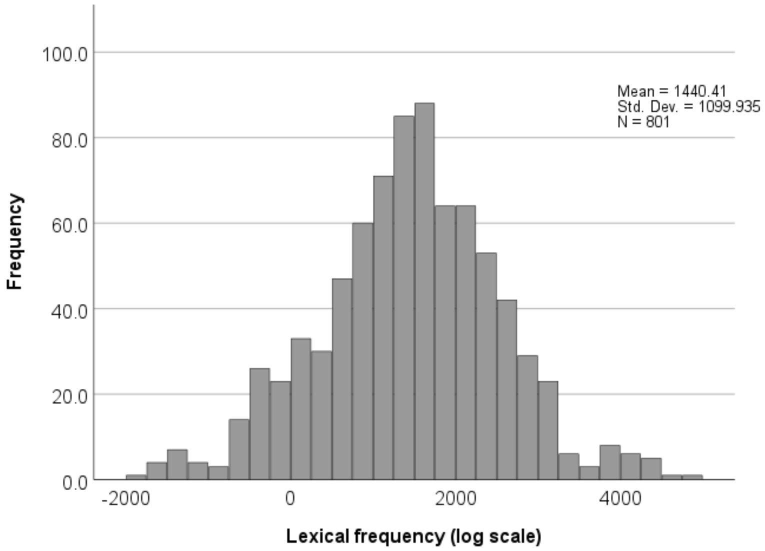
It is worth noting that, although we built a database with several lexical features, for this thesis, we focused on modelling lexical mTRFs using a numerical proxy of word class, leaving the other features as a database for future analysis. This is because these lexical representations are mutually redundant and highly correlated (Crosse et al., 2021). Thus, we decided to choose the one that has been more robustly described in previous studies. Initially, we attempted to use word predictability, as has been done in previous studies (e.g., Brocked & Simon, 2020), calculating a predictability index for each word according to its previous context using ChatGPT-3. However, this proved unsuccessful because even though ChatGPT-3 performed adequately for stories written in English, it did poorly for Spanish.

Thus, we decided to use the oral word frequency (lexical frequency) as a measure of lexical content because it is correlated to word class; function words (closed class) exhibit high lexical frequency, whereas content words (open class) are less frequent. For these purposes, we converted each word’s normalised value (pmw) to a log 10 scale and multiplied it by 1000 before mTRF modelling (Crosse et al., 2021). Figure 5.2 displays the distribution of lexical frequency values after logarithmic scaling.

Considering that the acoustic onset does not necessarily coincide with the most prominent part of the word and previous work in our lab showed better correlations when using the whole word duration rather than just the response to the onsets, lexical frequency values were extended over each word’s duration to create the lexical envelope (Figure 5.3). This allowed us to reconstruct a continuous representation from the originally sparse lexical vectors that contained mostly zeros and few numerical values, overcoming an important challenge of backward models (Gillis et al., 2021).

Figure 5.2

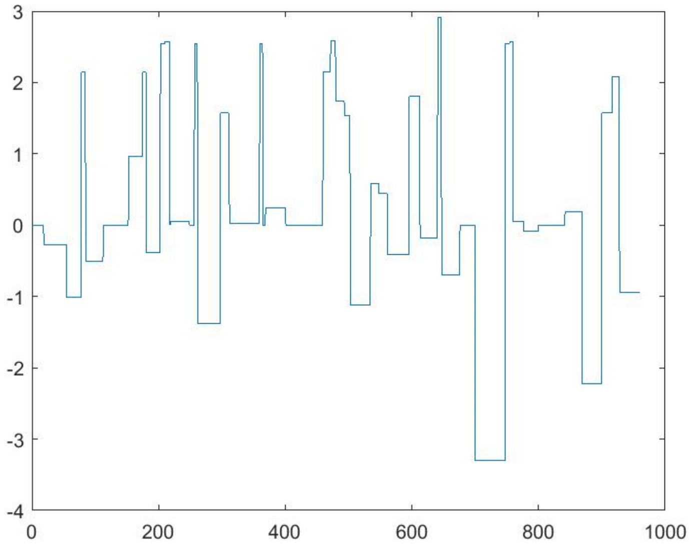
Histogram for Word Lexical Frequency Values



Note. Distribution of lexical frequency values (log scale) for the whole set of unique words in the speech stimuli.

Figure 5.3

Example of the Log-Transformed Lexical Frequency Envelope



Note. Example of the envelope created from the log-transformed lexical frequency values for the stories listened to by participant AdCH01. The vector of lexical frequency values after the log transformation is plotted in a 0-1000 sample segment.

5.2.3 Procedures

All stimuli were presented free-field at 70 dB SPL while the participants watched a silent cartoon. No response was required. During the experiment, a trigger pulse was delivered to each EEG file indicating the start of each story to align the audio tracks with the EEG data. All other procedures were the same as those described in Chapter 3.

5.2.4 EEG preprocessing

EEG data were analysed in MATLAB (versions R2018a-2023; MathWorks, Natick, MA), using EEGLab (Delorme & Makeig, 2004), the mTRF toolbox (Crosse et al., 2016), and custom made scripts, following the recommendations of Crosse et al. (2021).

EEG data were downsampled to 512 Hz and referenced to the average mastoids for the adult and to electrode Cz for the children groups. Continuous data were high-passed filtered at 1 Hz and then low-passed filtered at 40 Hz with a non-causal zero-phase Butterworth filter. Channel rejection and ICA were performed according to the criteria described in Chapter 2. Then, removed channels were spherically interpolated, and data were re-referenced to the average.

An important aspect when fitting mTRF models is to avoid significant differences in the amount and quality of data between participants (Crosse et al., 2021; Jessen et al., 2021), ideally defining a priori a minimum of artifact-free data per participant. In our study, the minimum amount of clean data for a single participant was 5.12 minutes (312 seconds), and the maximum was 15.27 minutes for participants who listened to the complete set of 18 stories (see Appendix 5.2), as seen in Table 5.1. Thus, our study's lowest amount of individual data is well above the minimum of 100 seconds used in previous studies for acoustic TRF modelling (e.g., Jessen et al., 2019; Kalashnikova et al., 2018). However, the amount of data was significantly larger for the adult group [*F* (2, 45) =25.45, p<.001, np2=, 542], although it did not differ between the groups of children, indicating data amount could be an essential factor to control in the statistical analysis, although it should not be used as a covariate if a non-linear relationship with the EEG measures is present.

Table 5.1

Average amount of Clean EEG Data per Group

Recording time *(*min*)*	TLD	DLD	Adults
Mean	11.53	10.9	14.92
SD	1.88	2.25	.81
Range (min-max)	8.55-15.27	5.12-15.27	12.73-15.27

Note. TLD, n=12; DLD, n=17; Adults, n=17.

After data cleaning, each EEG dataset was cut around the trigger pulse to produce separate files for each story of the same as the audio files (duration from 46.99 to 56.22 seconds). EEG data were visually inspected after the initial cleaning, and those that presented significant remaining noise were rejected from the analysis. Then, for each story, we aligned the starting points for EEG and the stimulus matrices according to their trigger pulses, creating a structure containing the EEG data (columns 1:32) matched with the speech features of interest (columns 33:39) coded as continuous or categorical variables.

EEG data was further down-sampled to 64 Hz, and files for each participant were concatenated after removing the initial second of each story and EEG data to avoid modelling the auditory response to the stimulus onset (Crosse et al., 2021). EEG datasets were filtered as the acoustic envelope (2-32 Hz) and between 1-32 Hz for lexical analysis to avoid preprocessing filtering artifacts around the 1 and 40 Hz edges. Before modelling, individual EEG was normalized using z-scores (Crosse et al., 2021). Finally, the matrices with the stimulus features and the EEG responses were organized with rows corresponding to observations and columns to variables and served as input for the decoder, aligning their starting points to the triggers.

5.2.5 Multivariate TRF analysis

Individual decoding (backward) models were estimated and averaged at the group level to describe the mapping between speech features and neural responses. Multivariate Temporal Response Functions (mTRFs) were used to reconstruct the speech signal from the EEG using the mTRF Toolbox (Crosse et al., 2015). The correlation between the original speech stimuli and the model prediction was used to measure cortical tracking for a given speech feature (greater correlation = greater neural response). Individual models were chosen as their performance is better than generic (subject-independent) ones, especially when the groups show high within and between participant variability, as if frequent in children or clinical populations (Jessen et al., 2021). Decoding models were preferred over encoding ones because they are more sensitive than encoding ones, as they include data from all the EEG channels in a multivariate manner, addressing at the same time their correlation (Crosse et al., 2016). The suitability of individual over generic and decoding over encoding was confirmed empirically by preliminary data analysis.

To improve the model fit, we used ridge regression for modelling (Crosse et al., 2016), a type of regularised regression that applies a penalty term (λ) to estimate reliable coefficients and avoid overfitting[7] when using regressors that may be highly correlated, such

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[7] Overfitting occurs when the TRF model reflects the particularities of the training dataset (noise, outliers) and does not generalise well to new, unseen data, resulting in poor prediction accuracy (Crosse et al., 2016).

as neighbouring EEG channels and speech features. Optimal lambda values were estimated individually to account for the high inter-individual variability within our children's groups (Jessen et al., 2021) and then averaged within groups,

Before modelling, the datasets of each participant were separated into a training and a testing set, containing 80% and 20% of the data, respectively. As neural responses do not occur simultaneously with the speech input, we used time lags from -100 to 600 ms to estimate the mTRFs, as those were consistent with previous studies on speech acoustic and lexical processing and our ERP findings from Chapter 3.

Model training (estimation)

In the training stage, we estimated the mTRFs between each one of the EEG response-speech stimulus pairs at each time point. To minimize the difference between the predicted values from the model and the actual values in the data, we empirically determined the optimal strength of the ridge regularization parameter (λ, lambda), iterating testing and training of the model across different λ values (ranging from 10−7 to 107) in the training set. For this step, data should differ from that for training (Poldrack et al., 2020), so a recommended procedure to avoid collecting additional data is performing successive k-fold, leave-one-out cross-validations on the training set. This means iterating between different lambda values to find the one that provides the best fit for the model parameters (Jessen et al., 2021). Thus, we divided the training sets into five equal parts (folds) and modelled 4/5 of the data to derive a prediction for the left-out 1/5 segment, iterating and rotating the sets until all were used for testing. The resulting correlation coefficients were averaged across folds to determine which lambda value provided better model performance, measured as the higher correlation coefficients (Pearson's r) and lower mean squared error (MSE) in the lambda tuning curves (Crosse et al., 2016). Once the optimal lambda was determined, we used it to estimate the mTRFs.

Model testing (evaluation)

In the testing phase, we evaluated how well the mTRF model generalized to new, independent data, testing the backward model in the remaining 20% of the data. The accuracy of the model to predict the speech stimulus was determined by comparing the reconstructed and the actual speech features (e.g., the amplitude envelope), again using Pearson's coefficient (r) and mean squared error (MSE) as prediction accuracy measures. The strength of the correlation (r value) represents the degree of cortical tracking of a given speech feature, whereas the error is the amount of variance the model cannot predict (Jessen et al., 2021).

These training and testing procedures were replicated separately for the stimuli acoustic envelope and lexical frequency data.

5.2.6 Study Design and Variables.

This observational, exploratory study measured cortical tracking of speech between groups of children with TLD, DLD and adults. Speech tracking was defined as the temporal synchronisation between cortical responses (neural oscillations) and two levels of speech representation: the acoustic amplitude envelope (in arbitrary units, a.u.) and word lexical frequency (log-scaled). As in Chapters 3 and 4, the independent variable was the language status of each group (TLD, DLD or adult-like). The dependent variable was the strength of the neural tracking (Jessen et al.., 2021), operationalised in two measures: (i) mTRFs amplitude values over time (in a.u.), and (ii) the model predictive accuracy, quantified by Pearson's r coefficients.

5.2.7 Statistical analysis

Both for the acoustic and lexical backward models, the first analysis focused on determining the model predictive power for each group, measuring whether the correlation values between the predicted envelopes and the actual speech stimuli significantly differed from the chance level. We used a permutation-based approach to create null distributions of r values for each participant, randomly sampling 100 pairs from the original EEG and speech stimuli, modelling them, and averaging the resulting coefficients into one vector of the same duration as the mTRF-predicted stimuli. Then, the actual mTRF correlation values were compared with the null distributions using paired-sample t-tests (or the non-parametric equivalent), which would indicate if our models performed above chance.

In the second analysis, we determined if there were differences between the groups of participants in the strength of neural tracking for the speech acoustic and lexical features. After checking for the required assumptions, we used mixed repeated-measures ANOVA to compare the model outputs (mTRFs and correlation coefficient values) for the acoustic and lexical envelope tracking, with ‘Group’ as a between-subject factor (3 levels: Adults/TLD/DLD) and ‘Neural tracking’ as a within-subjects factor (2 levels: Acoustic envelope/Lexical Frequency).

The third analysis examined the mTRF patterns over time, considering this neural response's amplitude, polarity, and scalp distribution at different latencies. Importantly, as the decoder mTRF weights cannot be interpreted at the neurophysiological level, we inverted them into a forward model, according to the previous literature, following Haufe et al. procedures (2014). Finally, we explored the relationship between neural tracking and behavioural measures in the groups of children, using linear mixed-effects models to determine if mTRF accuracy measures (r coefficients) predicted the performance in phonological awareness (Chapter 3) and filtered speech tests (Chapter 4).

5.3 Results

5.3.1 Model Integrity

Firstly, we evaluated the integrity of each mTRF backward model, determining if the performance metrics were above-chance level as Crosse et al. (2021) recommended. Using a permutation approach, we created a null distribution of 100 r values for each participant, randomly matching EEG and stimulus pairs, from which mTRF/correlation coefficients were estimated and pairwise compared at the group level with those obtained from modelling actual speech-EEG pairs.

For the acoustic envelope tracking, Pearson's correlation coefficients were significantly higher for 'true' values than from those in the null distribution (TLD, Z= -2.667, p=.008; DLD, Z= -3.636, p<.001; Adults, Z=-3.621, p<.001). At the individual level, statistically significant neural tracking was detected in 67.7% of the TLD children, 76.5% of the DLD children and 88.3% of the adults, as indicated by r values above the 95th percentile in comparison to the null distributions.

Likewise, for the lexical frequency envelope, statistically significant tracking was detected in all our groups of participants, with higher correlation coefficients (r) for actual speech-EEG data models than for null distributions (TLD, $t(11)$= 8.85, p<.001; DLD, $t(16)$= 10.559, p< .001; Adults, Z=-3.621, p<.001). Individually, significant neural tracking was detected in 100% of the children and 88.24% of the adults (r values >95th percentile of the null distributions).

These results indicate that the mTRF models actually reflected the neural responses for the acoustic and lexical frequency information, in all the participant's groups. In addition, there was no significant correlation between r values for the acoustic and lexical envelope (r=-.231, p=.469), suggesting that these measures reflect different cortical processing levels.

5.3.2 Model reconstruction accuracy (performance)

Our second analysis examined between-groups differences in the model's predictive accuracy measures (r coefficients) for the speech acoustic and lexical frequency envelopes. Descriptive statistics for the model performance measures are displayed in Table 5.2, indicating overall r values ranging from 0.115 and 0. 155.

Table 5.2

Descriptive Statistics for r Values, Acoustic and Lexical Frequency Envelopes.

Acoustic	TLD	DLD	Adults
M	.115	.123	.142
SD	.046	.053	.034
Range (min-max)	(.04 - .19)	(.03 - .19)	(.06 - .18)
95% Conf. Inter. for Mean	.086 - .144	.096 - .150	.125 - .159
Lexical	TLD	DLD	Adults
M	.154	.155	.115
SD	.040	.070	.059
Range (min-max)	.13 (.07 -.20)	.27(.02 -.29)	.23(.00-.23)
95% Conf. Inter. for Mean	.129- .180	.119-.192	.085-.145

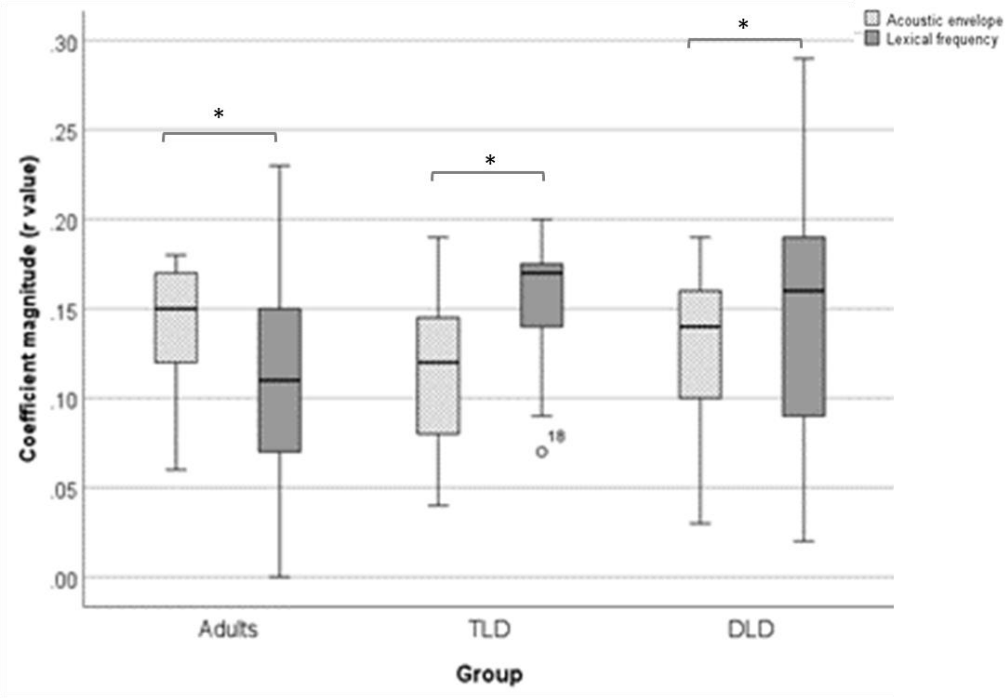
Note. TLD, n=12; DLD, n=17; Adults, n=17.

To determine if group-level differences were present, we performed a mixed repeated measures ANOVA using Greenhouse-Geisser correction for unmet sphericity (Mauchly's *W*=1, p< .001), after confirming r values were normally distributed for the acoustic and lexical mTRFs (Appendix 5.3). The results showed a non-significant main effect of 'Group' [*F*(2,43)=0.283, *p*=.755] or 'Neural tracking' [*F*(1,43)=2.210, *p*=.144], both with small effect size (ηp^2=.049 and ηp^2=.013, respectively) and low statistical power (9% and 31%, respectively), indicating no difference in the prediction performance for the acoustic and lexical frequency envelopes, and no differences between groups for the models for either speech feature. However, there was a significant Group*Neural tracking interaction [*F*(2,43)=4.919, *p*=.012], with a large effect size (ηp^2=.186) and adequate power (80%).

Interaction follow-up (paired-samples t-tests) indicated significantly lower neural tracking for the lexical than for the acoustic envelope in Adults (*M*acous=.142, *M*lexfq=.114, [*t*(16)=1.752, *p*=.049, *d*=.065]), whereas children showed the opposite pattern, with significantly greater tracking of the lexical than the acoustic envelope in the TLD (*M*acous=.115, *M*lexfq=.154, [*t*(11)= -2.015, *p*=.035., *d*=.067]) and DLD groups (*M*acous=.122, *M*lexfq= .155, [*t*(16)= -2.036, *p*= .029, *d*= .065]), all with small effect sizes. These results indicate that, although all groups showed similar cortical tracking of the speech stimuli, the neural response to the acoustic and lexical information varied within each group, suggesting that although both speech features are represented in the EEG, their relative importance may vary across the lifespan. Figure 5.4 displays group means for the acoustic and lexical frequency r coefficients.

Figure 5.4

Box Plots Comparing Correlation Coefficients for Acoustic and Lexical Tracking



Note. Group-averaged Pearson's *r* for the acoustic (light grey boxes) and the lexical frequency (dark grey boxes) envelopes. (*) significant at the .05 level.

5.3.3 Analysis of mTRF Model Weights

mTRF patterns

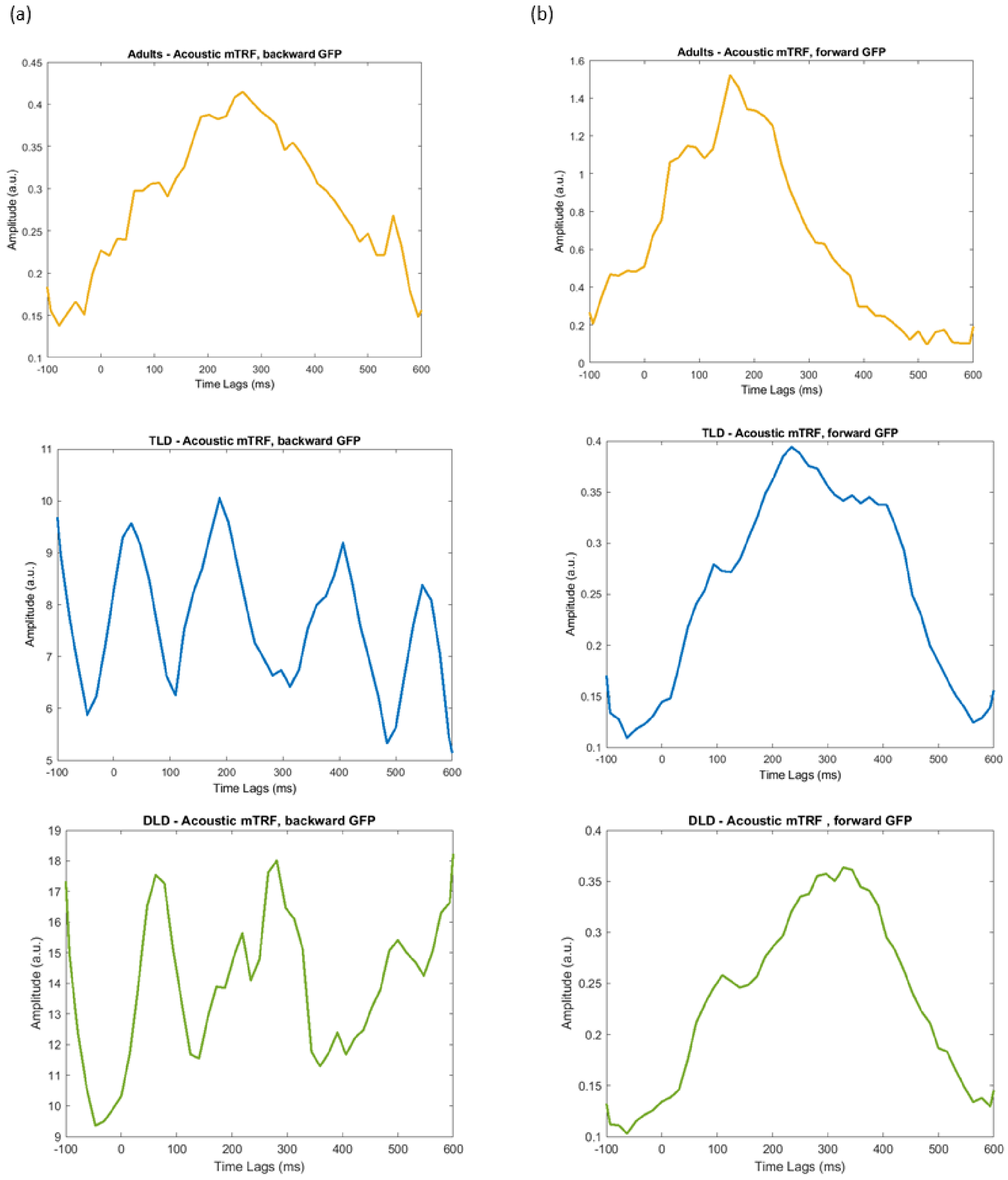
The third analysis focused on the mTRF temporal and spatial patterns. To get a channel-independent idea of the strength of neural tracking over time, we computed global field power (GFP) for each group, calculated as the standard deviation of the mTRFs, and averaged across all EEG channels and participants. The response amplitude (GFP) was plotted at each time lag for the acoustic (Figure 5.5a) and lexical frequency (Figure 5.6a) envelopes and forward-converted for neurophysiological interpretation (Figure 5.5b and 5.6b), as recommended in Haufe et al. (2014).

In Adults, the forward-converted GFP plots for the acoustic envelope showed a long positivity between ~100-400 ms, with two peaks, at ~50-100ms and 180-250 ms (Figure 5.5b, first row). We observed a similar pattern in children but with longer duration (~100-550 ms) and positive peaks at ~100 ms and between ~180-420 ms (Figure 5.5b, second and third row). The latency and polarity of these responses are similar to that of the P1 and P3 auditory ERP components, and their magnitude was larger in adults than in children.

For the lexical frequency envelope, forward-converted mTRFs for the Adult group (Figure 5.6b, first row) showed an early negative deflection before 200 ms, a positive peak between 200-300 ms and a long negative deflection between 300-600 ms, resembling an N400 ERP response. TLD and DLD children (Figure 5.6b) showed noisier waveforms with high initial values (time=0), in which it is hard to distinguish positive deflections. However, negative ones are present between ~ 50-200, ~420-600 ms for the TLD group and from ~200-300 ms and ~400-600 ms in the DLD group. The scale of the lexical mTRFs was larger in adults than in children and TLD than in DLD children (Figure 5.6b). Compared to the acoustic envelope, all the groups showed much larger mTRFs for lexical frequency.

Figure 5.5

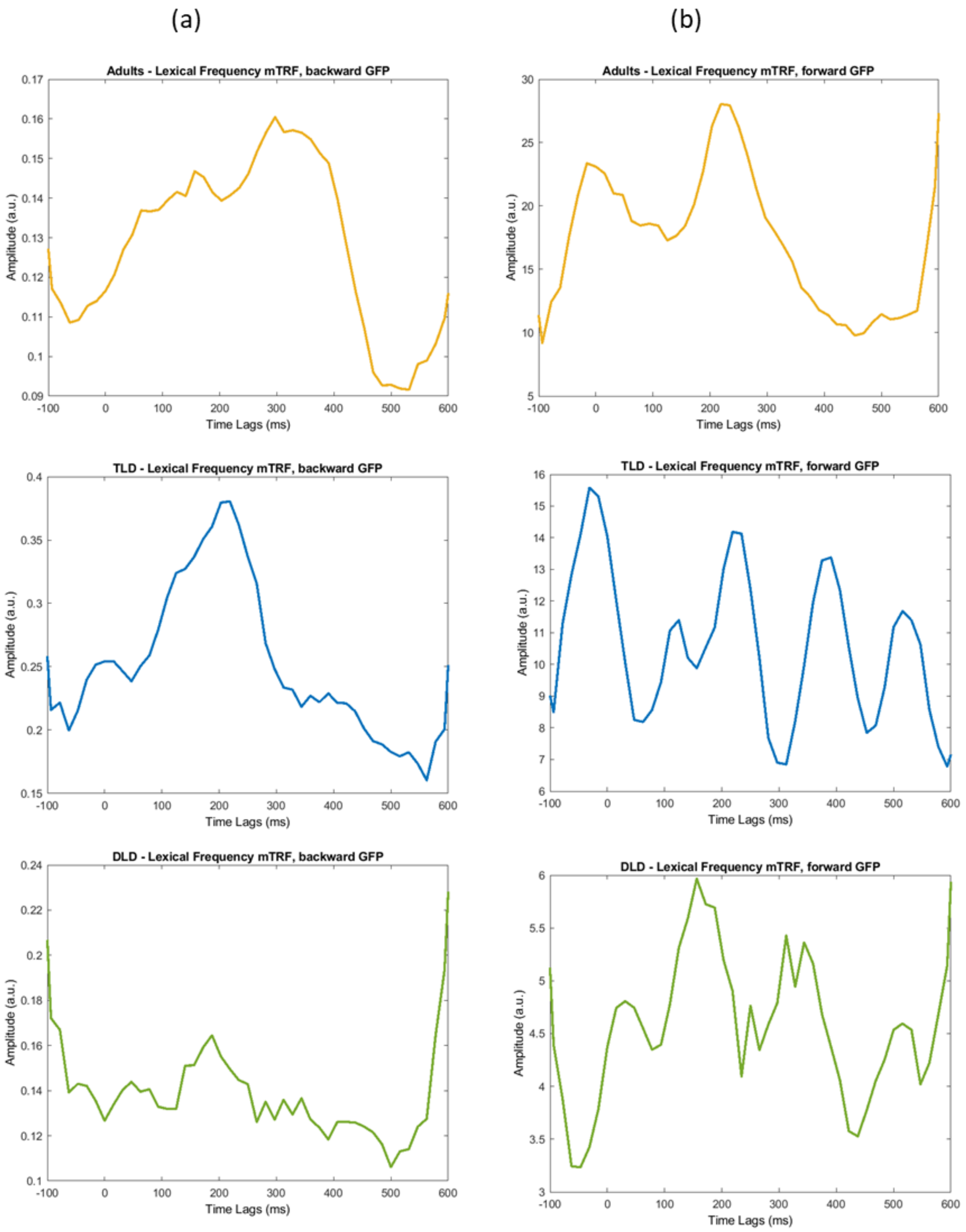
mTRF Waveforms for the Acoustic Envelope GFP (Decoder and Forward-Converted)



Note. GFP waveforms for the group-averaged mTRF, (a) from decoding weights, (b) from forward-converted weights. Top plot (orange): Adults (n=17), middle plot (blue): TLD, (n=12), bottom plot (green): DLD (n=17). TLD and DLD curves were smoothed for plotting with a 5-point moving average window. All values in arbitrary units (a.u.)

Figure 5.6

mTRF Waveforms for the Lexical Envelope GFP (Decoder and Forward-Converted)



Note. GFP waveforms for the group-averaged mTRF, (a) from decoding weights, (b) from forward-converted weights. Top plot (orange): Adults (n=17), middle plot (blue): TLD, (n=12), bottom plot (green): DLD (n=17). TLD and DLD curves were smoothed for plotting with a 5-point moving average window. All values in arbitrary units (a.u.)

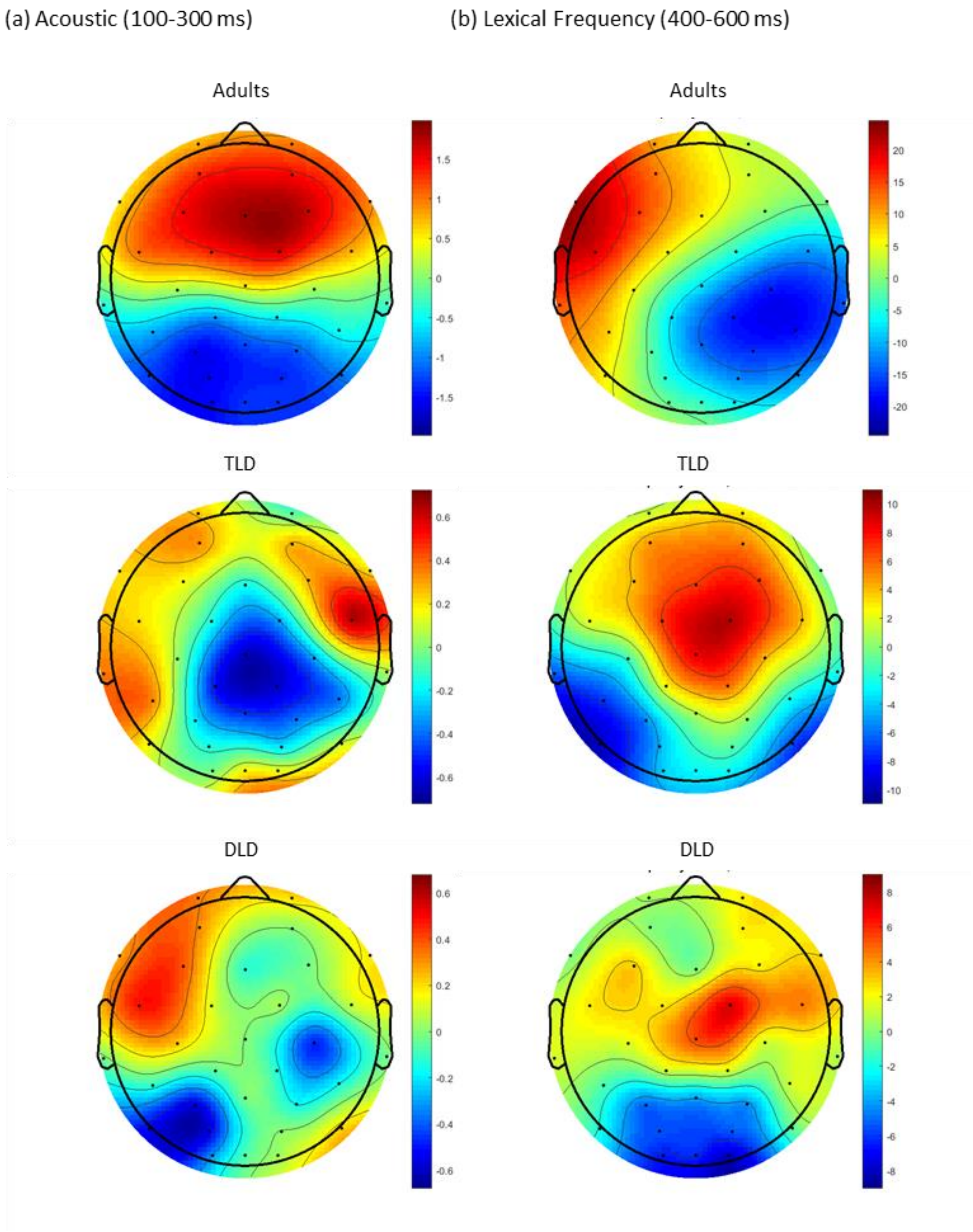
In the forward-converted GFP waveforms, we identified the time lags at which the weights were maximal in each group, defining intervals for mTRF mean amplitude analysis without double-dipping. According to the GFP peaks, for the acoustic envelope, the time range of interest was defined between 100-300 ms, whereas for the lexical frequency envelope, it comprised the range between 400-600 ms, which coincide with the early acoustic and lexical processing time windows in ERP research, and the hierarchical timeline of language processing in the brain. To illustrate the sensors that contributed most to the speech reconstructions (Crosse et al., 2016), forward-converted weights for each group were averaged across these time windows and plotted as scalp maps for the acoustic (Figure 5.7a), and lexical frequency envelope (Figure 5.7b).

For the acoustic mTRFs (100-300 ms), adults showed a broad bilateral frontal-central positivity and posterior negativity in a range of 1.5/-1.5 a.u, similar to a P300 ERP. In the TLD group, the acoustic mTRF had a central-posterior negative activation and a focal right temporal positive source. In contrast, the DLD group exhibited a left-lateralized frontal-temporal positive source and two negative sources: a left posterior and a right parietal one. For both groups of children, the magnitude of the response was in the 0.6/ -0.6 (a.u.) range.

The scalp topography for lexical mTRF (400-600 ms) showed a clear dipole in the adult group (Figure 5.7b, first row), with a marked left frontotemporal positivity and right-predominant temporal-posterior negativity, in a range of 20/-20 a.u. Both groups of children show a right-central positive source which extends frontally in the TLD group, and a negative posterior polarity, more centrally focalised in the DLD than the TLD group, which has two focuses, one on each hemisphere. In the children’s groups, the magnitude of the activation is approximately half as in the adults (TLD in the 10/-10 a.u. range, and DLD in the 8/-8 a.u. range). The posterior negative scalp patterns resemble an N400 ERP response.

Figure 5.7

Topography of the mTRF Forward-Converted Weights (Mean Amplitude)


(a) Acoustic (100-300 ms)

(b) Lexical Frequency (400-600 ms)

Note. Scalp maps showing the amplitude of the forward-converted mTRFs, averaged across the intervals of maximal GFP. Adult (top row, n=17), TLD (middle row, n=12) and DLD (bottom row, n=17) group. Responses for (a) Acoustic envelope, (b) Lexical frequency envelope.

mTRF statistical analysis

Next, we examined whether our groups' mTRFs amplitude for each speech feature significantly differed. To do so, we averaged the forward-converted mTRFs across two sets of electrodes to obtain an individual value for each speech feature; a frontocentral cluster for the auditory response (Fz, F3, F4, FC1, FC2, FC5, and FC6) in the 100-300 ms time window, and a centro-parietal cluster for the lexical response (C3, C4, CP1, CP2, Pz, P3 and P4), in the 400-600 ms window. Electrodes were chosen according to previous literature (e.g., Jessen et al., 2021; Song & Iverson, 2018) and avoided electrode Cz,, as this was used as a preprocessing reference for the children groups. Table 5.2 displays the descriptive statistics for the mTRF group-level measures, whereas Figures 5.8 and 5.9 present mean amplitude group-level values in the auditory (100-300 ms) and lexical (400-600 ms) intervals, showing a much larger mTRF for the lexical than the acoustical features in the adult group that was not observed in children. Although mTRFs have no clear interpretation yet, larger lexical responses in adults could indicate better neural tracking.

Table 5.3

Descriptive Statistics, Group mTRFs for Acoustic and Lexical Frequency Envelopes

Acoustic	TLD	DLD	Adults
M	0.092	0.138	1.39
SD	0.28	0.83	1.95
Range (min-max)	1.10 (-0.35-0.76)	3.26(-1.24-2.01)	8.22(-0.48-7.75)
95% Conf. Interval	-0.085 - 0.270	-0.286-0.563	0.383- 2.389
Lexical Frequency	TLD	DLD	Adults
M	- 0.05	-1.19	-9.68
SD	8.95	7.10	30.05
Range (min-max)	35.43(-17.58-17.85)	25.55(-20.21-5.34)	148.88(-71.40-77.49)
95% Conf. Interval	-5.735 -5.635	-4.838-2.461	-25.140 – 5.766

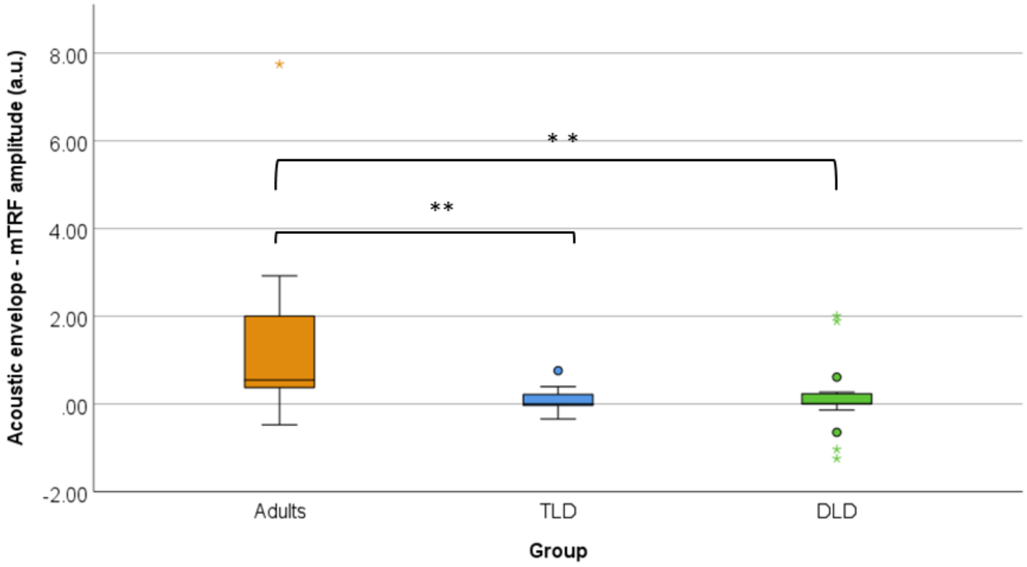
Note. TLD, n=12; DLD, n=17; Adults, n=17.

Given that most of the mTRF distributions were non-normal for the acoustic (for Adults, *W*= .732, *p*<.001; TLD, *W*= .882, *p*= .094; DLD, *W*= .849, *p*= .010), and lexical frequency envelopes (Adults, *W*= .849, *p*= .010; TLD, *W*= .968, *p*= .886; DLD, *W*= .788, *p*= .001), Independent-Samples Kruskal-Wallis tests were conducted to investigate between-group differences in the strength of the neural tracking. For the acoustic envelope mTRFs, results indicate a significant difference in amplitude between Groups (*H*(2)= 12.615, *p*= .002), with a mean rank of 32.65 for Adults, 17.25 for TLD children and 18.76 for DLD children. Post-hoc comparisons with Mann-Whitney U tests (Bonferroni-corrected alpha) indicated a significant difference in the mTRF amplitude between adults and children [TLD, *U* = 31, *p* <.001; DLD, *U* = 60, *p*=.001], but no difference between the groups of children [*U* = 98, *p* =.439], suggesting greater auditory tracking of the speech envelope in adults than children. Higher positive values suggest a more pronounced auditory response for the speech acoustic envelope in adults than children, but no evidence of language effects on the children‘s acoustic tracking.

Similarly, there was a significant difference between Groups in the amplitude of the mTRF for the lexical frequency envelope (*H* (2) = 8.153, *p*= .017), with a mean rank of 16.18 for Adults, 26.75 for TLD children and 28.53 for DLD children. Post-hoc comparisons with the Mann-Whitney U test indicate a significant difference between adults and DLD children [*U* = 60, *p*=.001] but no difference with TLD children [*U* = 57, *p*=.024] or between the groups of children [*U* = 96, *p* =.405], using corrected alpha at the 0.017 level. This indicates that lexical tracking is greater in adults than in DLD children but similar between children and between adults/TLD children. A greater negative amplitude indicates significantly greater processing of word lexical frequency (N400-like effect) in adults than DLD children, but similar between groups of children and between TLD children and adults.

Figure 5.8

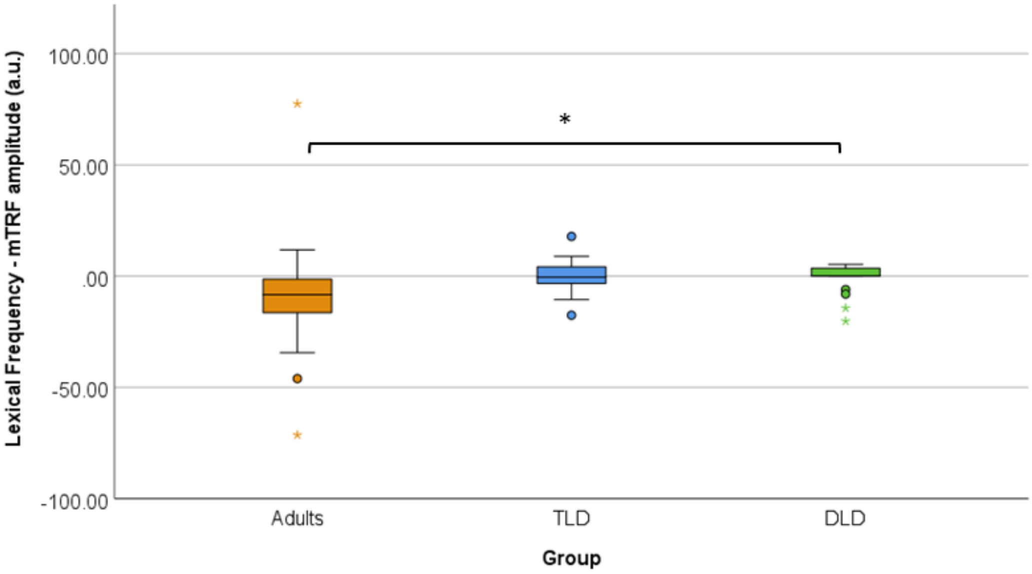
mTRF Amplitude Mean Values for the Acoustic Envelope on each Group



Note. TLD, n=12, DLD, n=17, and Adults, n=17. (**) indicates significance at α=0.01 level.

Figure 5.9

mTRF Amplitude Mean values for the Lexical Frequency Envelope on each Group



Note. TLD, n=12, DLD, n=17, and Adults, n=17. (*) indicates significance at α=0.05 level.

5.3.4 Neural tracking versus phonological measures

Our last analysis examined whether the degree of speech neural tracking predicted the children's scores in phonological awareness and filtered speech perception measures. As between-group differences in these tests were detected in chapters 3 and 4, respectively, we pooled all children together regardless of their groups for the current analysis. After confirming data assumptions (see Appendix 5.3), two separate linear mixed-effects models were estimated using maximum likelihood (ML); one model for phonological awareness and one for filtered speech test scores. In both models, group, acoustic and lexical r coefficients were treated as fixed effects, whereas 'Subject' (participant) was used as a random intercept, with the variance component as the covariance structure.

The results for both LME models are presented in Table 5.4. Statistical analysis revealed that neither acoustic r coefficients nor lexical r coefficients were significant predictors of phonological awareness performance ([$t(18)= -.010$, $p=0.993$], and [$t(18)= .893$, $p=.384$], respectively. This indicates that the strength of neural tracking of the acoustic or lexical frequency envelopes does not predict performance in phonological awareness tasks. Similarly, acoustic r coefficients and lexical r coefficients did not significantly predict the children's scores in filtered speech perception tests, with [$t(18)= -.902$, $p= 0.379$, and [$t(18)=1.56$, $p=0.137$], respectively.

Together, these results indicate that after controlling for random effects, r coefficient values obtained from decoding models for the acoustic and lexical frequency speech envelope did not predict test results.

Table 5.4

Results of Linear Mixed-Effect Models for Behavioural Tests and mTRF Accuracy Measures

	Phonological Awareness			Filtered Speech		
Predictors	Estimates	CI	p	Estimates	CI	p
(Intercept)	11.38	2.61-20.15	**.014**	42.21	21.93-62.52	**<.001**
Acoustic r values	-.215	-47.61-47.18	.993	-47.10	-156.82-62.63	.379
Lexical r values	16.57	-22.41-55.55	.384	66.93	23.31 – 157.17	.137
Random Effects (participant)						
σ^2	10.81			57.93		
χ2	1.658	3.315-35.25	.097	1.658	17.77-188.87	.097
ICC	0.5			0.5		
Observations	29			29		
Marginal R^2 / Conditional R^2	0.356 / 0.678			0.307 / 0.654		

Note: σ^2= variance; χ2 =Wald's *Z*; ICC =Intra-cluster coefficient. Phonological Awareness df = 22, Filtered Speech df =18. Bold font types indicate statistical significance at the 0.05 level.

5.4 Discussion

5.4.1 Summary of findings

This study investigated cortical tracking of continuous speech, comparing responses to the amplitude envelope and word lexical frequency in children with TLD, DLD and adults. We provided experimental evidence of robust cortical tracking of speech acoustic and lexical features in young children, with no between-group differences in the strength of the neural responses to the speech, regardless of children's language status. However, we observed different speech tracking patterns between children and adults; within-group analysis indicated that adults showed significantly lower r coefficients for lexical than acoustic information, whereas children presented the inverse pattern. In addition, we observed significantly larger mTRF amplitude in adults than in children at early (auditory) and later (lexical) processing stages. Finally, the acoustic and lexical tracking strength did not significantly predict phonological awareness and filtered speech perception tasks.

These results demonstrate that cortical tracking of speech acoustic and lexical information is robust and already in place by age 4.5 years, showing similar magnitude in children and adults, even under unattended listening conditions. However, cortical tracking did not differ between children with typical and atypical language development, which may be explained by an absence of speech processing deficits in children with DLD, at least for acoustic and lexical information. However, it could also be explained by high EEG and behavioural variability in our groups of children. Nevertheless, that the lack of differences between children with DLD and TLD and the finding that neural tracking does not predict phonological skills or the ability to perceive degraded speech could be determined by age (e.g., neuromaturation), and might change during development.

When interpreting mTRF results, an essential aspect is whether they reflect speech neural processing or arise from linear modelling problems. Thus, the first relevant finding of this study is that, for all our groups, the accuracy of our decoding models was significantly above the chance level, both for the acoustic and lexical features. Correlations significantly above zero indicate that the r values reflected cortical speech tracking. In addition, the interaction detected between 'Group' and 'Neural tracking measure' (acoustic/lexical) demonstrates that the lexical mTRF is not merely picking up acoustic tracking but represents an independent, unique contribution of lexical processing. This is supported by the fact that children and adults showed opposite patterns for acoustic and lexical features patterns, which would not be seen if both responses resulted from the same underlying neural process. That being said, word duration could be an intermediary factor at play here, as usually content word are less frequent than function words but have longer duration. This means that the lexical frequency values for content words are represented in more datapoints than those for function words, which could have influenced the backward models.

A second important consideration is that these results align with the range of r values and temporal-spatial patterns reported by previous studies. In adults, Crosse et al. (2015) reported mean correlations of 0.13 for backward mTRFs models in adults when listening to clear speech. Moreover, our correlation results are strikingly similar to those reported by Jessen et al. (2019), who detected average *r* values of 0.21 in 7-month-old infants and adults. We also corroborated their findings regarding latency (adults at 300-400 ms and infants at 250-500 ms) and frontocentral topography of the acoustic TRF, although their responses showed later negative deflections (after 500 ms). In our study, the forward-transformed decoder weights showed frontal positivity in all three groups. However, this was bilateral only for adults and lateralised in children (rightward for the TLD and leftward for the DLD group). In addition, our results partially supported those reported by Vander Ghinst et al. (2019), who detected similar speech acoustic tracking in children than adults at frequencies below 4 Hz, but significantly lower for children between 4-8 Hz. However, their study used attended listening and coherence measures and not mTRFs.

It is worth noting that correlation values are usually low for speech neural tracking, especially for encoding models, as they arise for an intrinsically noisy neural signal like the EEG. For example, Di Liberto et al. (2015) reported auditory envelope tracking values between r= 0.04-0.05 when using forward models. Importantly, r values tend to decrease for larger amounts of data, as in smaller datasets, correlations are more likely to reflect the sample particularities than the population patterns. Thus, leading authors in the field recommend not to interpret r values 'per se' (Crosse et al., 2021; Jessen et al., 2021), as they would only be comparable if resulting from models with the same parameters. Instead, it is suggested to use other methods for linear model comparison to balance the number of parameters and observations (e.g., data amount).

A third aspect to consider is why, contrary to our hypothesis, we found no differences in correlation values for acoustic and lexical tracking and no between-group differences for these speech features during unattended listening. This suggests that children and adults have the same degree of acoustic and linguistic tracking or that our study failed to detect any lexical tracking effect, meaning that the lexical correlation values we detected reflected the brain's acoustic response. However, the significant Group*Speech feature interaction demonstrates that r values in our study reflect linguistic processing, as different patterns of neural tracking were observed in children and adults for acoustic and lexical information. This interaction indicates that our results likely reflect age-related differences in speech cortical tracking (e.g., neuromaturation), although with no evidence of any modulations of children's language status, as we had expected.

The analysis of forward-converted mTRF patterns is somewhat consistent with the correlation results, showing tracking responses of significantly larger amplitude in adults than children for acoustic (100-300 interval) and lexical frequency (400-600 ms) features, indicating more pronounced P100-200 and N400 effects in adults. This supports previous literature indicating clearer, larger auditory peaks in adults than children (see Wunderlich & Cone-Wesson, 2006 for a review). However, our results for neural tracking of lexical features contradict previous studies such as Niesen et al. (2023), who reported immature, lower cortical tracking of lexical units in school-aged children than adults. However, their study had essential differences from the present one, making it hard to compare findings; they used SNR maps to measure and assess spectral correlation and used sentences composed only of monosyllabic words instead of natural speech.

Crucially, our findings can be interpreted differently at the functional level. For acoustic tracking results, the more straightforward interpretation is that adults show more efficient tracking of low-level speech features as the acoustic envelope, even when they are not attending to the stimulus. On the contrary, children show weaker acoustic tracking, but this seems not to be explained by differences in their language abilities (TLD/DLD status, phonological test scores) or speech perception skills, and could be related to the fact that at this age, their auditory system is still developing. Notably, some previous studies using clear speech stimuli, indicate no differences in acoustic envelope tracking for attended and unattended conditions, meaning that involuntary attention (and not only task-directed attention) is a relevant factor for acoustic envelope tracking (Brodbeck & Simon, 2020). Thus, for intelligible, easy-to-perceive speech as in our study (e.g., high SNRs, no background noise), we could still observe a good amount of automatic auditory tracking, especially in adults, as keeping some 'housekeeping' register of environmental sounds is behaviourally relevant.

Contrary to our hypothesis of neural tracking reflecting our group's language status, we found no evidence of atypical tracking in DLD children, despite their poorer phonological skills, which contradicts the hypothesis of impaired acoustic envelope tracking explaining phonological deficits in this group (Goswami, 2011; 2022). It is more likely that greater lexical tracking in children indicates that they are less able to ignore the narrated stories rather than the unlikely alternative of young children showing greater top-down language effects and better lexical processing than adults. Although this study did not control for attentional factors as we were looking at automatic speech processing, the adult's brain may be more efficient than children's at inhibiting attention to lexical content they have been instructed to ignore, which would explain smaller r values for lexical tracking in adults. However, this interpretation contradicts our findings of larger N400-like responses in adults' mTRFs, which, according to the vast ERP literature, are likely indexing better lexical processing. Thus, combining both mTRF findings in a single functional interpretation seems not straightforward and leaves an open question about how well neural tracking measures reflect the interplay of acoustic and linguistic processing during speech perception.

Moreover, our study did not detect any association between neural tracking and children's previous performance on phonological awareness and filtered speech perception tests. Acoustic and lexical mTRF accuracy values did not predict children's filtered speech test scores as we expected according to previous findings indicating high correlation of acoustic mTRFs r values with speech intelligibility (Crosse et al., 2015; Ding & Simons, 2013). However, these results could be explained because our experiment tested children on different speech stimuli (single words) than those that elicited neural tracking (full stories), rendering these comparisons inadequate. Similarly, we found that speech tracking (r values) did not predict phonological test scores, even though the TLD group performed significantly better than the DLD group. This contradicts previous literature that reported an association between acoustic envelope tracking and phonological skills using decoding models

(Keshavarzi et al., 2022). However, we did not examine the correlations at the spectral level (phase coherence) as these authors did.

Finally, at the neurophysiological level, our findings support the idea that language networks involved in processing syntactically simple speech (as our stories) are already established by the age of 4-5 years. These networks include, for example, the ventral tracts V1-V2, and dorsal tract D1, which are thought to be involved in speech acoustic and lexical processing, as well as in the processing of canonical grammatical structures (Friederici et al., 2017, see Chapter 1.2.1). However, our finding of smaller mTRF magnitude and less mature scalp patterns in children than adults indicates that these networks may not be fully developed at the age of our TLD/DLD groups. On the other hand, the lack of differences in neural tracking measures between the TLD and DLD groups could be explained because our stimuli were age-appropriate materials without syntactic complexities, which may have needed to be more sensitive to detect functional differences between TLD and DLD children.

5.4.2 Strengths, limitations, and future research

One of the main strengths of this study is that it demonstrates that decoding models are a feasible method to study natural speech processing in young children, not only at the acoustic but at the lexical level. Our results demonstrate robust speech cortical tracking not only in adults but in both groups of children, despite their small sample sizes and high variability in EEG magnitudes. The findings of this study contribute to a deeper understanding of the neural basis of speech processing in young children, revealing an early development of cortical tracking for the speech acoustic and lexical content, even in children with atypical language development.

An essential contribution to the DLD research field is that we found no evidence of atypical neural tracking of the acoustic or lexical envelopes in the DLD group despite this group showing poorer phonological and filtered speech test performance than TLD children. This is relevant as it demonstrates that this key speech-processing mechanism is preserved in children with DLD, thus contradicting previous hypothesis of its causal role in this disorder.

Notably, some relevant methodological aspects must be considered when interpreting backward models. In this study, three main methodological factors may have influenced our results: an unbalanced amount of data between children and adults, the type of lexical analysis we used, and the characteristics of our groups of children. However, one strength of this study is that we had a large amount of clean data for all participants.

The amount and quality of data are relevant factors for modelling the amplitude envelope tracking (Crosse et al., 2021). For small and medium-sized datasets, correlation values increase with the amount of good data. However, for large datasets, r values decrease because they are no longer driven by the sample particularities (outliers). Some previous children's studies have set a minimum of 100 seconds per participant (e.g., Jessen et al., 2021), which in our study was largely surpassed. Although having enough clean data for all participants is one of the strengths of our study, uncontrolled between-group differences in the amount of data may have influenced our results, for example, leading to artificially higher correlation values in the groups of children.

In future studies, addressing the potential bias introduced by data imbalances between participants will be important. For example, we could have randomly discarded epochs in adults' data to match the number of epochs in the three groups. However, we decided to retain as much data as possible and set the minimum individual data requirement at 300 sec, three times the minimum amount reported in previous studies (Jessen et al., 2021).

In addition, the operationalisation of lexical features could have been suboptimal to detecting group-level differences between TLD and DLD children, even when previous studies have reported that lexical frequency is a sensitive measure of linguistic processing (see Gillis et al. 2022). A strength of using mTRF models is that many analyses can be performed in the same datasets. In the future, instead of using continuous values for lexical frequency, we could divide the words into high and low-frequency ones. In addition, future research could investigate the effects of semantic similarity with this data or replicate this experiment by introducing new variables such as attention or background noise.

Finally, the previous literature has pointed out that encoding and decoding models may not perform very well in groups of participants that show significant variability because the model training usually captures the data's particular features (e.g., outliers) and generalises poorly, which may result in model overfitting and spurious group differences (Crosse et al., 2021). In our data, for example, we observed a great range for the optimal lambda values within groups, and poorer performance of generic than individual models during preliminary analysis, both indicators of great intra and inter-subject variability. Children could have been more affected by fatigue and boredom than adults, leading to differences in the strength of neural tracking between the initial and final stories. These potential effects were not controlled (e.g., by randomising the story presentation order), as we attempted to secure having as many EEG responses for the same stories across groups in case generic models showed better performance. Thus, future research should address these methodological issues.

Regardless of these limitations, a final aspect to consider is that the word database and stories created for this experiment are a significant methodological contribution. These materials can be used in future studies with children, for example, to confirm these findings or obtain normative values in larger samples. The materials will be made freely available to other researchers in the field, increasing their utility according to open science practices. In addition, this database can be easily expanded to include additional speech features such as phonemic, spectral, or syntactic features, allowing us to re-analyse our EEG data with new layers of information that could improve mTRF performance.

5.4.3 Conclusions

In conclusion, this study demonstrates that adult-like neural tracking of the speech acoustic and lexical frequency envelope is already in place between the ages of 4.7 to 5.7 years, with no evidence of being modulated by language abilities but by neuromaturation (age), at least, under unattended listening conditions. Importantly, it demonstrates intact processing of the speech acoustic envelope in the DLD group, supporting previous findings of a non-auditory origin for this disorder and indicating no relationship between phonological skills and speech neural tracking.

Chapter 6. General Discussion

6.1 Overall Summary of Findings

Over the last decades, much research has focused on understanding how language is processed in the brain, with major technological advances in neuroimaging and data analysis methods providing invaluable evidence to support language processing models in adults. However, we still lack a model of language acquisition that integrates neurobiological and behavioural data to explain age-related changes in typical and atypical development. The main goal of this thesis was to provide electrophysiological evidence on the role of neural oscillations in children's speech perception using different EEG paradigms and analysis methods. Specifically, I wanted to investigate how cortical oscillatory activity relates to speech perception in language development and if atypical neural patterns were present in children with DLD.

My central hypothesis was that, as children grow up and language processing networks become more efficient, so would their neural responses to speech, resulting in more synchronised EEG signals (although not necessarily in larger ones) until reaching adult-like speech processing. This better signalling would be not only dependent on age-related brain changes but enhanced by language knowledge via top-down processing. As predicted in Chapter 1 (page 46), I expected greater language effects in adults than children (P1) and in TLD than in DLD children (P2), which would be detected at the cortical level through different EEG paradigms. This central hypothesis was partially supported by the experiments of this thesis, as we detected significant differences in most EEG measures between children and adults, but in most measures, no differences between TLD and DLD children (no support for P2). This indicates that top-down language effects we observed in adults were not present yet in children, thus, did not modulate children EEG responses as age did (partially supporting P3). Finally, most EEG measures were not correlated or did not predict behavioural performance on phonological awareness or speech perception tests, providing little evidence to support P4.

The first experiment (Chapter 2) aimed to validate an ERP multi-feature paradigm in a group of adults to be used later in children's studies. Although acoustic differences between S-NS stimuli should be taken into account when interpreting our findings, we confirmed that the experiment elicited significant MMN/LDN responses for speech monosyllables and their NS analogues, and also confirmed our hypothesis of a language effect in phonemic change detection. However, rather than enhanced responses for more informative speech stimuli, we found that the effects of language content were consistent with the predictive processing framework, with smaller amplitude for less novel stimuli. On the other hand, the MMN latency showed significantly earlier peaks for words than non-words and content than function words, corroborating that neural processing is faster for higher-order linguistic content. These results confirm my third prediction (P3), indicating an interaction between linguistic content on the MMN responses.

In the second experiment (Chapter 3), we used the previously validated multi-feature experiment (speech condition) to test a group of children with TLD and DLD. Here, we extended the MMN/LDN analysis to time-frequency measures to include measures of neural synchrony and not only amplitude. As predicted, children showed significant but immature MMRs in the MMN/LDN intervals but no differences between the TLD and DLD groups on any EEG measures. Moreover, the EEG did not correlate with phonological awareness test scores, even though the TLD group performed significantly better than the DLD group. In adults, however, we observed more synchronised activity than in children but only for words and confirmed our hypothesis of greater language effects for higher-order linguistic content. These results does not support my second prediction (P2) and suggest that adult-like language modulations on speech perception may not be in place in children this age, or that our experiment failed to detect them, for example, because of higher variability in children.

The third experiment (Chapter 4) investigated whether there were any differences in the baseline cortical activity between children with TLD and DLD and with the group of adults, using EEG resting-state measures. We replicated previous findings in adults showing significantly lower average power than children for all the frequency bands. However, contrary to our hypothesis, there was no difference between TLD and DLD children in power or oscillatory hemispheric lateralisation. Despite children with TLD performing significantly better in the filtered speech perception test, there was no correlation between behavioural and EEG measures (gamma power and HF lateralisation) either. However, an unexpected finding was that the theta/alpha ratio was significantly smaller in groups with better language skills (adults<TLD<DLD) and inversely correlated with filtered speech scores in children.

My fourth experiment (Chapter 5) investigated cortical speech tracking using backward modelling (mTRFs) of EEG responses to continuous speech. We found significant cortical tracking for speech acoustic and lexical features in all groups. However, there were no differences between the TLD and DLD children and no relationship between mTRF measures and children's behavioural scores. Although these results indicate no effects of language differences between TLD-DLD children, the patterns of neural tracking in adults could indicate an effect of neuromaturation and age-related changes in speech cortical tracking, as they showed stronger, more mature auditory and lexical responses.

In summary, the main findings of this thesis indicate that (i) there were significant differences between adults and children's EEG responses, but no evidence of language effects in children, despite these being robustly detected in adults, (ii) there is no evidence of atypical cortical asymmetry or speech processing EEG responses in children with DLD, other than a reduced resting-state theta/alpha ratio, and (iii) most EEG measures do not reflect children behavioural test performance, except for an inverse correlation between theta/alpha ratio and filtered speech processing. Thus, it is possible that the differences between children and adults arise from brain maturation and not an effect of typical/atypical language development, but also from methodological issues, for example, related to the characteristics of the TLD/DLD groups. The results of these four studies need to be considered in an integrated manner into the broader context of current language neuroscience and EEG knowledge.

6.2 Results in the context of language neuroscience

Despite all theoretical and methodological progress, today, it is still not possible to describe the entire sequence of changes in the brain that allow children to achieve adult-like language processing. Experimental findings like those reported in this thesis must be interpreted feasibly within the language neuroscience context to understand early childhood's intricate speech perception mechanisms. Thus, it is essential to integrate the results of this thesis under current adult language models and our knowledge about the development of cortical language networks (Saby & Marshall, 2012) in order to explain speech perception and language development.

Firstly, at the level of brain level, a straightforward interpretation of our findings is that the differences between children and adults detected in most EEG measures are related to brain maturation. Although there is little information about the developmental patterns of speech neural tracking, a significant body of ERP literature reports U-shaped trajectories for the amplitude of different auditory ERP measures, which are the reflection of age-related changes in the brain's white and grey matter densities, skull thickness and neural synchronisation (de Haan, 2007; Uhlhaas et al., 2009; 2010). Our ERP and resting-state results confirm that children exhibit EEG signals of greater amplitude than adults, even though this is unlikely to represent better cortical speech processing in children. This suggests that oscillatory magnitude should be interpreted differently in adults and developing brains. On the other hand, we confirmed that when perceiving speech contrasts, children show longer latencies and less phase synchronisation (ITPC) than adults, indicating that these measures may more accurately reflect age-related differences in speech processing. In contrast, we observed that at the age of our groups (4.7-5.7 years), children's rhythms are quite analogue to those observed in adults in terms of frequency bands, except for the alpha band peaking around 8 Hz instead of the adult-like peak at 10 Hz.

In terms of brain structure, we know that by the age of our TLD-DLD groups, the ventral language tracts V1-V2 and dorsal D1 are already in place (Friederici et al., 2017), as well as functional language lateralisation (Thompson et al., 2016). The early development of these neural pathways allows children to process 'easy' stimuli as clear, continuous speech and isolated phonemic contrasts quite well at the acoustic and lexical levels. As our experiments did not involve complex syntax (processed in tract D2, not fully developed until after the age of seven years) and did not require important top-down modulations (as in attended or challenging listening conditions), it is possible that our stimuli did not require recruitment of pathway D2. This could have minimised the speech processing differences between TLD and DLD children, especially considering that grammatical processing deficits are a core symptom od DLD. Although this could explain the lack of EEG differences between TLD and DLD in children, it does not explain why children's responses significantly differed from those in adults and why adults showed significant language effects (experiment 2) and lexical processing effects (experiment 4).

The functional differences we observed between children and adults in speech-related cortical responses may be explained by differences in top-down language and attentional modulations. Although for children, the developmental trajectories of these effects are less defined, some studies indicate that bottom-up (stimulus-driven) processing directs speech perception approximately until the age of 3 years old, and after that, there is a progressive increase of top-down (language-driven) modulations until adulthood (Meyer et al., 2018; Skeide & Friederici, 2016), although this theory has not been investigated systematically. Our finding of top-down language influences present in adults but not yet in young children supports this timeline, confirming developmental differences in top-down modulations on speech perception during early childhood, and represents an essential contribution from the current thesis.

A remaining open question is to what extent it is possible to dissociate domain-specific and language-specific top-down effects in young children. Although we confirmed our hypothesis of greater lexical processing in adults than children, under these experimental conditions it is not possible to isolate the contributions of language-specific modulations from domain-general cognitive mechanisms. For example, the differences we observed in oscillatory power or neural tracking measures could be influenced by involuntary attention switching or differences in inhibitory control. Future research could explore how to determine the contributions of language and general cognitive processing to different EEG measures when testing young children.

Thirdly, it is important to consider the implications of these results for the current theories of typical and atypical language acquisition. In searching for a neural marker of DLD and other language disorders, several studies have proposed that atypical cortical dynamics may explain language processing difficulties, such as atypical language lateralisation (Badcock et al., 2012) or ERP responses (Kujala & Leminem, 2017). However, none of our results supports these explanations, apart from the already discussed differences in theta/alpha ratio between TLD and DLD children, which might be explained by cognitive and not by language differences. Instead, our null findings could be explained by similar, rather than different cortical dynamics for speech processing in children with DLD and those with TLD. If this is the case, this would contradict several past and current accounts of DLD proposing that low-level processing deficits could explain some behavioural deficits (e.g.in phonological processing) in this clinical population (see Goswami, 2022). In addition, our results did not replicate previous findings in individuals with dyslexia that indicate atypical oscillatory activity and auditory tracking in this disorder, also relating them to phonological deficits (e.g., Di Liberto et al., 2018).

Finally, it is crucial to reconsider the meaning of EEG findings when explaining language acquisition in the brain. So far, an obstacle to building an integrative model of language development is that the adult measures of brain activity may or may not represent the same things in children. For example, larger ERP deflections are typically interpreted as better cortical processing in adults. However, in children, it is not possible to determine whether greater amplitude in children represents ERP developmental curves, ERP responses to speech contrasts or their overlap. There is a need to determine the most suitable measures for studying speech and language development. Our results show that ITPC and latency could be better indices of more efficient cortical processing than amplitude-based measures. Moreover, it is essential to consider other measures and paradigms, for example, examining the potential role of neural noise and variability in language acquisition (Ostlund et al., 2022) or what larger EEG responses represent in developing cortical networks, for example, for neuronal energy balance during bottom-up processing (Vergara et al., 2019).

6.3 Methodological considerations and future directions

6.3.1 Methodological contributions

Several studies have pointed out that the evidence relating EEG and behavioural measures is full of inconsistencies and lacks replication (Sabi & Marshall, 2012). One of the strengths of this thesis is that all the experiments aimed to replicate previous studies (e.g., using similar methods). Although several of our predictions were not met, reproducing previous experiments helps furthering the current understanding of language development, and increases the validity of the limited EEG literature in this field. At the same time, this thesis addressed the importance of innovation in developmental science by using state-of-the-art methods, extending decoding models to study lexical processing, and including a clinical group that has not been studied before using a continuous speech paradigm (children with DLD).

A second strength of this thesis is that it demonstrates that data collection in challenging populations can be optimised using age-appropriate protocols and environmental adjustments. We collected data for three experiments with preschool-aged children in a single EEG session of approximately 40 minutes. This was possible because the ERP optimal paradigm was time-efficient, leaving enough time for the resting state and the continuous speech experiments. In addition, children tolerated well the testing time as they were distracted watching cartoons and not asked to perform any task.

Moreover, this thesis demonstrated that with some environmental adjustments, it is possible to get clean data in young children, even in clinical groups such as DLD. In my opinion, some relevant environmental factors that enabled successful data collection were: (i) the experimenter's skills and training to interact with children and parents, (ii) having at least one assistant for data collection, as this helps to speed up the EEG set-up and to distract the child, (iii) having everyone in the room so that children can be seated next to their parents, and the researchers close to them, so we could easily monitor if the child was still or needed a break, and check any problem with the EEG very quickly (e.g. to adjust channel's impedance).

Using these new paradigms and adjustments, we demonstrated the feasibility of conducting successful, reproducible EEG experiments in young children. This was a central goal of this thesis, as many researchers (as we were initially) may feel discouraged to test this age group because it poses extra challenges, contributing to a vicious cycle of lack of EEG evidence in early language development.

Finally, this thesis contributes to the global open science initiative, as all our experimental materials, scripts and datasets will be made freely available to other researchers upon request after the results of this thesis are published.

6.3.2 Methodological limitations

When interpreting the results of this thesis, it is essential to consider their generalisability and how our findings might have been affected by potential sources of bias at different levels. An important limitation to address concerns the possible presence of sampling bias. Firstly, all the experiments were conducted in the same three groups of participants, and all children were recruited from the same school in Chile. Although the invitation for the study was sent to all the children in the school that fit the inclusion criteria, from the 37 children that were invited, 34 passed the screening, and only 29 came to the EEG experiment, with two participants dropping-out during this session. Although these are low participant exclusion/drop-out rates, the size of our groups was small, particularly the control group (TLD), which should be considered when interpreting these findings.

Although we initially calculated that a larger sample size was needed (n=25 per group) for this thesis, the data collection process was severely disrupted by the COVID-19 pandemic, which impeded a second overseas trip to test more children from this school. Thus, we postponed collecting new data and emphasised acquiring more advanced EEG analysis skills. In the future, it is necessary to determine whether the findings of this thesis can be generalised to the broader population, replicating these experiments in a larger sample of children with typical language development and DLD diagnosis, for example, at different ages. In the short term, we have planned to conduct a final study at UCL's ICL Lab using these experiments to test bilingual children in a broader age range.

In addition, it is worth considering that there is usually high variability between children regarding their cognitive, language and social skills, even in typically developing groups. Even though children attended the same school allowed us to control for differences in socioeconomic status and medical history, and the screening process controlled for differences in children's age or hearing levels between the children with TLD and DLD, we did not control for the heterogeneity of language profiles in DLD children. Despite our DLD children being clinically diagnosed before the study according to valid SLT criteria, the variability in their language profiles (in the TLD group) may indicate that their cortical responses to speech are too different for being categorised only into typical/atypical groups. It would be interesting in the future, for example, to investigate the association of language and

EEG profiles at the individual level (e.g., how many children with DLD showed speech perception skills within the typical range).

Notably, the utility of binary classifications of children into control and clinical groups when investigating neurodevelopmental disorders is a long-lasting debate among language development clinicians and researchers. Although growing evidence indicates that children's language profiles are heterogeneous and change dynamically during development (Bishop et al., 2016; 2017), there is no agreement on how we can operationalise this continuum between typical and atypical language skills in developmental research.

In terms of background literature, an essential realisation from this PhD thesis is that there are still few EEG studies addressing the neural basis of language acquisition and any possible cortical signatures of DLD. This striking lack of EEG research in younger children was pointed out more than 15 years ago (de Haan, 2007) but remains an issue, explaining our limited understanding of cortical dynamics in early language development. On top of that, the heterogeneity of methodological approaches in the existing literature makes it very hard to compare and generalise findings across EEG studies on speech perception development.

In this scenario, an important contribution of this PhD thesis is that it builds upon several previous studies, confirming that replication and innovation in research are not mutually exclusive. However, some key findings of this thesis indicated null results, for example, no language top-down modulations in children and no left-lateralisation of oscillations. Thus, although we aimed for maximum confound control, some experimental aspects in this thesis need to be reconsidered in future studies. For example, the speech stimuli could focus on materials testing tract D2, as discussed in Chapter 5. Because these networks develop later and grammatical deficits are an important symptom of DLD, stimulus requiring D2 processing could reveal more subtle differences between children's groups.

Another aspect is that, although there is plenty of options for signal processing in EEG research, in practice, it can be difficult to determine 'a priori' what are the most appropriate, especially for exploratory studies. For example, despite efforts such as the CORE or MADE initiatives, there is no gold standard for the EEG processing pipeline or selection of channels and time windows for analysis. During this thesis, one of the greatest challenges was to decide the best data analysis steps for each experiment when each choice may substantially change the outcome of a given study (Clayson et al., 2021) or introduce biases (Cohen, 2017). In the future, this thesis may help inform the decision-making process of new EEG studies, for example, by providing easy-to-replicate pre-processing pipelines and data analysis methods for the different EEG paradigms.

Similarly, selecting statistical methods was a challenging aspect of all the experiments. Although the statistical analysis plan was carefully outlined beforehand when deciding on the experimental design, the collected data was full of non-normal distributions, non-linearities and high within and between-participant variability, which sometimes made it impossible to go ahead with the planned or most recommended methods. In this regard, I opted for maximum transparency in the reports, providing justifications when unplanned or suboptimal data analysis methods were used.

Notably, although data analysis difficulties are related to the small size of our sample, some effects appeared to be robust enough to show group-level differences and the experiment had sufficient power to detect them. For example, latency and synchrony measures are more informative when studying groups of children at different ages or for comparing children and adults. However, these findings need to be replicated in future studies.

6.4 Concluding remarks.

In sum, the current thesis provides new evidence about cortical speech processing during early childhood in typical and atypical language acquisition, indicating developmental changes in EEG responses between early childhood and adulthood, and no differences between children with and without DLD in cortical measures of speech processing.

The results of this thesis contribute to the field of language acquisition and could inform future models of language development that satisfies multiple levels of explanations, from neurons to behaviour. Importantly, our findings reinforce the need of revisiting theoretical assumptions about how to interpret EEG measures in children and of conducting larger studies to disentangle the effects of neuromaturation, cogntive and language development on speech perception.

In addition, the findings and EEG methods used in this thesis have great potential to inform future clinical measures of speech perception. Although we found no evidence of a neural marker for DLD, this thesis identified some EEG measures that are robust enough to compare and even differentiate adults and children. Hopefully, these results will lay the basis for future studies on the development of language top-down effects on speech perception and speech perception development in TLD and DLD.

References

Aboitiz, F. (2017). A brain for speech: A view from evolutionary neuroanatomy. Springer.

Abrams, D. A., Nicol, T., Zecker, S., & Kraus, N. (2009). Abnormal cortical processing of the syllable rate of speech in poor readers. *The Journal of Neuroscience: the official journal of the Society for Neuroscience,* 29(24), 7686–7693. doi.org/10.1523/JNEUROSCI.5242-08.2009

Alexandrou, A. M., Saarinen, T., Kujala, J., & Salmelin, R. (2020). Cortical entrainment: what we can learn from studying naturalistic speech perception. *Language, Cognition and Neuroscience,* 35(6), 681-693. https://doi.org/10.1080/23273798.2018.1518534

Alonso, M. A., Fernandez, A., & Díez, E. (2015). Subjective age-of-acquisition norms for 7,039 Spanish words. Behavior research methods, 47(1), 268–274.doi.org/10.3758/s13428-014-0454-2

American Speech-Language-Hearing Association. 1996. Central Auditory Processing: Current status of research and implications for clinical practice. *American Journal of Audiology.* 5 (2): 41-54.

Azami, H., Zrenner, C., Brooks, H. et al. Beta to theta power ratio in EEG periodic components as a potential biomarker in mild cognitive impairment and Alzheimer's dementia. Alz Res Therapy 15, 133 (2023). https://doi.org/10.1186/s13195-023-01280-z

Baart, M., & Samuel, A. G. (2015). Early processing of auditory lexical predictions revealed by ERPs. *Neuroscience Letters,* 585, 98-102. https://doi.org/10.1016/j.neulet.2014.11.044

Badcock, N. A., Bishop, D. V., Hardiman, M. J., Barry, J. G., & Watkins, K. E. (2012). Co-localisation of abnormal brain structure and function in specific language impairment. *Brain and Language,* 120(3), 310-320. https://doi.org/10.1016/j.bandl.2011.10.006

Bailey, P. J., & Snowling, M. J. (2002). Auditory processing and the development of language and literacy. *British Medical Bulletin, 63*(1), 135-146.

Baltzell, L. S., Srinivasan, R., & Richards, V. M. (2017). The effect of prior knowledge and intelligibility on the cortical entrainment response to speech. *Journal of Neurophysiology,* 118(6), 3144–3151. https://doi.org/10.1152/jn.00023.2017

Balmaceda Romero, V., Beiza Mas, M., Díaz Espina, J., Vargas Leclérc, S., & Vásquez Lara, P. (2008). Obtención de valores normativos para una batería de pruebas de Procesamiento Auditivo (Central) en niños de entre 5.0 y 6.11 años de edad.

Barrios, P., Benavides, C., Benavides, L. & Dellafiori. C. (1987). Evaluación de la conducta lingüística de niños de centros abiertos de 4 a 4.11 años. Seminario para optar al título de Fonoaudiólogo, Facultad de Medicina, Universidad de Chile.

Bastiaansen, M., & Hagoort, P. (2006). Oscillatory neuronal dynamics during language comprehension. *Progress in Brain Research*, 159, 179-196. https://doi.org/10.1016/S0079-6123(06)59012-0

Baltzell, L. S., Srinivasan, R., & Richards, V. M. (2017). The effect of prior knowledge and intelligibility on the cortical entrainment response to speech. *Journal of Neurophysiology*, 118(6), 3144–3151. https://doi.org/10.1152/jn.00023.2017

Beese, C., Meyer, L., Vassileiou, B., & Friederici, A. D. (2017). Temporally and spatially distinct theta oscillations dissociate a language-specific from a domain-general processing mechanism across the age trajectory. *Scientific Reports*, 7(1), 11202. doi.org/10.1038/s41598-017-11632-z

Bell, M. A., & Cuevas, K. (2012). Using EEG to study cognitive development: Issues and practices. *Journal of Cognition and Development*, 13(3), 281-294. https://doi.org/10.1080/15248372.2012.691143

Benasich, A. A., Gou, Z., Choudhury, N., & Harris, K. D. (2008). Early cognitive and language skills are linked to resting frontal gamma power across the first 3 years. *Behavioural Brain Research*, 195(2), 215-222. https://doi.org/10.1016/j.bbr.2008.08.049

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society. Series B (Methodological)*, 57(1), 289-300. https://doi.org/10.1111/j.2517-6161.1995.tb02031.x

Bertels, J., Niesen, M., Destoky, F., Coolen, T., Vander Ghinst, M., Wens, V., ... & Bourguignon, M. (2023). Neurodevelopmental oscillatory basis of speech processing in noise. *Developmental Cognitive Neuroscience*, 59, 101181, https://doi.org/10.1016/j.dcn.2022.101181

Bishop, D. V. M. (2007). Using mismatch negativity to study central auditory processing in developmental language and literacy impairments: Where are we, and where should we be going? *Psychological Bulletin, 133*(4), 651–672. https://doi.org/10.1037/0033-2909.133.4.651

Bishop, D.V.M. (2013). Cerebral asymmetry and language development: cause, correlate, or consequence? *Science*. 2013; 340(6138) doi: 10.1126/science.1230531.

Bishop, D.V. M., Anderson, M., Reid, C., & Fox, A. M. (2011). Auditory development between 7 and 11 years: an event-related potential (ERP) study. *PLoS One*, 6(5), e18993. https://doi.org/10.1371/journal.pone.0018993

Bishop, D.V. M., Carlyon, R. P., Deeks, J. M., & Bishop, S. J. (1999). Auditory temporal processing impairment: Neither necessary nor sufficient for causing language impairment in children.

Journal of Speech, Language, and Hearing Research, 42(6), 1295-1310. https://doi.org/10.1044/jslhr.4206.1295

Bishop, D. V. M., & Hardiman, M. J. (2010). Measurement of mismatch negativity in individuals: a study using single-trial analysis. *Psychophysiology*, 47(4), 697-705. https://doi.org/10.1111%2Fj.1469-8986.2009.00970.x

Bishop, D. V. M., Hardiman, M. J., & Barry, J. G. (2010a). Is auditory discrimination mature by middle childhood? A study using time-frequency analysis of mismatch responses from 7 years to adulthood. Developmental Science, 14(2), 402-416.

Bishop, D.V. M., Hardiman, M. J., & Barry, J. G. (2010b). Lower-frequency event-related desynchronization: a signature of late mismatch responses to sounds, which is reduced or absent in children with specific language impairment. *Journal of Neuroscience,* 30(46), 15578-15584. https://doi.org/10.1523/JNEUROSCI.2217-10.2010

Bishop, D. V. M., Hardiman, M. J., & Barry, J. G. (2012). Auditory deficit as a consequence rather than endophenotype of specific language impairment: electrophysiological evidence. *PLoS One,* 7(5), e35851. https://doi.org/10.1371/journal.pone.0035851

Bishop, D. V., M. & McArthur, G. M. (2005). Individual differences in auditory processing in specific language impairment: a follow-up study using event-related potentials and behavioural thresholds. *Cortex: A journal devoted to the study of the nervous system and behavior*, *41*(3), 327–341. https://doi.org/10.1016/s0010-9452(08)70270-3

Bishop, D. V., M. & Snowling, M. J. (2004). Developmental dyslexia and specific language impairment: Same or different? *Psychological Bulletin*, *130*(6), 858.

Bishop, D.V. M., Snowling, M. J., Thompson, P. A., Greenhalgh, T., & Catalise Consortium. (2016). CATALISE: A multinational and multidisciplinary Delphi consensus study. Identifying language impairments in children. *PLOS One, 11*(7), e0158753.

Bishop, D.V. M., Snowling, M. J., Thompson, P. A., Greenhalgh, T., Catalise-2 Consortium, 9Adams, C., ... & House, A. (2017). Phase 2 of CATALISE: A multinational and multidisciplinary Delphi consensus study of problems with language development: Terminology. *Journal of Child Psychology and Psychiatry*, *58*(10), 1068-1080.

Boersma, P.& Weenink, D. (2018). Praat: doing phonetics by computer [Computer program]. Version 6.2.06, retrieved 23 January 2022 from https://www.praat.org.

Bosl, W., Tierney, A., Tager-Flusberg, H., & Nelson, C. (2011). EEG complexity as a biomarker for autism spectrum disorder risk. *BMC Medicine,* 9(1), 1-16. /doi.org/10.1186/1741-7015-9-18

Bradlow, A. R., & Bent, T. (2002). The clear speech effect for non-native listeners. *The Journal of the Acoustical Society of America*, 112(1), 272-284. https://doi.org/10.1121/1.1487837

Brauer, J., Anwander, A., & Friederici, A. D. (2011). Neuroanatomical prerequisites for language functions in the maturing brain. *Cerebral Cortex*, 21(2), 459-466. https://doi.org/10.1093/cercor/bhq108

Brauer, J., Anwander, A., Perani, D., & Friederici, A. D. (2013). Dorsal and ventral pathways in language development. *Brain and Language*, 127(2), 289–295. https://doi.org/10.1016/j.bandl.2013.03.001

Breshears, J. D., Hamilton, L. S., & Chang, E. F. (2018). Spontaneous Neural Activity in the Superior Temporal Gyrus Recapitulates Tuning for Speech Features. *Frontiers in Human Neuroscience*, 12, 360. https://doi.org/10.3389/fnhum.2018.00360

British Society of Audiology. (2011). Recommended procedure: pure-tone air-conduction and bone-conduction threshold audiometry with and without masking. *Read. Br. Soc. Audiology.* Available on http://www.thebsa.org.uk/

Brodbeck, C., & Simon, J. Z. (2020). Continuous speech processing. *Current Opinion in Physiology,* 18, 25–31. https://doi.org/10.1016/j.cophys.2020.07.014

Broderick, M. P., Anderson, A. J., Di Liberto, G. M., Crosse, M. J., & Lalor, E. C. (2018). Electrophysiological correlates of semantic dissimilarity reflect the comprehension of natural, narrative speech. *Current Biology*, 28(5), 803-809. https://doi.org/10.1016/j.cub.2018.01.080

Brooker, R. J., Bates, J. E., Buss, K. A.,..., & Schmidt, L. A. (2020). Conducting Event-Related Potential (ERP) Research with Young Children: A Review of Components, Special Considerations and Recommendations for Research on Cognition and Emotion. *Journal of psychophysiology*, 34(3), 137–158. https://doi.org/10.1027/0269-8803/a000243

Buzsaki, G. (2006). *Rhythms of the Brain*. Oxford university press.

Buzsaki, G., & Draguhn, A. (2004). Neuronal oscillations in cortical networks. *Science*, 304(5679), 1926-1929. https://doi.org/10.1126/science.1099745

Calcus, A., Tuomainen, O., Campos, A., Rosen, S., & Halliday, L. F. (2019). Functional brain alterations following mild-to-moderate sensorineural hearing loss in children. *Elife*, 8, e46965. https://doi.org/10.7554/eLife.46965

Cantiani, C., Ortiz-Mantilla, S., Riva, V., Piazza, C., Bettoni, R., Musacchia, G., ... & Benasich, A. A. (2019). Reduced left-lateralized pattern of event-related EEG oscillations in infants at familial risk for language and learning impairment. *Neuroimage*: Clinical, 22, 101778. https://doi.org/10.1016/j.nicl.2019.101778

Čeponienė, R., Lepistö, T., Alku, P., Aro, H., & Näätänen, R. (2003). Event-related potential indices of auditory vowel processing in 3-year-old children. *Clinical neurophysiology: official journal of the International Federation of Clinical Neurophysiology*, 114(4), 652–661. https://doi.org/10.1016/s1388-2457(02)00436-4

Cheour, M., Alho, K., Čeponiené, R., Reinikainen, K., Sainio, K., Pohjavuori, M., ... & Näätänen, R. (1998). Maturation of mismatch negativity in infants. *International Journal of Psychophysiology*, 29(2), 217-226. https://doi.org/10.1016/S0167-8760(98)00017-8

Cheour, M., Korpilahti, P., Martynova, O., & Lang, A. H. (2001). Mismatch negativity and late discriminative negativity in investigating speech perception and learning in children and infants. *Audiology & Neuro-otology*, 6(1), 2–11. https://doi.org/10.1159/000046804

Cheour, M. (2007). Development of mismatch negativity (MMN) during infancy. In M. de Haan (Ed.), Infant EEG and event-related potentials (pp. 171–198). Psychology Press.

Clayson, P. E., Baldwin, S. A., Rocha, H. A., & Larson, M. J. (2021). The data-processing multiverse of event-related potentials (ERPs): A roadmap for the optimization and standardization of ERP processing and reduction pipelines. *NeuroImage*, 245, 118712. https://doi.org/10.1016/j.neuroimage.2022.119443

Clements, G. M., Bowie, D. C., Gyurkovics, M., Low, K. A., Fabiani, M., & Gratton, G. (2021). Spontaneous Alpha and Theta Oscillations Are Related to Complementary Aspects of Cognitive Control in Younger and Older Adults. Frontiers in human neuroscience, 15, 621620. https://doi.org/10.3389/fnhum.2021.621620

Cohen M. X. (2017). Rigor and replication in time-frequency analyses of cognitive electrophysiology data. *International journal of psychophysiology: official journal of the International Organization of Psychophysiology*, 111, 80–87. https://doi.org/10.1016/j.ijpsycho.2016.02.001

Cohen, M. X. (2014). Analyzing neural time series data: theory and practice. MIT press.

Cohen M. X. (2016). Where does EEG come from and what does it mean? *Trends in Neurosciences*, 40(4), 208–218. https://doi.org/10.1016/j.tins.2017.02.004

Corral, S., Ferrero, M. & Goikoetxea, E. LEXIN: A lexical database from Spanish kindergarten and first-grade readers. *Behavior Research Methods* 41, 1009–1017 (2009). https://doi.org/10.3758/BRM.41.4.1009

Crosse, M. J., Butler, J. S., & Lalor, E. C. (2015). Congruent Visual Speech Enhances Cortical Entrainment to Continuous Auditory Speech in Noise-Free Conditions. The *Journal of neuroscience*: *the official journal of the Society for Neuroscience*, 35(42), 14195–14204. https://doi.org/10.1523/JNEUROSCI.1829-15.2015

Crosse, M. J., Di Liberto, G. M., Bednar, A., & Lalor, E. C. (2016). The multivariate temporal response function (mTRF) toolbox: a MATLAB toolbox for relating neural signals to continuous stimuli. *Frontiers in Human Neuroscience*, 10, 604. https://doi.org/10.3389/fnhum.2016.00604

Crosse, M. J., Zuk, N. J., Di Liberto, G. M., Nidiffer, A. R., Molholm, S., & Lalor, E. C. (2021). Linear modeling of neurophysiological responses to speech and other continuous stimuli: methodological considerations for applied research. *Frontiers in Neuroscience,* 15, 705621. https://doi.org/10.3389/fnins.2021.705621

Csépe, V. (1995). On the origin and development of the mismatch negativity. *Ear and Hearing,* 16(1), 91-104. 16(1): p 91-104, February 1995.

Cutler, A. (2008). The 34th Sir Frederick Bartlett Lecture: The abstract representations in speech processing. *Quarterly Journal of Experimental Psychology,* 61(11), 1601-1619. https://doi.org/10.1080/13803390802218542

David, C., Roux, S., Bonnet-Brilhault, F., Ferré, S., & Gomot, M. (2020). Brain responses to change in phonological structures of varying complexity in children and adults. *Psychophysiology,* 57(9), e13621. https://doi.org/10.1111/psyp.13621

Davis, M. H., & Johnsrude, I. S. (2003). Hierarchical processing in spoken language comprehension. *Journal of Neuroscience*, 23(8), 3423-3431. https://doi.org/10.1523/JNEUROSCI.23-08-03423.2003

Debnath, R., Buzzell, G. A., Morales, S., Bowers, M. E., Leach, S. C., & Fox, N. A. (2020). The Maryland analysis of developmental EEG (MADE) pipeline. *Psychophysiology,* 57(6), e13580. https://doi.org/10.1111/psyp.13580

DeBoer , T. , Scott , L. S. , & Nelson , C. A. (2006). Methods of acquiring and analyzing infant event-related potentials. In M. de Haan (Ed.), *Infant EEG and Event-Related Potentials* (pp. 5 – 38). London, UK, Psychology Press

de Guibert, C., Maumet, C., Jannin, P., Ferré, J. C., Tréguier, C., Barillot, C., Le Rumeur, E., Allaire, C., & Biraben, A. (2011). Abnormal functional lateralization and activity of language brain areas in typical specific language impairment (developmental dysphasia). *Brain: A journal of neurology,* 134(Pt 10), 3044–3058. https://doi.org/10.1093/brain/awr141 de Haan, M. (Ed.). (2007). Infant EEG and Event-Related Potentials (1st ed.). Psychology Press. https://doi.org/10.4324/9780203759660

Dehaene-Lambertz, G., & Baillet, S. (1998). A phonological representation in the infant brain. *Neuroreport*, 9(8), 1885-1888. 9(8):p 1885-1888, June 1, 1998.

Delorme A, Makeig S (2004) EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *J Neurosci Methods* 134(1):9–21 https://doi.org/10.1016/j.jneumeth.2003.10.009

Di Liberto, G. M., & Lalor, E. C. (2017). Indexing cortical entrainment to natural speech at the phonemic level: Methodological considerations for applied research. *Hearing Research*, 348, 70-77. https://doi.org/10.1016/j.heares.2017.02.015

Di Liberto, G. M., O'Sullivan, J. A., & Lalor, E. C. (2015). Low-frequency cortical entrainment to speech reflects phoneme-level processing. *Current Biology*, 25(19), 2457-2465 http://dx.doi.org/10.1016/j.cub.2015.08.030

Di Liberto, G. M., Peter, V., Kalashnikova, M., Goswami, U., Burnham, D., & Lalor, E. C. (2018). Atypical cortical entrainment to speech in the right hemisphere underpins phonemic deficits in dyslexia. *NeuroImage*, 175, 70-79. https://doi.org/10.1016/j.neuroimage.2018.03.072

Dineen, L. C., & Blakesley, B. C. (1973). Algorithm AS 62: Generator for the sampling distribution of the Mann-Whitney U statistic. *Applied Statistics*, 22, 269-273. https://doi.org/10.2307/2346934

Ding, N., Melloni, L., Zhang, H. et al. Cortical tracking of hierarchical linguistic structures in connected speech. *Nat Neurosci* 19, 158–164 (2016). https://doi.org/10.1038/nn.4186

Ding, N., & Simon, J. Z. (2013). Adaptive temporal encoding leads to a background-insensitive cortical representation of speech. *Journal of Neuroscience*, 33(13), 5728-5735. doi: 10.1523/JNEUROSCI.5297-12.2013.

Ding, N., & Simon, J. Z. (2014). Cortical entrainment to continuous speech: functional roles and interpretations. *Frontiers in Human Neuroscience*, 8, 311. https://doi.org/10.3389/fnhum.2014.00311

Doelling, K. B., Arnal, L. H., Ghitza, O., & Poeppel, D. (2014). Acoustic landmarks drive delta–theta oscillations to enable speech comprehension by facilitating perceptual parsing. *NeuroImage*, 85, 761-768. https://doi.org/10.1016/j.neuroimage.2013.06.035

Doesburg, S. M., Tingling, K., MacDonald, M. J., & Pang, E. W. (2016). Development of network synchronization predicts language abilities. *Journal of Cognitive Neuroscience*, 28(1), 55-68. https://doi.org/10.1162/jocn_a_00879

Donoghue, T., Dominguez, J., & Voytek, B. (2020). Electrophysiological Frequency Band Ratio Measures Conflate Periodic and Aperiodic Neural Activity. *eNeuro*, 7(6), ENeuro.0192-20.2020. https://doi.org/10.1523/ENEURO.0192-20.2020

Dudley, H. (1939). “Remaking speech,” *J. Acoust. Soc. Am.* 11, 169–177. https://doi.org/10.1121/1.1916020

Eggermont, J. J., & Ponton, C. W. (2003). Auditory-evoked potential studies of cortical maturation in normal hearing and implanted children: correlations with changes in structure and speech perception. *Acta Oto-Laryngologica,* 123(2), 249-252. https://doi.org/10.1080/0036554021000028098

Evans, J. L., & Brown, T. T. (2016). Specific language impairment. In Neurobiology of Language (pp. 899-912). Academic press https://doi.org/10.1016/B978-0-12-407794-2.00072-9

Field, A. (2013). Discovering statistics using IBM SPSS statistics. London: Sage.

Field, A., Miles, J., & Field, Z. (2012). Discovering statistics using R (Vol. 3). London: Sage.

Fields, E. C., & Kuperberg, G. R. (2020). Having your cake and eating it too: Flexibility and power with mass univariate statistics for ERP data. *Psychophysiology,* 57(2), e13468. https://doi.org/10.1111/psyp.13468

François, C, Rodriguez-Fornells, A, Teixidó, M, Agut, T, Bosch, L. Attenuated brain responses to speech sounds in moderate preterm infants at term age. *Dev Sci.* 2021; 24:e12990. https://doi.org/10.1111/desc.12990

Friedrich, M., Weber, C., & Friederici, A. D. (2004). Electrophysiological evidence for delayed mismatch response in infants at-risk for specific language impairment. *Psychophysiology,* 41(5), 772-782, https://doi.org/10.1111/j.1469-8986.2004.00202.x

Friederici, A. D. The neural basis of language development and its impairment. *Neuron* 52, 941–952 (2006). https://doi.org/10.1016/j.neuron.2006.12.002

Friederici, A. D. (2011). The brain basis of language processing: from structure to function. *Physiological Reviews,* 91(4), 1357-1392 https://doi.org/10.1152/physrev.00006.2011

Friederici A. D. (2012a). The cortical language circuit: from auditory perception to sentence comprehension. *Trends in Cognitive Sciences,* 16(5), 262–268. https://doi.org/10.1016/j.tics.2012.04.001

Friederici, A. D. (2012b). Language development and the ontogeny of the dorsal pathway. *Frontiers in Evolutionary Neuroscience,* 4, 3.https://doi.org/10.3389/fnevo.2012.00003

Friederici, A. D. (2015). White-matter pathways for speech and language processing. *Handbook of clinical neurology*, *129*, 177-186. https://doi.org/10.1016/B978-0-444-62630-1.00010-X

Friederici, A.D., Chomsky, N., Berwick, R.C. et al. Language, mind and brain. *Nat Hum Behav* 1, 713–722 (2017). https://doi.org/10.1038/s41562-017-0184-4

Friederici, A. D., & Gierhan, S. M. (2013). The language network. *Current opinion in Neurobiology*, 23(2), 250-254. https://doi.org/10.1016/j.conb.2012.10.002

Fuente, A. & McPherson, B. (2006). Auditory Processing test for Spanish - *Speaking adults: An initial study. International Journal of Audiology. 45: 645 –659.*

Fuentemilla, L. L., Marco-Pallarés, J., Münte, T. F., & Grau, C. (2008). Theta EEG oscillatory activity and auditory change detection. *Brain Research*, 1220, 93-101. https://doi.org/10.1016/j.brainres.2007.07.079

Gansonre, C., Højlund, A., Leminen, A., Bailey, C., & Shtyrov, Y. (2018). Task-free auditory EEG paradigm for probing multiple levels of speech processing in the brain. *Psychophysiolog*y, 55(11), e13216. https://doi.org/10.1111/psyp.13216

Garrido, M. I., Kilner, J. M., Stephan, K. E., & Friston, K. J. (2009). The mismatch negativity: a review of underlying mechanisms. *Clinical Neurophysiology*, 120(3), 453-463. https://doi.org/10.1016/j.clinph.2008.11.029

Gillis, M., Kries, J., Vandermosten, M., & Francart, T. (2023). Neural tracking of linguistic and acoustic speech representations decreases with advancing age. *NeuroImage*, 267, 119841.

Gillis, M., Vanthornhout, J., Simon, Tom Francart, & Brodbeck, C.(2021). Neural Markers of Speech Comprehension: Measuring EEG Tracking of Linguistic Speech Representations, Controlling the Speech Acoustics. *Journal of Neuroscience*, 41 (50) 10316-10329; DOI: 10.1523/JNEUROSCI.0812-21.2021

Gillis, M., Van Canneyt, J., Francart, T. & Vanthornhout, J. (2022). Neural tracking as a diagnostic tool to assess the auditory pathway. *Hearing Research,* Volume 426, 108607, ISSN 0378-5955, https://doi.org/10.1016/j.heares.2022.108607

Giraud, A. L., & Poeppel, D. (2012). Cortical oscillations and speech processing: emerging computational principles and operations. *Nature Neuroscience,* 15(4), 511-517. https://doi.org/10.1038/nn.3063

Giraud, A.-L., Kleinschmidt, A., Poeppel, D., Lund, T. E., Frackowiak, R. S. J., and Laufs, H. (2007). Endogenous cortical rhythms determine cerebral specialization for speech perception and production. *Neuron* 56, 1127–1134. https://doi.org/10.1016/j.neuron.2007.09.038

Glass, E., Sachse, S., & von Suchodoletz, W. (2008). Development of auditory sensory memory from 2 to 6 years: an MMN study. *Journal of Neural Transmission*, 115, 1221-1229. https://doi.org/10.1007/s00702-008-0088-6

Goswami, U. (2011). A temporal sampling framework for developmental dyslexia. *Trends in Cognitive Sciences, 15*(1), 3-10. https://doi.org/10.1016/j.tics.2010.10.001

Goswami U. (2022). Language acquisition and speech rhythm patterns: an auditory neuroscience perspective. *Royal Society Open Science*, 9(7), 211855. https://doi.org/10.1098/rsos.211855

Gou, Z., Choudhury, N., & Benasich, A. A. (2011). Resting frontal gamma power at 16, 24 and 36 months predicts individual differences in language and cognition at 4 and 5 years. *Behavioural Brain Research*, 220(2), 263-270. https://doi.org/10.1016/j.bbr.2011.01.048

Groppe, D.M., Urbach, T.P. and Kutas, M. (2011), Mass univariate analysis of event-related brain potentials/fields I: A critical tutorial review. *Psychophysiology*, 48: 1711-1725. https://doi.org/10.1111/j.1469-8986.2011.01273.

Guardia Gutiérrez, P. A. (2010). The effect of linguistic, phonetic and lexical factors on phonological skills and reading acquisition in Spanish: A longitudinal study (Doctoral dissertation, University of Cambridge). Available on https://ethos.bl.uk/OrderDetails.do?uin=uk.bl.ethos.608697

Guthrie, D., & Buchwald, J. S. (1991). Significance testing of difference potentials. *Psychophysiology,* 28(2), 240-244. https://doi.org/10.1111/j.1469-8986.1991.tb00417.x

Guttorm, T. K., Leppänen, P. H. T., Hämäläinen, J. A., Eklund, K. M., & Lyytinen, H. J. (2010). Newborn Event-Related Potentials Predict Poorer Pre-Reading Skills in Children at Risk for Dyslexia. *Journal of Learning Disabilities*, 43(5), 391–401. https://doi.org/10.1177/0022219409345005

Hamilton, L. S., & Huth, A. G. (2020). The revolution will not be controlled: natural stimuli in speech neuroscience. *Language, Cognition, and Neuroscience*, 35(5), 573-582, DOI: 10.1080/23273798.2018.1499946

Hämmerer, D., Li, S. C., Völkle, M., Müller, V., & Lindenberger, U. (2013). A lifespan comparison of the reliability, test-retest stability, and signal-to-noise ratio of event-related potentials assessed during performance monitoring. *Psychophysiology*, 50(1), 111-123. https://doi.org/10.1111/j.1469-8986.2012.01476.x

Hagoort, P. (2019). The neurobiology of language beyond single-word processing. *Science*, 366(6461), 55-58. https://doi.org/10.1126/science.aax0289

Hazan, V., & Barrett, S. (2000). The development of phonemic categorization in children aged 6–12. *Journal of Phonetics*, 28(4), 377-396. https://doi.org/10.1006/jpho.2000.0121

Heilbron, M., & Chait, M. (2018). Great expectations: is there evidence for predictive coding in auditory cortex?. *Neuroscience*, 389, 54-73. DOI: 10.1016/j.neuroscience.2017.07.061

Heilbron, M., Armeni, K., Schoffelen, J. M., Hagoort, P., & De Lange, F. P. (2022). A hierarchy of linguistic predictions during natural language comprehension. *Proceedings of the National Academy of Sciences*, 119(32), e2201968119 https://doi.org/10.1073/pnas.2201968119

Heim, S., Friedman, J. T., Keil, A., & Benasich, A. A. (2011). Reduced sensory oscillatory activity during rapid auditory processing as a correlate of language-learning impairment. *Journal of Neurolinguistics*, *24*(5), 538-555. DOI: 10.1016/j.jneuroling.2010.09.006

Heim, S., Keil, A., Choudhury, N., Thomas Friedman, J., & Benasich, A. A. (2013). Early gamma oscillations during rapid auditory processing in children with a language-learning impairment: changes in neural mass activity after training. *Neuropsychologia*, *51*(5), 990–1001. https://doi.org/10.1016/j.neuropsychologia.2013.01.011

Hickok, G., & Poeppel, D. (2016). Neural basis of speech perception. *Neurobiology of Language*, 299-310. https://doi.org/10.1016/B978-0-12-407794-2.00025-0

Houweling, T., Becker, R., & Hervais-Adelman, A. (2020). The noise-resilient brain: Resting-state oscillatory activity predicts words-in-noise recognition. *Brain and Language,* 202, 104727. https://doi.org/10.1016/j.bandl.2019.104727

Hsiao, F. J., Cheng, C. H., Liao, K. K., & Lin, Y. Y. (2010). Cortico-cortical phase synchrony in auditory mismatch processing. *Biological Psychology*, 84(2), 336-345. https://doi.org/10.1016/j.biopsycho.2010.03.019

Hsiao, F. J., Wu, Z. A., Ho, L. T., & Lin, Y. Y. (2009). Theta oscillation during auditory change detection: an MEG study. *Biological Psychology*, 81(1), 58-66. https://doi.org/10.1016/j.biopsycho.2009.01.007

Hudson, M. R., & Jones, N. C. (2022). Deciphering the code: Identifying true gamma neural oscillations. Experimental neurology, 357, 114205. https://doi.org/10.1016/j.expneurol.2022.114205

Jääskeläinen, I. P., Ahveninen, J., Bonmassar, G., Dale, A. M., Ilmoniemi, R. J., Levänen, S., ... & Belliveau, J. W. (2004). Human posterior auditory cortex gates novel sounds to consciousness. *Proceedings of the National Academy of Sciences*, 101(17), 6809-6814. https://doi.org/10.1073/pnas.0303760101

Jacobsen, T., Bäß, P., Roye, A., Winkler, I., Schröger, E., & Horváth, J. (2021). Word class and word frequency in the MMN looking glass. *Brain and Language*, 218, 104964. https://doi.org/10.1016/j.bandl.2021.104964

Jackson, A.F. and Bolger, D.J. (2014), Neurophysiological bases of EEG. *Psychophysiol*, 51: 1061-1071. https://doi.org/10.1111/psyp.12283

Jessen, S., Fiedler, L., Münte, T. F., & Obleser, J. (2019). Quantifying the individual auditory and visual brain response in 7-month-old infants watching a brief cartoon movie. *NeuroImage*, 202, 116060. https://doi.org/10.1016/j.neuroimage.2019.116060

Jessen, S., Obleser, J., & Tune, S. (2021). Neural tracking in infants–An analytical tool for multisensory social processing in development. *Developmental Cognitive Neuroscience,* 52, 101034. doi: 10.1016/j.dcn.2021.101034

Jochaut, D., Lehongre, K., Saitovitch, A., Devauchelle, A. D., Olasagasti, I., Chabane, N. ... & Giraud, A. L. (2015). Atypical coordination of cortical oscillations in response to speech in autism. *Frontiers in Human Neuroscience*, 9, 171. https://doi.org/10.3389/fnhum.2015.00171

Kalashnikova, M., Peter, V., Di Liberto, G.M. et al. Infant-directed speech facilitates seven-month-old infants' cortical tracking of speech. *Sci Rep* 8, 13745 (2018). doi:10.1038/s41598-018-32150-6

Kappenman, E. S., Farrens, J. L., Zhang, W., Stewart, A. X., & Luck, S. J. (2021). ERP CORE: An open resource for human event-related potential research. *NeuroImage,* 225, 117465. https://doi.org/10.1016/j.neuroimage.2020.117465

Kawahara, H., Morise, M., Takahashi, T., Nisimura, R., Irino, T., & Banno, H. (2008). "TANDEM-STRAIGHT: A temporally stable power spectral representation for periodic signals and applications to interference-free spectrum, F0, and aperiodicity estimation," in *Proceedings of International Conference on Acoustics, Speech and Signal Processing,* pp. 3933–3936.

Kikuchi, M., Shitamichi, K., Yoshimura, Y., Ueno, S., Remijn, G. B., Hirosawa, T., . Minabe, Y. (2011). Lateralized theta wave connectivity and language performance in 2- to 5-year-old children. *J Neurosci*, 31(42), 14984-14988. doi:10.1523/jneurosci.2785-11.2011

Kisler, T. and Reichel U. D. and Schiel, F. (2017). WebMAUS: Multilingual processing of speech via web services, *Computer Speech & Language*, Volume 45, September 2017, pages 326–347, https://doi.org/10.1016/j.csl.2017.01.005

Klimesch, W. (2012). Alpha-band oscillations, attention, and controlled access to stored information. Trends in cognitive sciences, 16(12), 606-617.

Ko, D., Kwon, S., Lee, G. T., Im, C. H., Kim, K. H., & Jung, K. Y. (2012). Theta oscillation related to the auditory discrimination process in mismatch negativity: oddball versus control paradigm. *Journal of Clinical Neurology*, 8(1), 35-42. https://doi.org/10.3988/jcn.2012.8.1.35

Kösem, A., & Van Wassenhove, V. (2017). Distinct contributions of low-and high-frequency neural oscillations to speech comprehension. *Language, Cognition and Neuroscience*, 32(5), 536-544. https://doi.org/10.1080/23273798.2016.1238495

Kraus, N., McGee, T., Micco, A., Sharma, A., Carrell, T., & Nicol, T. (1993). Mismatch negativity in school-age children to speech stimuli that are just perceptibly different. *Electroencephalography and Clinical Neurophysiology/Evoked Potentials Section,* 88(2), 123-130. https://doi.org/10.1016/0168-5597(93)90063-U

Kubanek, J., Brunner, P., Gunduz, A., Poeppel, D., & Schalk, G. (2013). The tracking of speech envelope in the human cortex. *PloS One,* 8(1), e53398. doi.org/10.1371/journal.pone.0053398

Kuhl, P. K. (2010). Brain mechanisms in early language acquisition. *Neuron*, 67(5), 713-727. DOI 10.1016/j.neuron.2010.08.038

Kuhl, P., & Rivera-Gaxiola, M. (2008). Neural substrates of language acquisition. *Annu. Rev. Neurosci.,* 31, 511-534. https://doi.org/10.1146/annurev.neuro.30.051606.094321

Kujala, T., & Leminen, M. (2017). Low-level neural auditory discrimination dysfunctions in specific language impairment—A review on mismatch negativity findings. *Developmental Cognitive Neuroscience*, 28, 65-75. DOI: 10.1016/j.dcn.2017.10.005

Kujala, T., Tervaniemi, M., & Schröger, E. (2007). The mismatch negativity in cognitive and clinical neuroscience: theoretical and methodological considerations. *Biological Psychology*, 74(1), 1-19. https://doi.org/10.1016/j.biopsycho.2006.06.001

Kuuluvainen, S., Nevalainen, P., Sorokin, A., Mittag, M., Partanen, E., Putkinen, V., & Kujala, T. (2014). The neural basis of sublexical speech and corresponding nonspeech processing: a combined EEG–MEG study. *Brain and Language,* 130, 19-32. https://doi.org/10.1016/j.bandl.2014.01.008

Kuuluvainen, S., Alku, P., Makkonen, T., Lipsanen, J., & Kujala, T. (2016). Cortical speech and non-speech discrimination in relation to cognitive measures in preschool children. *European Journal of Neuroscience,* 43(6), 738-750. https://doi.org/10.1111/ejn.13141

Kwok, E. Y., Cardy, J. O., Allman, B. L., Allen, P., & Herrmann, B. (2019). Dynamics of spontaneous alpha activity correlate with language ability in young children. *Behavioural Brain Research*, 359, 56-65 https://doi.org/10.1016/j.bbr.2018.10.024

Ladányi, E., Persici, V., Fiveash, A., Tillmann, B., & Gordon, R. L. (2020). Is atypical rhythm a risk factor for developmental speech and language disorders? Wiley interdisciplinary reviews. *Cognitive Science*, 11(5), e1528. https://doi.org/10.1002/wcs.1528

Lakatos P, Karmos G, Mehta AD, Ulbert I, Schroeder CE. Entrainment of neuronal oscillations as a mechanism of attentional selection. *Science.* 2008;320: 110–113 DOI: 10.1126/science.1154735

Lakatos, P., Gross, J., & Thut, G. (2019). A new unifying account of the roles of neuronal entrainment. *Current Biology*, *29*(18), R890-R905. https://doi.org/10.1016/j.cub.2019.07.075

Lee, C. Y., Yen, H. L., Yeh, P. W., Lin, W. H., Cheng, Y. Y., Tzeng, Y. L., & Wu, H. C. (2012). Mismatch responses to lexical tone, initial consonant, and vowel in Mandarin-speaking preschoolers. *Neuropsychologia*, 50(14), 3228-3239. https://doi.org/10.1016/j.neuropsychologia.2012.08.025

Leonard, L. B. (2014). Children with specific language impairment. MIT press.

Leonard, M. K., & Chang, E. F. (2014). Dynamic speech representations in the human temporal lobe. *Trends in Cognitive Sciences*, 18(9), 472-479. doi: 10.1016/j.tics.2014.05.001

Leong, V., & Goswami, U. (2014). Impaired extraction of speech rhythm from temporal modulation patterns in speech in developmental dyslexia. *Frontiers in Human Neuroscience,* 8, 96. https://doi.org/10.3389/fnhum.2014.00096

Leong, V., & Goswami, U. (2015). Acoustic-emergent phonology in the amplitude envelope of child-directed speech. *PloS One,* 10(12), e0144411. https://doi.org/10.1371/journal.pone.0144411

Linnavalli, T., Putkinen, V., Huotilainen, M., & Tervaniemi, M. (2017). Phoneme processing skills are reflected in children's MMN responses. *Neuropsychologia*, 101, 76-84. https://doi.org/10.1016/j.neuropsychologia.2017.05.013

Lohvansuu, K., Hämäläinen, J. A., Ervast, L., Lyytinen, H., & Leppänen, P. H. (2018). Longitudinal interactions between brain and cognitive measures on reading development from 6 months to 14 years. *Neuropsychologia*, 108, 6-12. https://doi.org/10.1016/j.neuropsychologia.2017.11.018

Lopez-Calderon, J., & Luck, S. J. (2014). ERPLAB: an open-source toolbox for the analysis of event-related potentials. *Frontiers in Human Neuroscience*, 8, 213. https://doi.org/10.3389/fnhum.2014.00213

Lovio, R., Pakarinen, S., Huotilainen, M., Alku, P., Silvennoinen, S., Näätänen, R., & Kujala, T. (2009). Auditory discrimination profiles of speech sound changes in 6-year-old children as determined with the multi-feature MMN paradigm. *Clinical Neurophysiology*, 120(5), 916-921. https://doi.org/10.1016/j.clinph.2009.03.010

Luck, S. J. (2014). An introduction to the event-related potential technique. MIT press.

Luck, S. J., & Gaspelin, N. (2017). How to get statistically significant effects in any ERP experiment (and why you shouldn't). *Psychophysiology,* 54(1), 146-157. https://doi.org/10.1111/psyp.12639

Luck, S. J., & Kappenman, E. S. (Eds.). (2011). The Oxford handbook of event-related potential components. Oxford University Press.

Lum, J. A., Clark, G. M., Bigelow, F. J., & Enticott, P. G. (2022). Resting state electroencephalography (EEG) correlates with children’s language skills: Evidence from sentence repetition. *Brain and Language*, 230, 105137. https://doi.org/10.1016/j.bandl.2022.105137

Maguire, M. J., & Abel, A. D. (2013). What changes in neural oscillations can reveal about developmental cognitive neuroscience: Language development as a case in point. *Developmental Cognitive Neuroscience,* 6, 125-136. https://doi.org/10.1016/j.dcn.2013.08.002

Mai, G., Minett, J. W., & Wang, W. S. Y. (2016). Delta, theta, beta, and gamma brain oscillations index levels of auditory sentence processing. *Neuroimage*, 133, 516-528. https://doi.org/10.1016/j.neuroimage.2016.02.064

Makeig, S., Debener, S., Onton, J., & Delorme, A. (2004). Mining event-related brain dynamics. *Trends in Cognitive Sciences*, 8(5), 204-210. https://doi.org/10.1016/j.tics.2004.03.008

Martin, A. E., & Doumas, L. A. (2017). A mechanism for the cortical computation of hierarchical linguistic structure. *PLoS Biology,* 15(3), e2000663 https://doi.org/10.1371/journal.pbio.2000663

Maurer, U., Bucher, K., Brem, S., & Brandeis, D. (2003). Development of the automatic mismatch response: from frontal positivity in kindergarten children to the mismatch negativity. *Clinical Neurophysiology*, 114(5), 808-817 doi: 10.1016/s1388-2457(03)00032-4

Mayes, A. K., Reilly, S., & Morgan, A. T. (2015). Neural correlates of childhood language disorder: A systematic review. *Developmental Medicine & Child Neurology*, 57(8), 706-717. https://doi.org/10.1111/dmcn.12714

Meng, X., Sun, C., Du, B., Liu, L., Zhang, Y., Dong, Q., ... & Nan, Y. (2022). The development of brain rhythms at rest and its impact on vocabulary acquisition. *Developmental Science*, 25(2), e13157. https://doi.org/10.1111/desc.13157

Meyer, L. (2018). The neural oscillations of speech processing and language comprehension: state of the art and emerging mechanisms. *European Journal of Neuroscience*, 48(7), 2609-2621. https://doi.org/10.1111/ejn.13748

Meyer, L., Sun, Y., & Martin, A. E. (2020). Synchronous, but not entrained: exogenous and endogenous cortical rhythms of speech and language processing. *Language, Cognition and Neuroscience,* 35(9), 1089-1099. https://doi.org/10.1080/23273798.2019.1693050

Millman, R. E., Johnson, S. R., & Prendergast, G. (2015). The role of phase-locking to the temporal envelope of speech in auditory perception and speech intelligibility. *Journal of Cognitive Neuroscience*, 27(3), 533-545. doi: https://doi.org/10.1162/jocn_a_00719

Miskovic, V., Ma, X., Chou, C. A., Fan, M., Owens, M., Sayama, H., & Gibb, B. E. (2015). Developmental changes in spontaneous electrocortical activity and network organization from early to late childhood. *Neuroimage*, 118, 237-247. https://doi.org/10.1016/j.neuroimage.2015.06.013

Molinaro, N., Lizarazu, M., Lallier, M., Bourguignon, M., & Carreiras, M. (2016). Out-of-synchrony speech entrainment in developmental dyslexia. *Human Brain Mapping*, 37(8), 2767–2783. https://doi.org/10.1002/hbm.23206

Morillon, B., Lehongre, K., Frackowiak, R. S., Ducorps, A., Kleinschmidt, A., Poeppel, D., & Giraud, A. L. (2010). Neurophysiological origin of human brain asymmetry for speech and language. *Proceedings of the National Academy of Sciences*, 107(43), 18688-18693. https://doi.org/10.1073/pnas.1007189107

Morr, M. L., Shafer, V. L., Kreuzer, J. A., & Kurtzberg, D. (2002). Maturation of mismatch negativity in typically developing infants and preschool children. *Ear and Hearing*, 23(2), 118–136. https://doi.org/10.1097/00003446-200204000-00005

Musacchia, G., Choudhury, N. A., Ortiz-Mantilla, S., Realpe-Bonilla, T., Roesler, C. P., & Benasich, A. A. (2013). Oscillatory support for rapid frequency change processing in infants. *Neuropsychologia*, 51(13), 2812-2824. https://doi.org/10.1016/j.neuropsychologia.2013.09.006

Müller, V., Gruber, W., Klimesch, W., & Lindenberger, U. (2009). Lifespan differences in cortical dynamics of auditory perception. *Developmental Science,* 12(6), 839-853. https://doi.org/10.1111/j.1467-7687.2009.00834.x

Näätänen, R. (2003). Mismatch negativity: clinical research and possible applications. *International Journal of Psychophysiology*, 48(2), 179-188. https://doi.org/10.1016/S0167-8760(03)00053-9

Näätänen, R., & Alho, K. (1997). Mismatch negativity–the measure for central sound representation accuracy. *Audiology and Neurotology, 2*(5), 341-353. https://doi.org/10.1159/000259255

Näätänen, R., Jacobsen, T., & Winkler, I. (2005). Memory-based or afferent processes in mismatch negativity (MMN): A review of the evidence. *Psychophysiology*, 42(1), 25-32. https://doi.org/10.1111/j.1469-8986.2005.00256.x

Näätänen, R., Kujala, T. & Light, G. (2019). 'The development of MMN', The Mismatch Negativity: A Window to the Brain (Oxford; online edn, Oxford Academic, 23 May 2019), https://doi.org/10.1093/oso/9780198705079.003.0003 , accessed 5 May 2023.

Näätänen R, Lehtokoski A, Lennes M, Cheour M, Huotilainen M, Iivonen A, Vainio M, Alku P, Ilmoniemi RJ, Luuk A, Allik J, Sinkkonen J, Alho K. Language-specific phoneme representations revealed by electric and magnetic brain responses. *Nature.* 1997 Jan 30;385(6615):432-4. doi: 10.1038/385432a0. PMID: 9009189.

Näätänen, R., Pakarinen, S., Rinne, T., & Takegata, R. (2004). The Mismatch Negativity (MMN): Towards the optimal paradigm. *Clinical Neurophysiology,* 115, 140–144.

Näätänen, R., Paavilainen, P., Rinne, T., & Alho, K. (2007). The mismatch negativity (MMN) in basic research of central auditory processing: a review. *Clinical Neurophysiology*, 118(12), 2544-2590.

Nallet, C. & Gervain, J. (2022) Atypical neural oscillations in response to speech in infants and children with speech and language impairments: a systematic review, *Hearing, Balance and Communication*, 20:3, 145-154, https://doi.org/10.1080/21695717.2022.2084864

Newbury, D. F., & Monaco, A. P. (2010). Genetic advances in the study of speech and language disorders. *Neuron,* 68(2), 309-320. DOI 10.1016/j.neuron.2010.10.001

Niemitalo-Haapola, E., Lapinlampi, S., Kujala, T., Alku, P., Kujala, T., Suominen, K., & Jansson-Verkasalo, E. (2013). Linguistic multi-feature paradigm as an eligible measure of central auditory processing and novelty detection in 2-year-old children. *Cognitive Neuroscience*, 4(2), 99–106. https://doi:10.1080/17588928.2013.781146

Neuman, A. C., Wroblewski, M., Hajicek, J., & Rubinstein, A. (2010). Combined effects of noise and reverberation on speech recognition performance of normal-hearing children and adults. *Ear and Hearing,* 31(3), 336-344. DOI: 10.1097/AUD.0b013e3181d3d514

Niesen, M., Bourguignon, M., Bertels, J., Vander Ghinst, M., Wens, V., Goldman, S., & De Tiège, X. (2023). Cortical tracking of lexical speech units in a multi-talker background is immature in school-aged children. *NeuroImage,* 265, 119770. https://doi.org/10.1016/j.neuroimage.2022.119770

Nittrouer, S., Caldwell-Tarr, A., Tarr, E., Lowenstein, J. H., Rice, C., & Moberly, A. C. (2013). Improving speech-in-noise recognition for children with hearing loss: Potential effects of language abilities, binaural summation, and head shadow. *International Journal of Audiology,* 52(8), 513-525. https://doi.org/10.3109/14992027.2013.792957

Norton, E. S., MacNeill, L. A., Harriott, E. M., Allen, N., Krogh-Jespersen, S., Smyser, C. D., ... & Wakschlag, L. (2021). EEG/ERP as a pragmatic method to expand the reach of infant-toddler neuroimaging in HBCD: Promises and challenges. *Developmental Cognitive Neuroscience*, 51, 100988. https://doi.org/10.1016/j.dcn.2021.100988

Obleser, J., & Kayser, C. (2019). Neural entrainment and attentional selection in the listening brain. *Trends in Cognitive Sciences*, 23(11), 913-926. https://doi.org/10.1016/j.tics.2019.08.004

Ortiz Barajas, M. C., Guevara, R., & Gervain, J. (2021). The origins and development of speech envelope tracking during the first months of life. *Developmental Cognitive Neuroscience*, 48, 100915. https://doi.org/10.1016/j.dcn.2021.100915

Ortiz-Mantilla, S., Hämäläinen, J. A., Musacchia, G., & Benasich, A. A. (2013). Enhancement of gamma oscillations indicates preferential processing of native over foreign phonemic contrasts in infants. *Journal of Neuroscience*, 33(48), 18746-18754. https://doi.org/10.1523/JNEUROSCI.3260-13.2013

Ortiz-Mantilla, S., Roesler, C. P., Realpe-Bonilla, T., & Benasich, A. A. (2022). Modulation of Theta Phase Synchrony during Syllable Processing as a Function of Interactive Acoustic Experience in Infancy. *Cerebral Cortex* (New York, N.Y.: 1991), 32(5), 919–932. https://doi.org/10.1093/cercor/bhab256

Oostenveld, R., Fries, P., Maris, E. & Schoffelen, JM. FieldTrip: Open Source Software for Advanced Analysis of MEG, EEG, and Invasive Electrophysiological Data. *Computational Intelligence and Neuroscience*, 2011; 2011:156869. https://doi.org/10.1155/2011/156869

Ostlund, B., Donoghue, T., Anaya, B., Gunther, K. E., Karalunas, S. L., Voytek, B., & Pérez-Edgar, K. E. (2022). Spectral parameterization for studying neurodevelopment: How and why. *Developmental Cognitive Neuroscience*, 54, 101073 https://doi.org/10.1016/j.dcn.2022.101073

Palana, J., Schwartz, S., & Tager-Flusberg, H. (2022). Evaluating the use of cortical entrainment to measure atypical speech processing: a systematic review. *Neuroscience & Biobehavioral Reviews*, *133*, 104506 https://doi.org/10.1016/j.neubiorev.2021.12.029

Paquette, N., Vannasing, P., Lefrançois, M., Lefebvre, F., Roy, M. S., McKerral, M. ... & Gallagher, A. (2013). Neurophysiological correlates of auditory and language development: a mismatch negativity study. *Developmental Neuropsychology,* 38(6), 386-401. https://doi.org/10.1080/87565641.2013.805218

Park, H., Ince, R. A., Schyns, P. G., Thut, G., & Gross, J. (2015). Frontal top-down signals increase coupling of auditory low-frequency oscillations to continuous speech in human listeners. *Current Biology*, 25(12), 1649-1653. http://dx.doi.org/10.1016/j.cub.2015.04.049

Pavez, M. (2003). Test exploratorio de gramática española de A. Toronto, Aplicación en Chile. Santiago, Ediciones Universidad Católica de Chile.

Pavez, M. (2004). Test de Comprensión Auditiva del Lenguaje de E. Carrow, Aplicación en Chile. Santiago, Chile. Escuela de Fonoaudiología, Facultad de Medicina, Universidad de Chile.

Pavez, M., Coloma, C. J., & Maggiolo, M. (2008). Test para evaluar procesos de simplificación fonológica: Teprosif-R (2a ed.). Eds. Universidad Católica de Chile.

Peelle, J. E., Johnsrude, I., & Davis, M. H. (2010). Hierarchical processing for speech in human auditory cortex and beyond. *Frontiers in Human Neuroscience*, *4*, 1735. https://doi.org/10.3389/fnhum.2010.00051

Peña, M., Maki, A., Kovačić, D., Dehaene-Lambertz, G., Koizumi, H., Bouquet, F., & Mehler, J. (2003). Sounds and silence: an optical topography study of language recognition at birth. *Proceedings of the National Academy of Sciences*, 100(20), 11702-11705. https://doi.org/10.1073/pnas.1934290100

Peña, M., & Melloni, L. (2012). Brain oscillations during spoken sentence processing. *Journal of Cognitive Neuroscience*, 24(5), 1149–1164. https://doi.org/10.1162/jocn_a_00144

Perone, S., Palanisamy, J., & Carlson, S. M. (2018). Age-related change in brain rhythms from early to middle childhood: Links to executive function. *Developmental Science*, 21(6), e12691. https://doi.org/10.1111/desc.12691

Petit, S., Badcock, N. A., Grootswagers, T., & Woolgar, A. (2020). Unconstrained multivariate EEG decoding can help detect lexical-semantic processing in individual children. *Scientific Reports*, 10(1), 10849. https://doi.org/10.1038/s41598-020-67407-6

Poeppel, D. (2001). Pure word deafness and the bilateral processing of the speech code. *Cognitive Science*, 25(5), 679-693. https://doi.org/10.1016/S0364-0213(01)00050-7

Poeppel, D. (2003). The analysis of speech in different temporal integration windows: cerebral lateralization as 'asymmetric sampling in time'. *Speech Communication*, 41(1), 245-255. https://doi.org/10.1016/S0167-6393(02)00107-3

Poeppel, D., & Assaneo, M. F. (2020). Speech rhythms and their neural foundations. *Nature Reviews Neuroscience*, 21(6), 322-334. https://doi.org/10.1038/s41583-020-0304-4

Poulsen, C., Picton, T. W., & Paus, T. (2009). Age-related changes in transient and oscillatory brain responses to auditory stimulation during early adolescence. *Developmental Science,* 12(2), 220-235. https://doi.org/10.1111/j.1467-7687.2008.00760.x

Power, A. J., Colling, L. J., Mead, N., Barnes, L., & Goswami, U. (2016). Neural encoding of the speech envelope by children with developmental dyslexia. *Brain and Language,* 160, 1-10. https://doi.org/10.1016/j.bandl.2016.06.006

Pulvermüller, F., T. Kujala, Y. Shtyrov, J. Simola, H. Tiitinen, P. Alku, K. Alho, S. Martinkauppi, R.J. Ilmoniemi, R. Näätänen, Memory traces for words as revealed by the mismatch negativity, *NeuroImage* 14 (2001) 607–616.

Ramus, F., Marshall, C. R., Rosen, S., & van der Lely, H. K. (2013). Phonological deficits in specific language impairment and developmental dyslexia: Towards a multidimensional model. *Brain, 136*(2), 630-645, doi: 10.1093/brain/aws356

Reetzke, R., Gnanateja, G. N., & Chandrasekaran, B. (2021). Neural tracking of the speech envelope is differentially modulated by attention and language experience. *Brain and Language*, 213, 104891. https://doi.org/10.1016/j.bandl.2020.104891

Richards, S., & Goswami, U. (2019). Impaired recognition of metrical and syntactic boundaries in children with developmental language disorders. *Brain Sciences*, 9(2), 33 https://doi.org/10.3390/brainsci9020033

Ríos-López, P., Molinaro, N., Bourguignon, M., & Lallier, M. (2020). Development of neural oscillatory activity in response to speech in children from 4 to 6 years old. *Developmental Science,* 23(6), e12947. https://doi.org/10.1111/desc.12947

Rivera-Gaxiola, M., Silva-Pereyra, J., & Kuhl, P. K. (2005). Brain potentials to native and non-native speech contrasts in 7-and 11-month-old American infants. *Developmental Science*, 8(2), 162-172. https://doi.org/10.1111/j.1467-7687.2005.00403.x

Rodríguez-Martínez, E. I., Barriga-Paulino, C. I., Rojas-Benjumea, M. A., & Gómez, C. M. (2015). Co-maturation of theta and low-beta rhythms during child development. *Brain Topography*, 28(2), 250–260. https://doi.org/10.1007/s10548-014-0369-3

Rodríguez-Martínez, E. I., Ruiz-Martínez, F. J., Barriga Paulino, C. I., & Gómez, C. M. (2017). Frequency shift in topography of spontaneous brain rhythms from childhood to adulthood. *Cognitive Neurodynamics*, 11(1), 23-33. https://doi.org/10.1007/s11571-016-9402-4

Rosen, S. (1992). Temporal information in speech: acoustic, auditory, and linguistic aspects. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, 336(1278), 367-373.

Rosen, S. (2003). Auditory processing in dyslexia and specific language impairment: Is there a deficit? What is its nature? Does it explain anything? *Journal of Phonetics*, 31(3-4), 509-527. https://doi.org/10.1016/S0095-4470(03)00046-9

Saby, J. N., & Marshall, P. J. (2012). The utility of EEG band power analysis in the study of infancy and early childhood. *Developmental Neuropsychology*, 37(3), 253–273. https://doi.org/10.1080/87565641.2011.614663

Sadowsky, Scott, & Martínez-Gamboa, R. 2012. LIFCACH 2.0: Word Frequency List of Chilean Spanish (Lista de Frecuencias de Palabras del Castellano de Chile), version 2.0. Zenodo. http://doi.org/10.5281/zenodo.268043

Saffran, J. R., Aslin, R. N., & Newport, E. L. (1996). Statistical learning by 8-month-old infants. *Science*, 274(5294), 1926-1928. https://doi.org/10.1126/science.274.5294.1926

Sanes, D. H., & Woolley, S. M. (2011). A behavioral framework to guide research on central auditory development and plasticity. *Neuron*, 72(6), 912-929. https://doi.org/10.1016/j.neuron.2011.12.005

Sassenhagen, J. (2019). How to analyse electrophysiological responses to naturalistic language with time-resolved multiple regression. *Language, Cognition and Neuroscience*, 34(4), 474-490. https://doi.org/10.1080/23273798.2018.1502458

Scharinger, M., Monahan, P. J., & Idsardi, W. J. (2016). Linguistic category structure influences early auditory processing: Converging evidence from mismatch responses and cortical oscillations. *NeuroImage*, 128, 293–301. https://doi.org/10.1016/j.neuroimage.2016.01.003

Schmidt, M. T., Kanda, P. A., Basile, L. F., da Silva Lopes, H. F., Baratho, R., Demario, J. L., Jorge, M. S., Nardi, A. E., Machado, S., Ianof, J. N., Nitrini, R., & Anghinah, R. (2013). Index of alpha/theta ratio of the electroencephalogram: a new marker for Alzheimer's disease. *Frontiers in Aging Neuroscience*, 5, 60. https://doi.org/10.3389/fnagi.2013.00060

Schwartz, R. G. (Ed.). (2017). Handbook of child language disorders. Psychology press.

Shafer, V. L., Morr, M. L., Kreuzer, J. A., & Kurtzberg, D. (2000). Maturation of mismatch negativity in school-age children. *Ear and Hearing*, 21(3), 242–251. https://doi.org/10.1097/00003446-200006000-00008

Shafer, V. L., Yan, H. Y., & Datta, H. (2010). Maturation of speech discrimination in 4-to 7-yr-old children as indexed by event-related potential mismatch responses. *Ear and Hearing*, 31(6), 735-745. DOI: 10.1097/AUD.0b013e3181e5d1a7

Shtyrov, Y., Kimppa, L., Pulvermüller, F., & Kujala, T. (2011). Event-related potentials reflecting the frequency of unattended spoken words: A neuronal index of connection strength in lexical memory circuits? *Neuroimage*, 55(2), 658-668. https://doi.org/10.1371/journal.pone.0022999

Skeide, M. A., & Friederici, A. D. (2016). The ontogeny of the cortical language network. *Nature reviews. Neuroscience*, 17(5), 323–332. https://doi.org/10.1038/nrn.2016.23

Skeide, M. A., Brauer, J. & Friederici, A. D., (2015). Brain functional and structural predictors of language performance. *Cereb. Cortex* http://dx.doi.org/10.1093/cercor/bhv042

Skipper, J. I. (2014). Echoes of the spoken past: how auditory cortex hears context during speech perception. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 369(1651), 20130297. https://doi.org/10.1098/rstb.2013.0297

Sohoglu, E., Peelle, J. E., Carlyon, R. P., & Davis, M. H. (2012). Predictive top-down integration of prior knowledge during speech perception. *Journal of Neuroscience*, 32 (25), 8443-8453. DOI: https://doi.org/10.1523/JNEUROSCI.5069-11.2012

Song, J., & Iverson, P. (2018). Listening effort during speech perception enhances auditory and lexical processing for non-native listeners and accents. *Cognition*, 179, 163–170. https://doi.org/10.1016/j.cognition.2018.06.001

Song, J., Martin, L., & Iverson, P. (2020). Auditory neural tracking and lexical processing of speech in noise: Masker type, spatial location, and language experience. *The Journal of the Acoustical Society of America,* 148(1), 253. https://doi.org/10.1121/10.0001477

Strauß, A., Wöstmann, M., & Obleser, J. (2014). Cortical alpha oscillations as a tool for auditory selective inhibition. *Frontiers in Human Neuroscience,* 8, 350. https://doi.org/10.3389/fnhum.2014.00350

Stroganova, T. A. and Orekhova, E. V. 2007. “EEG and infant states”. In Infant EEG and event-related potentials, Edited by: de Hann, M. 251–287. New York, NY: Psychology Press.

Sussman, E., Kujala, T., Halmetoja, J., Lyytinen, H., Alku, P., & Näätänen, R. (2004). Automatic and controlled processing of acoustic and phonetic contrasts. *Hearing Research,* 190(1-2), 128-140. https://doi.org/10.1016/S0378-5955(04)00016-4

Takano, T., & Ogawa, T. (1998). Characterization of developmental changes in EEG-gamma band activity during childhood using the autoregressive model. *Pediatrics International,* 40(5), 446-452. https://doi.org/10.1111/j.1442-200X.1998.tb01966.x

Tallal P, Miller SL, Jenkins WM, Merzenich MM. The role of temporal processing in developmental language-based learning disorders: research and clinical implications. In:

Blachman BA. (ed) *Foundations of Reading Acquisition and Dyslexia: Implications for Early Intervention*. Mahwah, NJ: Lawrence Erlbaum, 1997; 49–66

Thompson, E. C., Carr, K. W., White-Schwoch, T., Otto-Meyer, S., & Kraus, N. (2017). Individual differences in speech-in-noise perception parallel neural speech processing and attention in preschoolers. *Hearing Research,* 344, 148-157. https://doi.org/10.1016/j.heares.2016.11.007

Thompson, E. C., Krizman, J., White-Schwoch, T., Nicol, T., Estabrook, R., & Kraus, N. (2019). Neurophysiological, linguistic, and cognitive predictors of children's ability to perceive speech in noise. *Developmental Cognitive Neuroscience,* 39, 100672. https://doi.org/10.1016/j.dcn.2019.100672

Thompson, E. C., Woodruff Carr, K., White-Schwoch, T., Tierney, A., Nicol, T., & Kraus, N. (2016). Hemispheric asymmetry of endogenous neural oscillations in young children: implications for hearing speech in noise. *Scientific Reports,* 6(1), 19737. https://doi.org/10.1038/srep19737

Tierney, A., Strait, D. L., O'Connell, S., & Kraus, N. (2013). Developmental changes in resting gamma power from age three to adulthood. *Clinical neurophysiology: official journal of the International Federation of Clinical Neurophysiology,* 124(5), 1040. https://doi.org/10.1016%2Fj.clinph.2012.09.023

Tomblin, J. B., Records, N. L., Buckwalter, P., Zhang, X., Smith, E., & O'Brien, M. (1997). Prevalence of specific language impairment in kindergarten children. *Journal of Speech, Language, and Hearing Research,* 40(6), 1245-1260. https://doi.org/10.1044/jslhr.4006.1245

Trainor, J. L., Samuel, S. S., Desjardins, N. R., & Sonnadara, R. R. (2001). Measuring temporal resolution in infants using mismatch negativity. *NeuroReport,* 12(11), 2443–8, https://doi.org/10.1097/00001756-200108080-00031

Uhlhaas, P. J., Roux, F., Singer, W., Haenschel, C., Sireteanu, R., & Rodriguez, E. (2009). The development of neural synchrony reflects late maturation and restructuring of functional networks in humans. *Proceedings of the National Academy of Sciences,* 106(24), 9866-9871. https://doi.org/10.1073/pnas.0900390106

Uhlhaas, P. J., Roux, F., Rodriguez, E., Rotarska-Jagiela, A., & Singer, W. (2010). Neural synchrony and the development of cortical networks. *Trends in Cognitive Sciences*, 14(2), 72–80. https://doi.org/10.1016/j.tics.2009.12.002

van Diepen, R. M., & Mazaheri, A. (2018). The caveats of observing inter-trial phase-coherence in cognitive neuroscience. *Scientific Reports*, 8(1), 2990. doi.org/10.1038/s41598-018-20423-z

van Linden, S., Stekelenburg, J. Tuomainen, J.& Vroomen, J. (2007). Lexical effects on auditory speech perception: an electrophysiological study, *Neurosci. Lett*. 420, 49–52. DOI: 10.1016/j.neulet.2007.04.006

Volpert-Esmond, H. I., Page-Gould, E., & Bartholow, B. D. (2021). Using multilevel models for the analysis of event-related potentials. *International Journal of Psychophysiology*, 162, 145-156. https://doi.org/10.1016/j.ijpsycho.2021.02.006

Walley, A. C. (2008). Speech perception in childhood. In D. B. Pisoni & R. E. Remez (Eds.), The handbook of speech perception (pp. 449–468). Blackwell Publishing.

Weiss-Croft, L. J., & Baldeweg, T. (2015). Maturation of language networks in children: A systematic review of 22 years of functional MRI. *NeuroImage*, 123, 269-281. https://doi.org/10.1016/j.neuroimage.2015.07.046

Vander Ghinst, M., Bourguignon, M., Niesen, M., Wens, V., Hassid, S., Choufani, G., Jousmäki, V., Hari, R., Goldman, S., & De Tiège, X. (2019). Cortical Tracking of Speech-in-Noise Develops from Childhood to Adulthood. *The Journal of Neuroscience: The official journal of the Society for Neuroscience*, 39(15), 2938–2950. https://doi.org/10.1523/JNEUROSCI.1732-18.2019

Vanvooren, S., Hofmann, M., Poelmans, H., Ghesquière, P., & Wouters, J. (2015). Theta, beta and gamma rate modulations in the developing auditory system. *Hearing Research*, 327, 153-162. https://doi.org/10.1016/j.heares.2015.06.011

Varela, F., Lachaux, J. P., Rodriguez, E., & Martinerie, J. (2001). The brainweb: phase synchronization and large-scale integration. *Nature Reviews Neuroscience*, 2(4), 229-239. https://doi.org/10.1038/35067550

Varela Moraga, V. M., & Barbieri, Z. D. (2015). PECFO. Prueba de evaluación de conciencia fonológica: manual anual y set de láminas.

Vergara, R. C., Jaramillo-Riveri, S., Luarte, A., Moënne-Loccoz, C., Fuentes, R., Couve, A., & Maldonado, P. E. (2019). The Energy Homeostasis Principle: Neuronal Energy Regulation Drives Local Network Dynamics Generating Behavior. *Frontiers in Computational Neuroscience*, 13, 49. https://doi.org/10.3389/fncom.2019.00049

Wang, L., Krishnan, A., & Gandour, J. T. (2021). Neural tracking of the temporal envelope of speech in children. *Journal of Speech, Language, and Hearing Research*, 64(3), 758-769. doi: 10.1016/j.bandl.2020.104891

Wacongne, C., Labyt, E., van Wassenhove, V., Bekinschtein, T., Naccache, L., & Dehaene, S. (2011). Evidence for a hierarchy of predictions and prediction errors in human cortex. *Proceedings of the National Academy of Sciences of the United States of America*, 108(51), 20754–20759. https://doi.org/10.1073/pnas.1117807108

Wechsler, D. (2011). Wechsler Abbreviated Scale of Intelligence–Second Edition Manual. Bloomington, MN: Pearson.

Wilson, A. C., & Bishop, D. V. M. (2018). Resounding failure to replicate links between developmental language disorder and cerebral lateralisation. *PeerJ,* 6, e4217. https://doi.org/10.7717/peerj.421

Wunderlich, J. L., & Cone-Wesson, B. K. (2006). Maturation of CAEP in infants and children: a review. *Hearing Research*, 212(1-2), 212-223. DOI: 10.1016/j.heares.2005.11.008

Yordanova, J., & Kolev, V. (2008). Event-related brain oscillations in normal development. In L. A. Schmidt & S. J. Segalowitz (Eds.), *Developmental Psychophysiology: Theory, Systems, and Methods* (pp. 15–68). Cambridge University Press.

Zatorre R. & Gandour J (2008). Neural specializations for speech and pitch: moving beyond the dichotomies. *Phil. Trans. R. Soc.* B3631087–1104 http://doi.org/10.1098/rstb.2007.2161

Ziegler, J. C., Pech-Georgel, C., George, F., & Lorenzi, C. (2011). Noise on, voicing off: Speech perception deficits in children with specific language impairment. *Journal of Experimental Child Psychology*, 110(3), 362-37 https://doi.org/10.1016/j.jecp.2011.05.001

Zoefel, B., Archer-Boyd, A., & Davis, M. H. (2018). Phase entrainment of brain oscillations causally modulates neural responses to intelligible speech. *Current Biology*, 28(3), 401-408. https://doi.org/10.1016/j.cub.2017.11.071

Zuk, N. J., Murphy, J. W., Reilly, R. B., & Lalor, E. C. (2021). Envelope reconstruction of speech and music highlights stronger tracking of speech at low frequencies. *PLoS Computational Biology,* 17(9), e1009358. https://doi.org/10.1371/journal.pcbi.1009358

Appendices

Appendix 2.1

Epoch Rejection Percentages per Participants for the Speech and Non-Speech Condition

TOTAL EPOCH REJECTION (%)

Participant	Speech					Nonspeech				
	St	Dev1	Dev2	Dev3	Dev4	St	Dev1	Dev2	Dev3	Dev4
ADCH_01	7.9	4.1	8.3	9.7	9.7	22.9	19.4	18.0	20.8	22.2
ADCH_02	4.8	0.0	2.7	8.3	4.1	23.6	16.6	20.8	19.4	20.8
ADCH_03	7.6	6.9	8.3	4.1	6.9	22.5	12.5	18.0	11.1	18.0
ADCH_04	11.1	6.9	9.7	13.8	9.7	9.3	9.7	9.7	6.9	6.9
ADCH_05	4.5	2.7	4.1	2.7	4.1	2.0	2.7	2.7	2.7	2.7
ADCH_06	1.7	0.0	2.7	2.7	0.0	5.2	5.5	4.1	9.7	2.7
ADCH_07	14.9	15.2	11.1	15.2	15.2	3.1	4.1	0.0	2.7	1.3
ADCH_08	26.3	27.7	22.2	23.6	18.0	3.4	8.3	2.7	4.1	0.0
ADCH_09	0.0	0.0	0.0	0.0	0.0	2.0	4.1	2.7	2.7	2.7
ADCH_10	1.3	0.0	2.7	0.0	0.0	1.0	2.7	0.0	0.0	1.3
ADCH_11	11.8	9.7	11.1	8.3	11.1	13.1	4.1	13.8	11.1	12.5
ADCH_12	18.4	12.5	19.4	11.1	15.2	15.2	16.6	11.1	13.8	11.1
ADCH_13	7.2	4.1	8.3	8.3	4.1	10.0	8.3	9.7	16.6	6.9
ADCH_14	1.3	1.3	2.7	1.3	4.1	4.5	2.7	2.7	6.9	2.7
ADCH_15	3.4	1.3	2.7	5.5	5.5	0.0	0.0	0.0	0.0	0.0
ADCH_16	26.3	25.0	26.3	19.4	16.6	26.7	20.8	22.2	23.6	22.2
ADCH_17	1.0	0.00	4.1	1.3	2.7	8.6	2.7	8.3	8.3	1.3
ADCH_18	51.7	0.0	0.0	0.0	16.6	1.3	0.0	0.0	0.0	66.6
ADCH_19	18.4	18.0	19.4	19.4	22.2	12.5	11.1	13.8	5.5	12.5
ADCH_20	17.0	18.0	18.6	15.2	11.1	28.1	23.6	20.8	23.6	25.0

Appendix 2.2

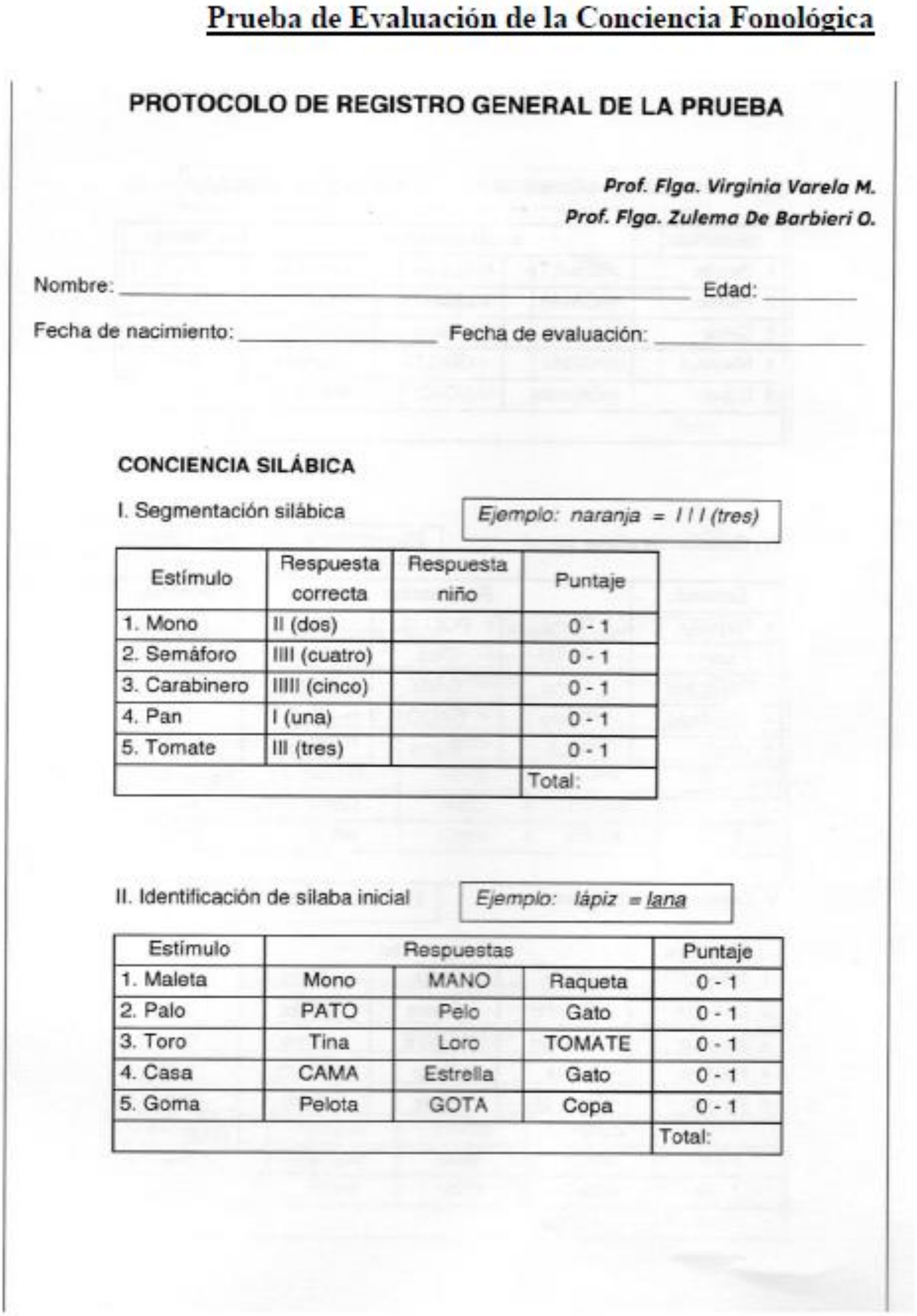
Normality Tests (Shapiro-Wilk) for the Speech and Non-Speech Condition (Experiment 1, Adults)

ERP Measure	Time Window	Stimulus Type	Speech W	Speech *p*	Non-Speech W	Non-Speech *p*
Peak Latency	TW1	DW1	0.916	.084	.837	**.003**
		DW2	0.971	.768	.856	**.007**
		DW3	0.811	**.001**	.813	**.001**
		DW4	0.805	**.001**	.970	.748
		Words	0.76	**<.001**	--	--
	TW2	DW1	0.736	**<.001**	.681	**<.001**
		DW2	0.82	**.002**	.868	**.011**
		DW3	0.835	**.003**	.902	**.045**
		DW4	0.944	.285	.902	**.046**
		Words	0.976	.865	--	--
Mean Amplitude	TW1	DW1	0.943	.277	.978	.899
		DW2	0.97	.761	.909	.062
		DW3	0.922	.109	.957	.485
		DW4	0.981	.943	.937	.208
		Words	0.927	.133	--	--
	TW2	DW1	0.929	.151	.962	.576
		DW2	0.979	.92	.977	.896
		DW3	0.961	.574	.955	.447
		DW4	0.849	**.005**	.961	.555
		Words	0.857	**.007**	--	--

Note. Significant tests are indicated in bold fonts. All df = 20

Appendix 3.1

Phonological awareness Test Forms



Prueba de Evaluación de la Conciencia Fonológica

PROTOCOLO DE REGISTRO GENERAL DE LA PRUEBA

Prof. Flga. Virginia Varela M.
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Nombre: ______________________________ Edad: ________

Fecha de nacimiento: ______________ Fecha de evaluación: ______________

CONCIENCIA SILÁBICA

I. Segmentación silábica

Ejemplo: naranja = I I I (tres)

Estímulo	Respuesta correcta	Respuesta niño	Puntaje
1. Mono	II (dos)		0 - 1
2. Semáforo	IIII (cuatro)		0 - 1
3. Carabinero	IIIII (cinco)		0 - 1
4. Pan	I (una)		0 - 1
5. Tomate	III (tres)		0 - 1
			Total:

II. Identificación de sílaba inicial

Ejemplo: lápiz = lana

Estímulo	Respuestas			Puntaje
1. Maleta	Mono	MANO	Raqueta	0 - 1
2. Palo	PATO	Pelo	Gato	0 - 1
3. Toro	Tina	Loro	TOMATE	0 - 1
4. Casa	CAMA	Estrella	Gato	0 - 1
5. Goma	Pelota	GOTA	Copa	0 - 1
				Total:

III. Identificación de sílaba final

Ejemplo: gato = zapato

Estímulo	Respuestas			Puntaje
1. Pelota	PEINETA	Lana	Mosca	0 - 1
2. Pluma	CAMA	Plato	Luna	0 - 1
3. Casa	Lana	Vaso	MESA	0 - 1
4. Naranja	Jirafa	OREJA	Conejo	0 - 1
5. Espejo	Espada	OJO	Esponja	0 - 1
				Total:

IV. Omisión de sílaba inicial

Ejemplo: cortina = tina

Estímulo	Respuestas			Puntaje
1. Repollo	Remo	POLLO	Pozo	0 - 1
2. Zapato	PATO	Tiza	Casa	0 - 1
3. Cuncuna	Luna	Copa	CUNA	0 - 1
4. Candado	Codo	DADO	Dedo	0 - 1
5. Koala	ALA	Rana	Cola	0 - 1
				Total:

V. Omisión de sílaba final

Ejemplo: casata = casa

Estímulo	Respuestas			Puntaje
1. Piñata	Pelo	PIÑA	Pizza	0 - 1
2. Cometa	COME	Cama	Mesa	0 - 1
3. Llavero	Conejo	LLAVE	Perro	0 - 1
4. Paloma	Pila	Pato	PALO	0 - 1
5. Pelota	PELO	Pala	Moto	0 - 1
				Total:

VI. Inversión silábica

Ejemplo: llasi = silla

Estímulo	Respuestas			Puntaje
1. Nalu	Cuna	LUNA	Nariz	0 – 1
2. Cafo	FOCA	Boca	Café	0 – 1
3. Vella	Estrella	Chala	LLAVE	0 – 1
4. Mago	Mano	Gota	GOMA	0 – 1
5. Maca	Pala	CAMA	Taza	0 – 1
				Total:

Appendix 3.2

Children Individual Artifact Rejection Values

	TOTAL EPOCH REJECTION (%)					
TLD (n=11)	St	Dev1	Dev2	Dev3	Dev4	Total
P03	16.8	19.4	19.4	18.1	15.3	17.4
P04	2.4	2.8	0	2.8	5.6	2.6
P05	0.9	1.4	0	0	0	0.6
P06	25.3	18.1	23.6	19.4	23.6	23.4
P07	17.1	13.9	18.1	15.3	20.8	17
P11	6.1	11.1	6.9	11.1	5.6	7.3
P14	13.7	13.9	15.3	11.1	11.1	13.3
P15	27.1	20.7	23.6	26.4	30.6	26.3
P16	3.4	8.3	2.8	6.9	5.6	4.5
P17	12.5	8.3	5.6	12.5	9.7	10.9
P19	12.5	16.7	15.3	8.3	8.3	12.3
DLD (n=16)	St	Dev1	Dev2	Dev3	Dev4	Total
L01	11.9	14.1	9.7	16.7	11.1	12.4
L03	13.1	19.4	16.7	16.7	18.1	15.3
L04	11.9	12.5	12.5	6.9	6.9	10.9
L05	10.4	13.9	12.5	6.9	12.5	10.9
L06	12.8	12.5	11.1	9.7	9.7	11.9
L07	7.3	5.6	8.3	5.6	6.9	7
L08	15.5	19.4	23.6	20.8	13.9	17.4
L09	1.2	0	1.4	0	1.4	1
L11	18.6	19.4	19.4	23.6	16.7	19.2
L12	16.8	12.5	18.1	11.1	5.6	14.4
L14	23.2	18.1	18.1	22.2	16.7	21.1
L15	7.9	5.6	5.6	2.8	6.9	6.7
L16	20.7	33.3	16.7	20	24.1	22
L17	6.4	9.7	8.3	8.3	11.1	7.8
L19	13.8	8.3	12.5	11.3	5.6	11.7
L21	25.1	19.4	22.2	20.8	16.7	22.6

Appendix 3.3

ANOVA Assumptions Check for Experiment 2 (MMR)

Mean Amplitude (100-250 ms, Peak Centred)								
Homogeneity of Variance[a]					Normality[b]			
DW type	Levene Statistic	df1	df2	*p*	Group	Shapiro-Wilk Statistic	df	*p*
DW1	3.7	2	44	**.033**	Adults	.943	20	.277
					TLD	.975	11	.935
					DLD	.92	16	.168
DW2	0.429	2	44	.654	Adults	.97	20	.761
					TLD	.79	11	**.007**
					DLD	.939	16	.336
Words	4.659	2	44	**.015**	Adults	.927	20	.133
					TLD	.929	11	.398
					DLD	.98	16	.966
DW3	5.104	2	44	**.01**	Adults	.922	20	.109
					TLD	.865	11	.066
					DLD	.946	16	.436
DW4	5.046	2	44	**.011**	Adults	.981	20	.943
					TLD	.922	11	.334
					DLD	.933	16	.276
					Phonological Awareness Test			
					TLD	.873	8	.162
					DLD	.909	14	.151
Within Subjects Effect: Stimulus Type								
Equality of Covariance Matrices[c]					Sphericity[d]			
Box's M	F	df1	df2	*p*	Mauchly's W	Approx. Chi^2	df	*p*
93.16	2.538	30	3795	**<.001**	0.181	72.46	9	**<.001**

Note. Significant tests are indicated in bold fonts.

[a] Tests the null hypothesis of equal variances across groups

[b] Tests the null hypothesis of a normal data distribution

[c] Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.

[d] Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

Appendix 3.4

ANOVA Assumptions Check for Experiment 2 (MMR), Variable: Mean Amplitude TW2

Mean Amplitude (250-400 ms, Peak Centred)

Homogeneity of Variance[a]					Normality[b]			
DW type	Levene Statistic	df1	df2	*p*	Group	Shapiro-Wilk Statistic	df	*p*
DW1	4.087	2	44	.024	Adults	.929	20	.151
					TLD	.916	11	.288
					DLD	.983	16	.981
DW2	4.533	2	44	.016	Adults	.979	20	.920
					TLD	.910	11	.242
					DLD	.878	16	**.036**
Words	1.048	2	44	.359	Adults	.857	20	**.007**
					TLD	.767	11	**.003**
					DLD	.959	16	.645
DW3	3.070	2	44	.056	Adults	.961	20	.574
					TLD	.970	11	.884
					DLD	.939	16	.340
DW4	4.675	2	44	.014	Adults	.849	20	**.005**
					TLD	.937	11	.489
					DLD	.946	16	.433

Within Subjects Effect: Stimulus Type

Equality of Covariance Matrices[c]					Sphericity[d]			
Box's M	F	df1	df2	*p*	Mauchly's W	Approx. Chi^2	df	*p*
109.75	2.99	30	3795	**<.001**	.240	60.53	9	**<.001**

Note. Significant tests are indicated in bold fonts.

[a] Tests the null hypothesis of equal variances across groups

[b] Tests the null hypothesis of a normal data distribution

[c] Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.

[d] Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

Appendix 3.5

ANOVA Assumptions Check for Experiment 2 (MMR), Variable: ERSP

ERSP

Homogeneity of Variance[a]					Normality[b]			
Stimulus Type	Levene Statistic	df1	df2	*p*	Group	Shapiro-Wilk Statistic	df	*p*
D1	2.043	2	44	.142	Adults	.940	20	.235
					TLD	.881	11	.108
					DLD	.919	16	.163
D2	1.657	2	44	.202	Adults	.965	20	.658
					TLD	.894	11	.157
					DLD	.922	16	.180
D3	.274	2	44	.762	Adults	.959	20	.519
					TLD	.859	11	.056
					DLD	.955	16	.573
D4	1.033	2	44	.364	Adults	.969	20	.726
					TLD	.788	11	**.007**
					DLD	.963	16	.711
St	1.005	2	44	.374	Adults	.955	20	.441
					TLD	.903	11	.203
					DLD	.960	16	.661

Within Subjects Effect: Stimulus Type

Equality of Covariance Matrices[c]					Sphericity[d]			
Box's M	F	df1	df2	*p*	Mauchly's W	Approx. Chi^2	df	*p*
69.32	1.89	30	3795	**.002**	.355	43.91	9	**<.001**

Note. Significant tests are indicated in bold fonts.

[a] Tests the null hypothesis of equal variances across groups

[b] Tests the null hypothesis of a normal data distribution

[c] Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.

[d] Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

Appendix 3.6

ANOVA Assumptions Check for Experiment 2 (MMR), Variable: ITPC

ROI 1								
Homogeneity of Variance[a]					Normality[b]			
Stimulus Type	Levene Statistic	df1	df2	p	Group	Shapiro-Wilk Statistic	df	p
D1	2.806	2	44	.071	Adults	.953	20	.407
					TLD	.967	11	.86
					DLD	.891	16	.059
D2	.316	2	44	.731	Adults	.928	20	.141
					TLD	.932	11	.428
					DLD	.879	16	**.037**
D3	2.198	2	44	.123	Adults	.965	20	.64
					TLD	.928	11	.39
					DLD	.931	16	.25
D4	2.291	2	44	.113	Adults	.944	20	.286
					TLD	.945	11	.583
					DLD	.968	16	.811
St	2.746	2	44	.075	Adults	.872	20	**.013**
					TLD	.983	11	.982
					DLD	.926	16	.211

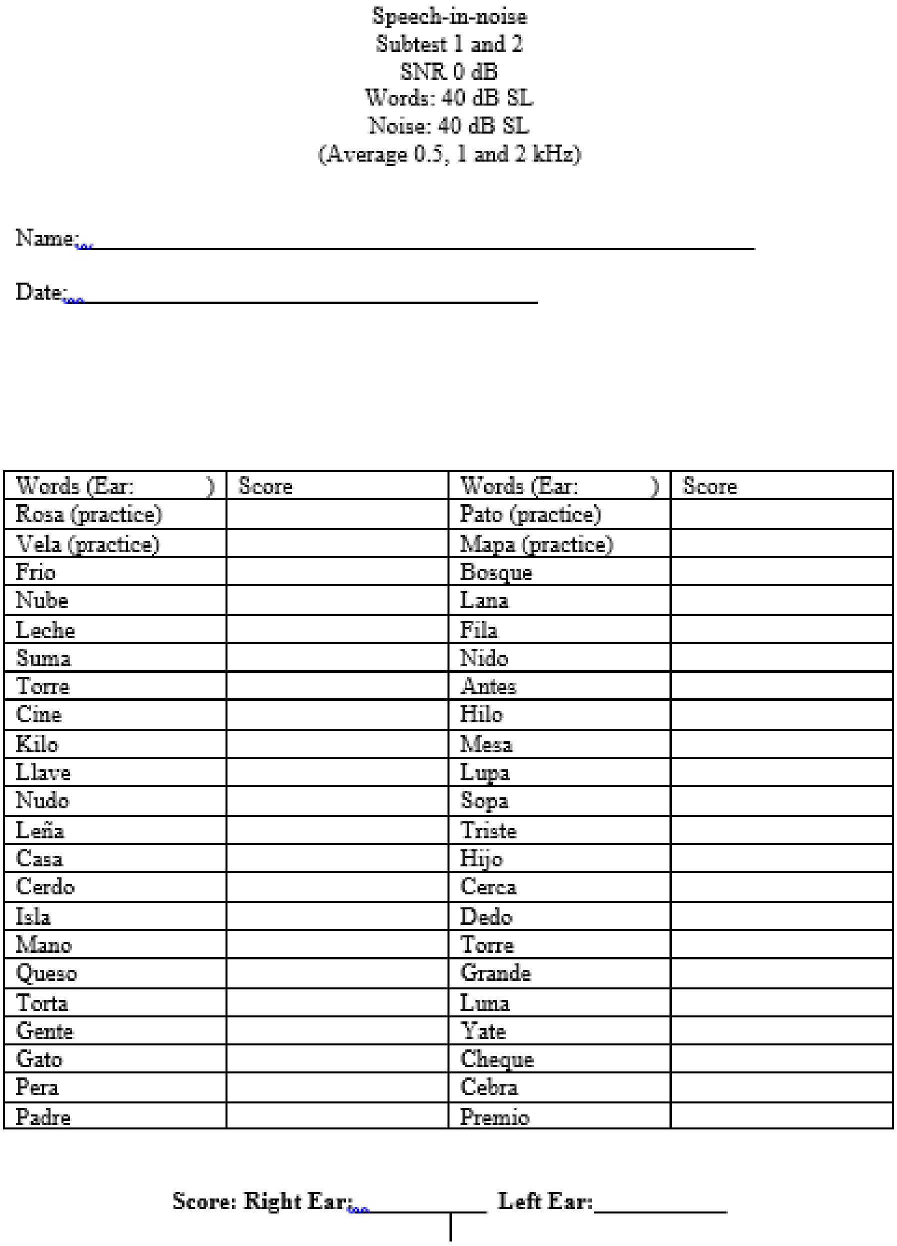
ROI2								
Homogeneity of Variance[a]					Normality[b]			
Stimulus Type	Levene Statistic	df1	df2	p	Group	Shapiro-Wilk Statistic	df	p
D1	1.748	2	44	.186	Adults	.97	20	.761
					TLD	.849	11	**.042**
					DLD	.981	16	.97
D2	.980	2	44	.383	Adults	.941	20	.245
					TLD	.972	11	.903
					DLD	.945	16	.419
D3	4.083	2	44	**.024**	Adults	.961	20	.555
					TLD	.915	11	.278
					DLD	.956	16	.592
D4	1.916	2	44	.159	Adults	.912	20	.069
					TLD	.933	11	.439
					DLD	.877	16	**.035**
St	.453	2	44	.639	Adults	.97	20	.761
					TLD	.849	11	**.042**
					DLD	.981	16	.97

Equality of Covariance Matrices[c]						Sphericity[d]			
ROI	Box's M	F	df1	df2	p	Mauchly's W	Approx. Chi^2	df	p
1	35.75	.974	30	3795	.506	.779	10.57	9	.306
2	36.03	.982	30	3795	.495	.845	7.13	9	.624

Note. Significant tests are indicated in bold fonts. [a], [b],[c], [d], as in Appendix 3.5.

Appendix 4.1

Speech in Babble (Noise) Test Form



Speech-in-noise
Subtest 1 and 2
SNR 0 dB
Words: 40 dB SL
Noise: 40 dB SL
(Average 0.5, 1 and 2 kHz)

Name:____

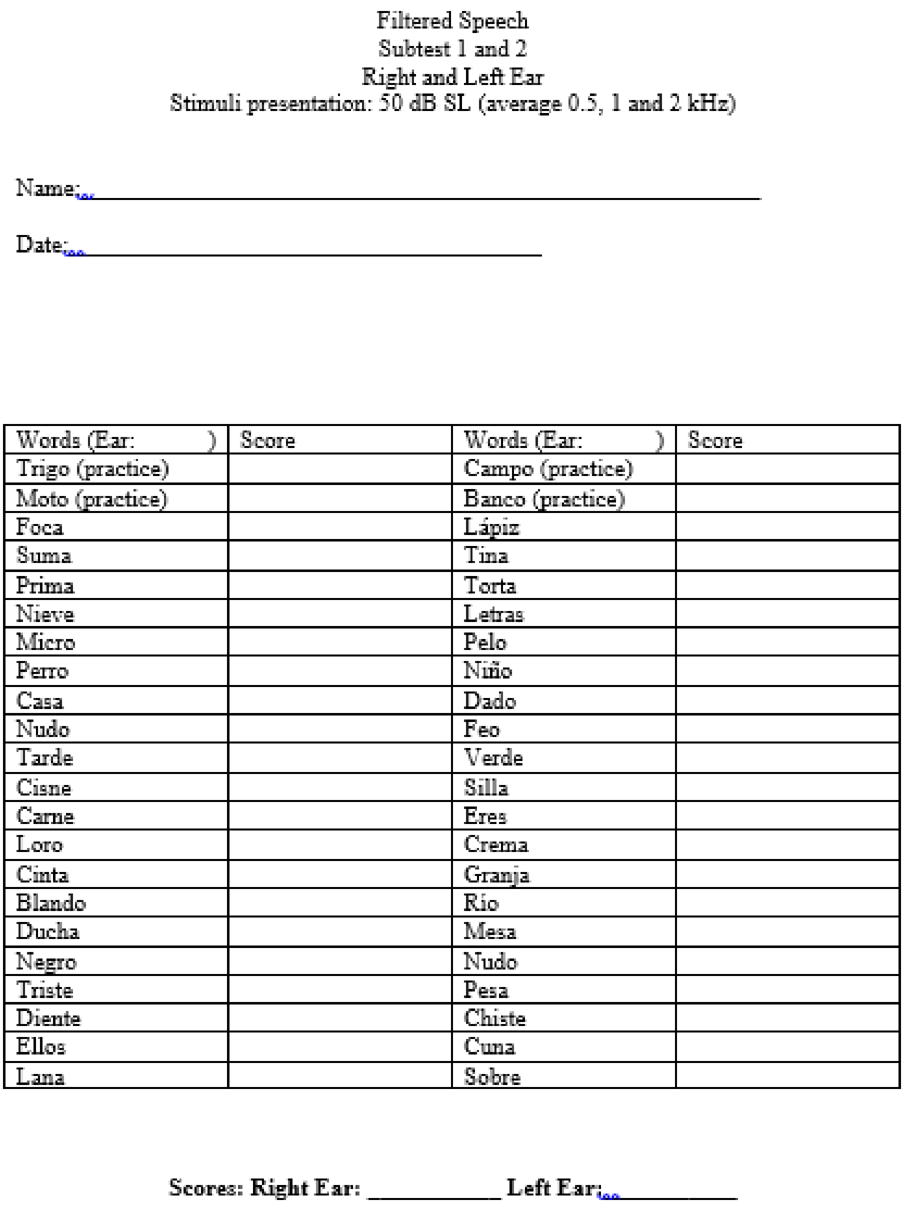
Date:_______________________________

Words (Ear:)	Score	Words (Ear:)	Score
Rosa (practice)		Pato (practice)	
Vela (practice)		Mapa (practice)	
Frio		Bosque	
Nube		Lana	
Leche		Fila	
Suma		Nido	
Torre		Antes	
Cine		Hilo	
Kilo		Mesa	
Llave		Lupa	
Nudo		Sopa	
Leña		Triste	
Casa		Hijo	
Cerdo		Cerca	
Isla		Dedo	
Mano		Torre	
Queso		Grande	
Torta		Luna	
Gente		Yate	
Gato		Cheque	
Pera		Cebra	
Padre		Premio	

Score: Right Ear:__________ Left Ear:__________

Appendix 4.2

Filtered Speech Test Form



Filtered Speech
Subtest 1 and 2
Right and Left Ear
Stimuli presentation: 50 dB SL (average 0.5, 1 and 2 kHz)

Name:____

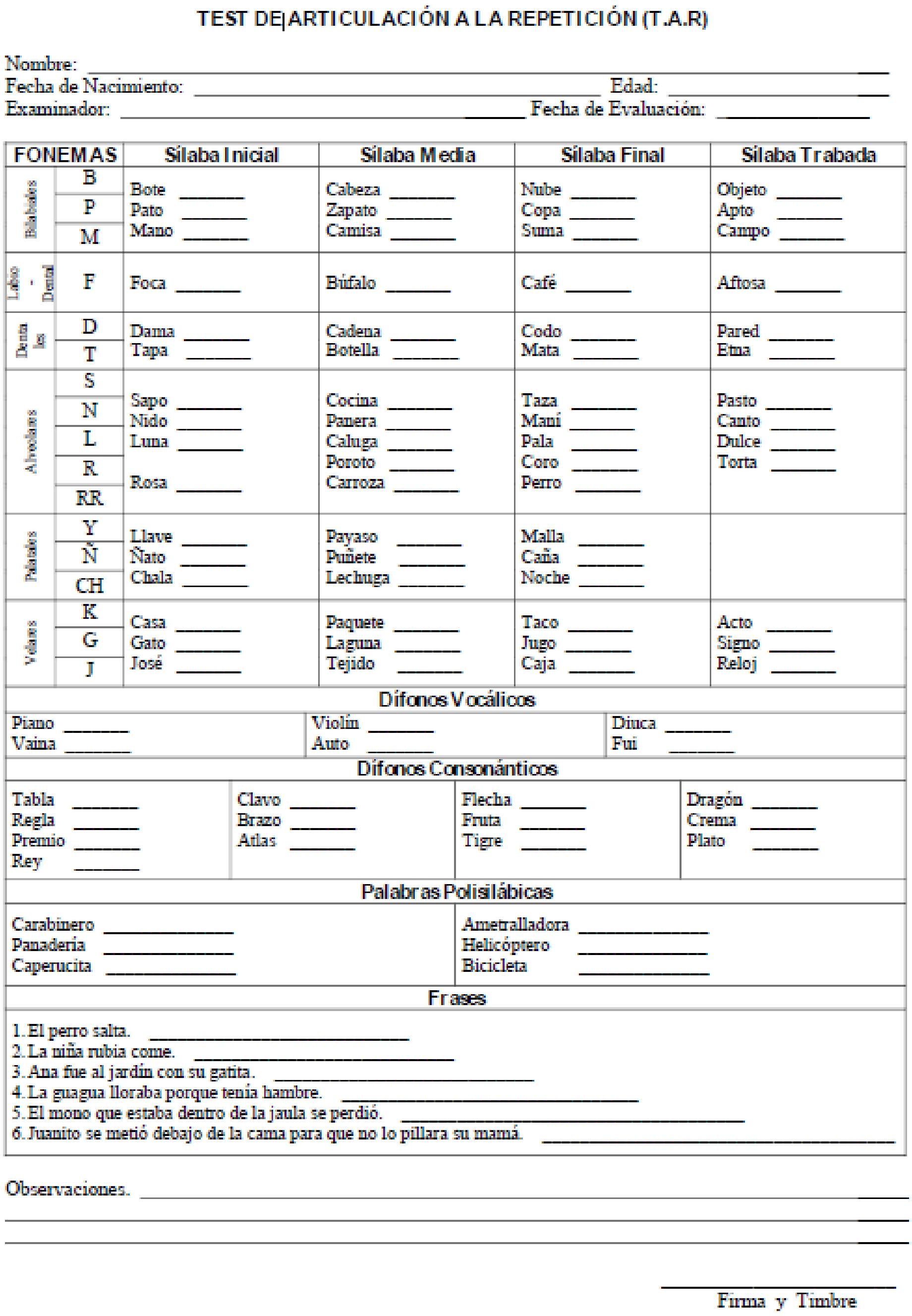
Date:______________________________

Words (Ear:)	Score	Words (Ear:)	Score
Trigo (practice)		Campo (practice)	
Moto (practice)		Banco (practice)	
Foca		Lápiz	
Suma		Tina	
Prima		Torta	
Nieve		Letras	
Micro		Pelo	
Perro		Niño	
Casa		Dado	
Nudo		Feo	
Tarde		Verde	
Cisne		Silla	
Carne		Eres	
Loro		Crema	
Cinta		Granja	
Blando		Rio	
Ducha		Mesa	
Negro		Nudo	
Triste		Pesa	
Diente		Chiste	
Ellos		Cuna	
Lana		Sobre	

Scores: Right Ear: ___________ Left Ear:___________

Appendix 4.3

Articulation screening (T.A.R) Test Form



TEST DE ARTICULACIÓN A LA REPETICIÓN (T.A.R)

Nombre: ______________________________
Fecha de Nacimiento: ______________________ Edad: ____________
Examinador: ______________________ Fecha de Evaluación: ____________

FONEMAS		Sílaba Inicial	Sílaba Media	Sílaba Final	Sílaba Trabada
Bilabiales	B P M	Bote ______ Pato ______ Mano ______	Cabeza ______ Zapato ______ Camisa ______	Nube ______ Copa ______ Suma ______	Objeto ______ Apto ______ Campo ______
Labio - Dental	F	Foca ______	Búfalo ______	Café ______	Aftosa ______
Dentales	D T	Dama ______ Tapa ______	Cadena ______ Botella ______	Codo ______ Mata ______	Pared ______ Etna ______
Alveolares	S N L R RR	Sapo ______ Nido ______ Luna ______ Rosa ______	Cocina ______ Panera ______ Caluga ______ Poroto ______ Carroza ______	Taza ______ Maní ______ Pala ______ Coro ______ Perro ______	Pasto ______ Canto ______ Dulce ______ Torta ______
Palatales	Y Ñ CH	Llave ______ Ñato ______ Chala ______	Payaso ______ Puñete ______ Lechuga ______	Malla ______ Caña ______ Noche ______	
Velares	K G J	Casa ______ Gato ______ José ______	Paquete ______ Laguna ______ Tejido ______	Taco ______ Jugo ______ Caja ______	Acto ______ Signo ______ Reloj ______

Dífonos Vocálicos

Piano ______ Vaina ______	Violín ______ Auto ______	Diuca ______ Fui ______

Dífonos Consonánticos

Tabla ______ Regla ______ Premio ______ Rey ______	Clavo ______ Brazo ______ Atlas ______	Flecha ______ Fruta ______ Tigre ______	Dragón ______ Crema ______ Plato ______

Palabras Polisilábicas

Carabinero ____________ Panadería ____________ Caperucita ____________	Ametralladora ____________ Helicóptero ____________ Bicicleta ____________

Frases

1. El perro salta. ________________________
2. La niña rubia come. ________________________
3. Ana fue al jardín con su gatita. ________________________
4. La guagua lloraba porque tenía hambre. ____________________________
5. El mono que estaba dentro de la jaula se perdió. ________________________________
6. Juanito se metió debajo de la cama para que no lo pillara su mamá. ________________________________

Observaciones. ____
____
____

____
Firma y Timbre

Appendix 4.4

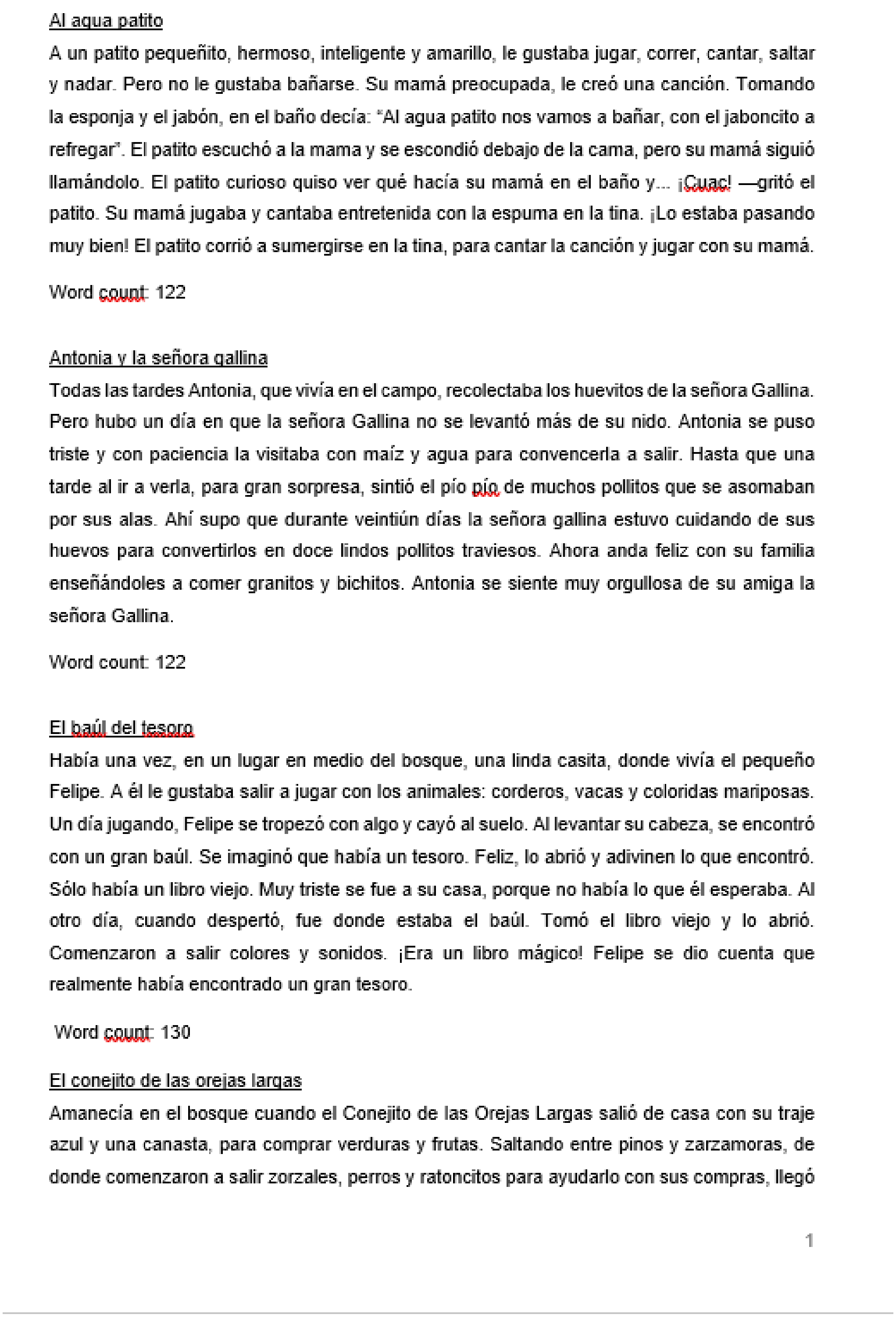
Normality and Variance Homogeneity Tests for Experiment 3 (Resting State EEG)

		Test						
		Normality			Homogeneity of Variances			
Measure	Group	Shapiro-Wilk Statistic	df	*p*	Levene Statistic	df1	df2	*p*
Age	Adults	0.959	18	.592				
	TLD children	0.743	11	**.002**				
	DLD children	0.855	16	**.016**				
Theta Band Power	Adults	0.936	18	.246	9.285	2	42	**<.001**
	TLD children	0.973	11	.917				
	DLD children	0.892	16	.059				
Alpha Band Power	Adults	0.737	18	**<.001**	4.187	2	42	**.022**
	TLD children	0.934	11	.456				
	DLD children	0.866	16	**.023**				
Beta Band Power	Adults	0.932	18	.214	5.606	2	42	**.007**
	TLD children	0.967	11	.859				
	DLD children	0.91	16	.118				
Gamma Band Power	Adults	0.795	18	**.001**	5.133	2	42	**.01**
	TLD children	0.826	11	**.02**				
	DLD children	0.797	16	**.002**				
Laterality Index LF	Adults	0.933	18	.224	1.275	2	42	.29
	TLD children	0.945	11	.576				
	DLD children	0.901	16	.083				
Laterality Index HF	Adults	0.912	18	.093	1.941	2	42	.156
	TLD children	0.875	11	.091				
	DLD children	0.945	16	.42				
Theta/Alpha Ratio	Adults	0.927	18	.173	4.54	2	42	**.016**
	TLD children	0.946	11	.597				
	DLD children	0.853	16	**.015**				
Theta/Beta Ratio	Adults	0.971	18	.813	2.801	2	42	.072
	TLD children	0.95	11	.647				
	DLD children	0.865	16	**.023**				
Speech in Babble	TLD children	0.967	8	.872				
	DLD children	0.96	14	.718				
Filtered Speech	TLD children	0.816	8	**.043**				
	DLD children	0.951	14	.572				

Note. Bold fonts indicate test is significant at the p=0.05 level (non-normal data distribution).

Appendix 5.1

Continuous speech stimuli



Al agua patito

A un patito pequeñito, hermoso, inteligente y amarillo, le gustaba jugar, correr, cantar, saltar y nadar. Pero no le gustaba bañarse. Su mamá preocupada, le creó una canción. Tomando la esponja y el jabón, en el baño decía: "Al agua patito nos vamos a bañar, con el jaboncito a refregar". El patito escuchó a la mama y se escondió debajo de la cama, pero su mamá siguió llamándolo. El patito curioso quiso ver qué hacía su mamá en el baño y... ¡Cuac! —gritó el patito. Su mamá jugaba y cantaba entretenida con la espuma en la tina. ¡Lo estaba pasando muy bien! El patito corrió a sumergirse en la tina, para cantar la canción y jugar con su mamá.

Word count: 122

Antonia y la señora gallina

Todas las tardes Antonia, que vivía en el campo, recolectaba los huevitos de la señora Gallina. Pero hubo un día en que la señora Gallina no se levantó más de su nido. Antonia se puso triste y con paciencia la visitaba con maíz y agua para convencerla a salir. Hasta que una tarde al ir a verla, para gran sorpresa, sintió el pío pío de muchos pollitos que se asomaban por sus alas. Ahí supo que durante veintiún días la señora gallina estuvo cuidando de sus huevos para convertirlos en doce lindos pollitos traviesos. Ahora anda feliz con su familia enseñándoles a comer granitos y bichitos. Antonia se siente muy orgullosa de su amiga la señora Gallina.

Word count: 122

El baúl del tesoro

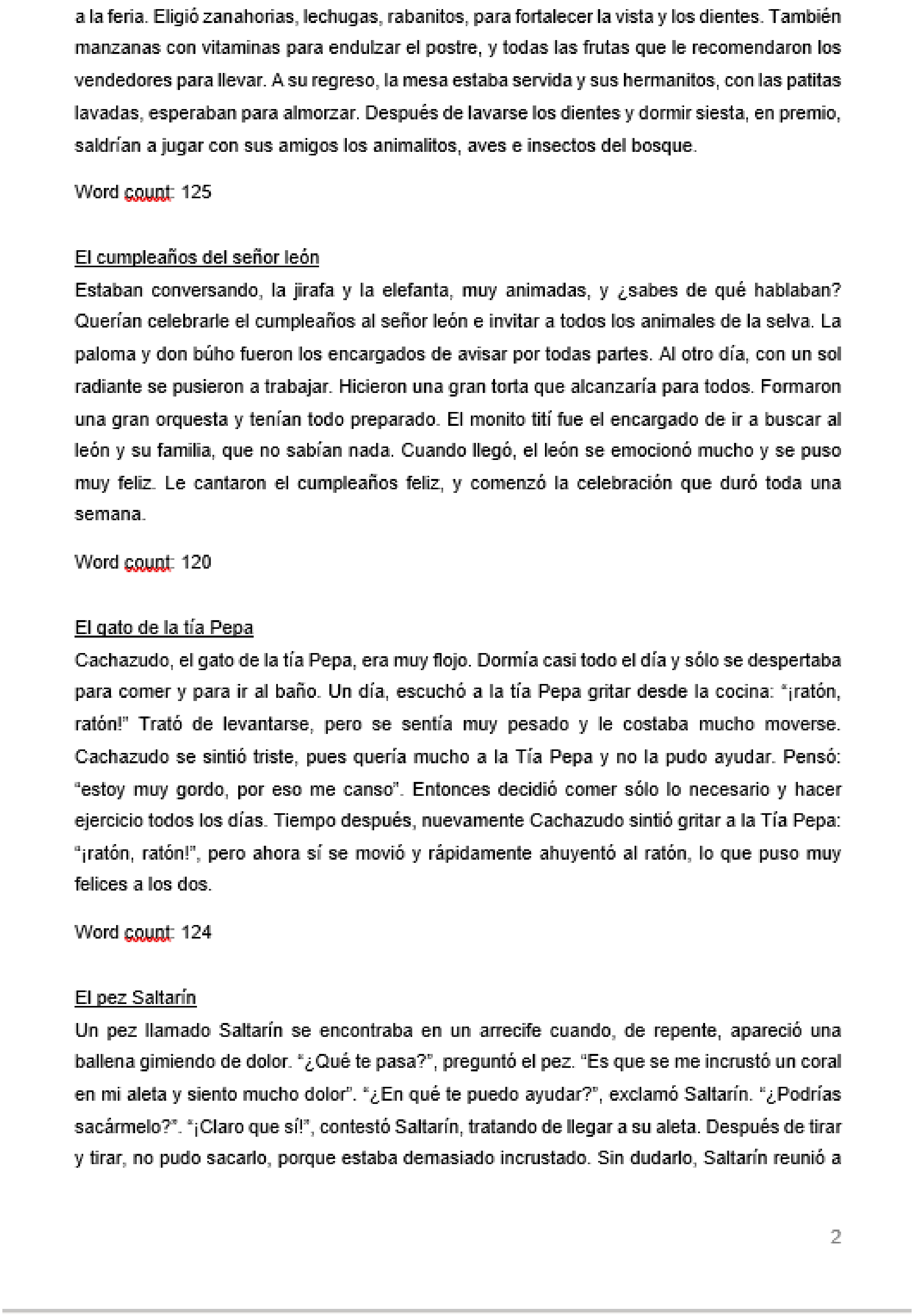
Había una vez, en un lugar en medio del bosque, una linda casita, donde vivía el pequeño Felipe. A él le gustaba salir a jugar con los animales: corderos, vacas y coloridas mariposas. Un día jugando, Felipe se tropezó con algo y cayó al suelo. Al levantar su cabeza, se encontró con un gran baúl. Se imaginó que había un tesoro. Feliz, lo abrió y adivinen lo que encontró. Sólo había un libro viejo. Muy triste se fue a su casa, porque no había lo que él esperaba. Al otro día, cuando despertó, fue donde estaba el baúl. Tomó el libro viejo y lo abrió. Comenzaron a salir colores y sonidos. ¡Era un libro mágico! Felipe se dio cuenta que realmente había encontrado un gran tesoro.

Word count: 130

El conejito de las orejas largas

Amanecía en el bosque cuando el Conejito de las Orejas Largas salió de casa con su traje azul y una canasta, para comprar verduras y frutas. Saltando entre pinos y zarzamoras, de donde comenzaron a salir zorzales, perros y ratoncitos para ayudarlo con sus compras, llegó

1



a la feria. Eligió zanahorias, lechugas, rabanitos, para fortalecer la vista y los dientes. También manzanas con vitaminas para endulzar el postre, y todas las frutas que le recomendaron los vendedores para llevar. A su regreso, la mesa estaba servida y sus hermanitos, con las patitas lavadas, esperaban para almorzar. Después de lavarse los dientes y dormir siesta, en premio, saldrían a jugar con sus amigos los animalitos, aves e insectos del bosque.

Word count: 125

El cumpleaños del señor león

Estaban conversando, la jirafa y la elefanta, muy animadas, y ¿sabes de qué hablaban? Querían celebrarle el cumpleaños al señor león e invitar a todos los animales de la selva. La paloma y don búho fueron los encargados de avisar por todas partes. Al otro día, con un sol radiante se pusieron a trabajar. Hicieron una gran torta que alcanzaría para todos. Formaron una gran orquesta y tenían todo preparado. El monito tití fue el encargado de ir a buscar al león y su familia, que no sabían nada. Cuando llegó, el león se emocionó mucho y se puso muy feliz. Le cantaron el cumpleaños feliz, y comenzó la celebración que duró toda una semana.

Word count: 120

El gato de la tía Pepa

Cachazudo, el gato de la tía Pepa, era muy flojo. Dormía casi todo el día y sólo se despertaba para comer y para ir al baño. Un día, escuchó a la tía Pepa gritar desde la cocina: "¡ratón, ratón!" Trató de levantarse, pero se sentía muy pesado y le costaba mucho moverse. Cachazudo se sintió triste, pues quería mucho a la Tía Pepa y no la pudo ayudar. Pensó: "estoy muy gordo, por eso me canso". Entonces decidió comer sólo lo necesario y hacer ejercicio todos los días. Tiempo después, nuevamente Cachazudo sintió gritar a la Tía Pepa: "¡ratón, ratón!", pero ahora sí se movió y rápidamente ahuyentó al ratón, lo que puso muy felices a los dos.

Word count: 124

El pez Saltarín

Un pez llamado Saltarín se encontraba en un arrecife cuando, de repente, apareció una ballena gimiendo de dolor. "¿Qué te pasa?", preguntó el pez. "Es que se me incrustó un coral en mi aleta y siento mucho dolor". "¿En qué te puedo ayudar?", exclamó Saltarín. "¿Podrías sacármelo?". "¡Claro que sí!", contestó Saltarín, tratando de llegar a su aleta. Después de tirar y tirar, no pudo sacarlo, porque estaba demasiado incrustado. Sin dudarlo, Saltarín reunió a

todos sus amigos peces para que lo ayudaran y empezaron a tirar y tirar hasta que lograron arrancarlo. Se escuchó un último gemido de la ballena, pero al final sonrió y agradeció a Saltarín y a sus amigos por todo el esfuerzo que hicieron por ayudarla.

Word count: 124

El viaje de Tomás

Tomás tenía mucho sueño. Su papá llegó del trabajo, lo abrazó y lo besó. Su mamá lo acostó y le contó un cuento. Esa tarde, Tomás había jugado con sus amigos y les había prestado su bicicleta nueva. Ellos no tenían bicicleta y él quiso que la usaran primero. Tomás estaba cansado, pero eso no le impedía soñar. Soñó que volaba. Recorrió los distintos planetas, pero en ninguno había niños, gente grande, árboles, pájaros, ni juguetes como en la Tierra, que se veía a lo lejos como un puntito diminuto. Pensó: "¡Qué chiquitita se ve y yo creía que era tan grande! ¡Les diré a todos que es la más linda y que debemos cuidarla bien para que nos dure harto!".

Word count: 125

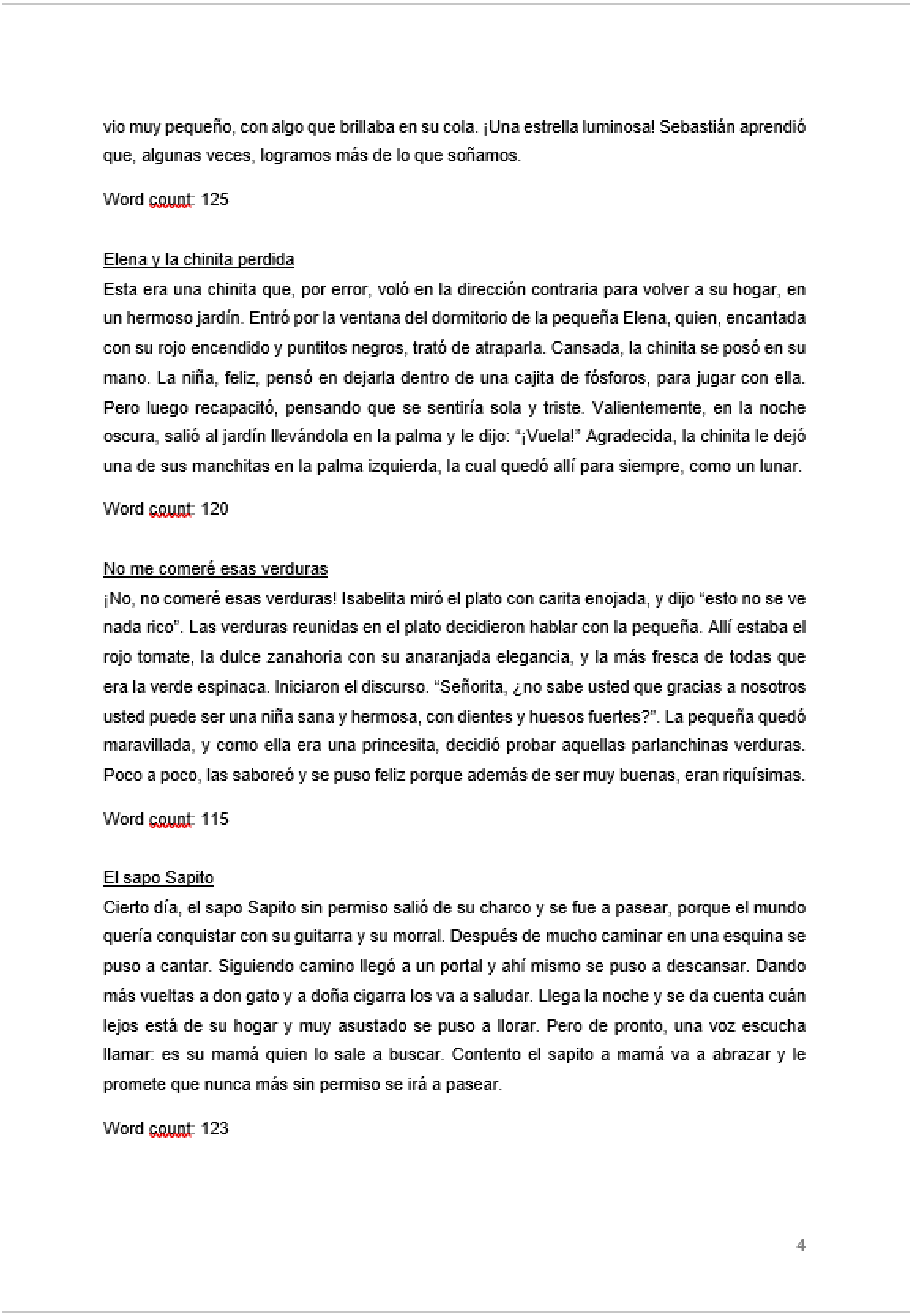
Pepita araña

Pepita araña, se creía superior, porque con sus ocho largas patas, llegaba a todos lados. Un día, vio a Jaimito gusano y le preguntó: "¿Cómo te mueves, si no tienes patas?" Y se largó a reír. Jaimito un poco enojado, respondió: "No necesito patas, me arrastro con mi cuerpo". Luego vio a Rosita colibrí y le preguntó: "¿Cómo te mueves?" "Soy un pájaro y tengo alas para volar" —le dijo. Finalmente, vio a Freddy pez y le preguntó: "¿Cómo haces para moverte, si no tienes patas ni alas?" Freddy respondió: "Yo tengo aletas y con ellas nado a través del océano". Pepita quedó sorprendida y se dio cuenta que todos eran tan especiales como ella. Así, decidió no molestar más a los animales.

Word count: 125

Sebastián y el volantín

Sebastián amaba las nubes. Siempre las miraba en el cielo, y descubría sus movimientos y formas. Las que más le gustaban eran esas blancas, como azúcar de algodón, limpiecitas en el cielo azul. Quería tocarlas, pero no alcanzaba. Entonces pensó algo genial: tomó su volantín y lo elevó, para que le trajera un pedacito de nube amarrado a su cola. El volantín voló y voló cada vez más lejos, hasta que Sebastián no lo pudo ver. Sólo lo sentía tirando de su mano. Llegó la noche y Sebastián, cansado, empezó a recoger su volantín. De pronto lo



vio muy pequeño, con algo que brillaba en su cola. ¡Una estrella luminosa! Sebastián aprendió que, algunas veces, logramos más de lo que soñamos.

Word count: 125

Elena y la chinita perdida

Esta era una chinita que, por error, voló en la dirección contraria para volver a su hogar, en un hermoso jardín. Entró por la ventana del dormitorio de la pequeña Elena, quien, encantada con su rojo encendido y puntitos negros, trató de atraparla. Cansada, la chinita se posó en su mano. La niña, feliz, pensó en dejarla dentro de una cajita de fósforos, para jugar con ella. Pero luego recapacitó, pensando que se sentiría sola y triste. Valientemente, en la noche oscura, salió al jardín llevándola en la palma y le dijo: "¡Vuela!" Agradecida, la chinita le dejó una de sus manchitas en la palma izquierda, la cual quedó allí para siempre, como un lunar.

Word count: 120

No me comeré esas verduras

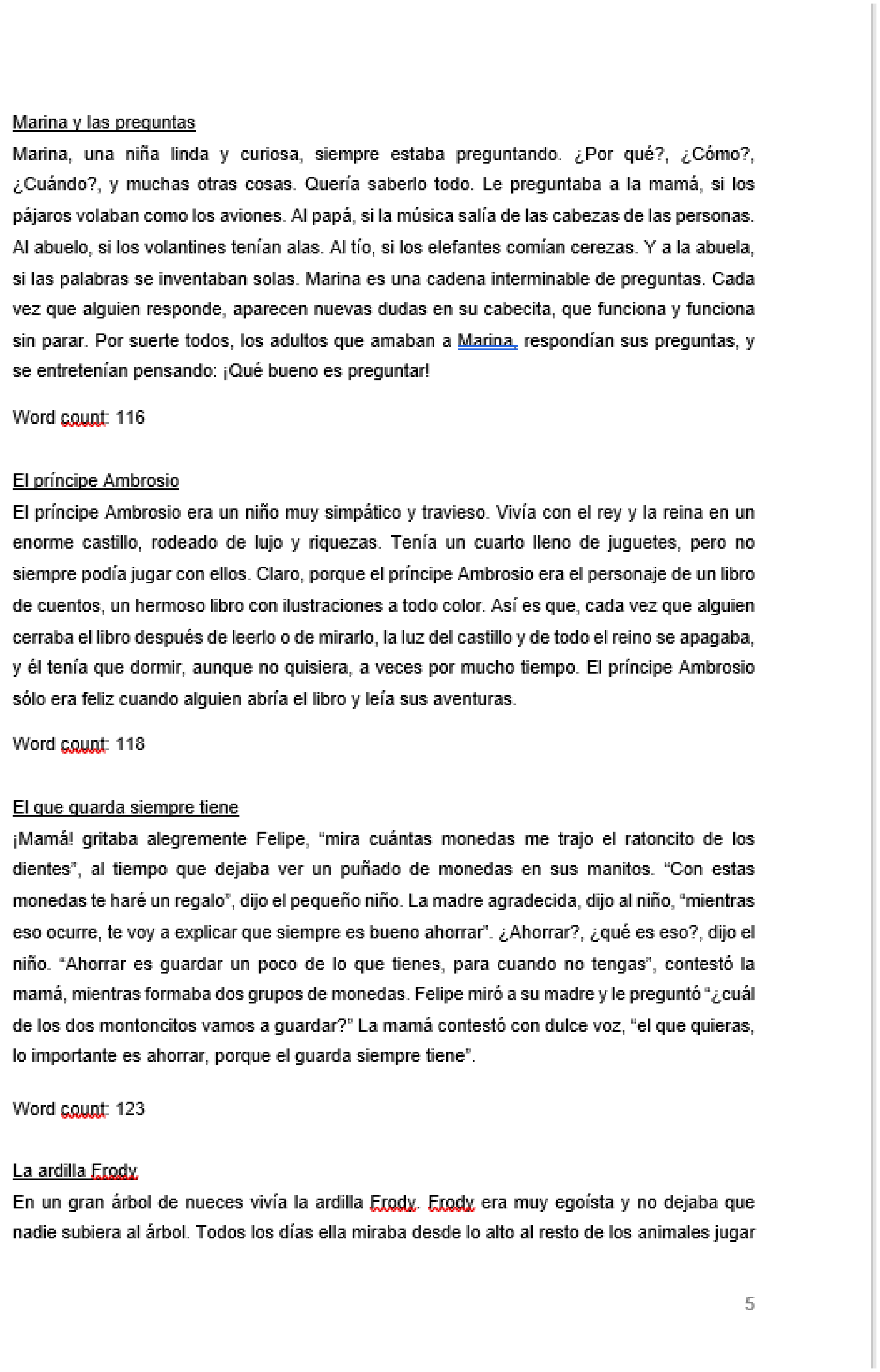
¡No, no comeré esas verduras! Isabelita miró el plato con carita enojada, y dijo "esto no se ve nada rico". Las verduras reunidas en el plato decidieron hablar con la pequeña. Allí estaba el rojo tomate, la dulce zanahoria con su anaranjada elegancia, y la más fresca de todas que era la verde espinaca. Iniciaron el discurso. "Señorita, ¿no sabe usted que gracias a nosotros usted puede ser una niña sana y hermosa, con dientes y huesos fuertes?". La pequeña quedó maravillada, y como ella era una princesita, decidió probar aquellas parlanchinas verduras. Poco a poco, las saboreó y se puso feliz porque además de ser muy buenas, eran riquísimas.

Word count: 115

El sapo Sapito

Cierto día, el sapo Sapito sin permiso salió de su charco y se fue a pasear, porque el mundo quería conquistar con su guitarra y su morral. Después de mucho caminar en una esquina se puso a cantar. Siguiendo camino llegó a un portal y ahí mismo se puso a descansar. Dando más vueltas a don gato y a doña cigarra los va a saludar. Llega la noche y se da cuenta cuán lejos está de su hogar y muy asustado se puso a llorar. Pero de pronto, una voz escucha llamar: es su mamá quien lo sale a buscar. Contento el sapito a mamá va a abrazar y le promete que nunca más sin permiso se irá a pasear.

Word count: 123



Marina y las preguntas

Marina, una niña linda y curiosa, siempre estaba preguntando. ¿Por qué?, ¿Cómo?, ¿Cuándo?, y muchas otras cosas. Quería saberlo todo. Le preguntaba a la mamá, si los pájaros volaban como los aviones. Al papá, si la música salía de las cabezas de las personas. Al abuelo, si los volantines tenían alas. Al tío, si los elefantes comían cerezas. Y a la abuela, si las palabras se inventaban solas. Marina es una cadena interminable de preguntas. Cada vez que alguien responde, aparecen nuevas dudas en su cabecita, que funciona y funciona sin parar. Por suerte todos, los adultos que amaban a Marina, respondían sus preguntas, y se entretenían pensando: ¡Qué bueno es preguntar!

Word count: 116

El príncipe Ambrosio

El príncipe Ambrosio era un niño muy simpático y travieso. Vivía con el rey y la reina en un enorme castillo, rodeado de lujo y riquezas. Tenía un cuarto lleno de juguetes, pero no siempre podía jugar con ellos. Claro, porque el príncipe Ambrosio era el personaje de un libro de cuentos, un hermoso libro con ilustraciones a todo color. Así es que, cada vez que alguien cerraba el libro después de leerlo o de mirarlo, la luz del castillo y de todo el reino se apagaba, y él tenía que dormir, aunque no quisiera, a veces por mucho tiempo. El príncipe Ambrosio sólo era feliz cuando alguien abría el libro y leía sus aventuras.

Word count: 118

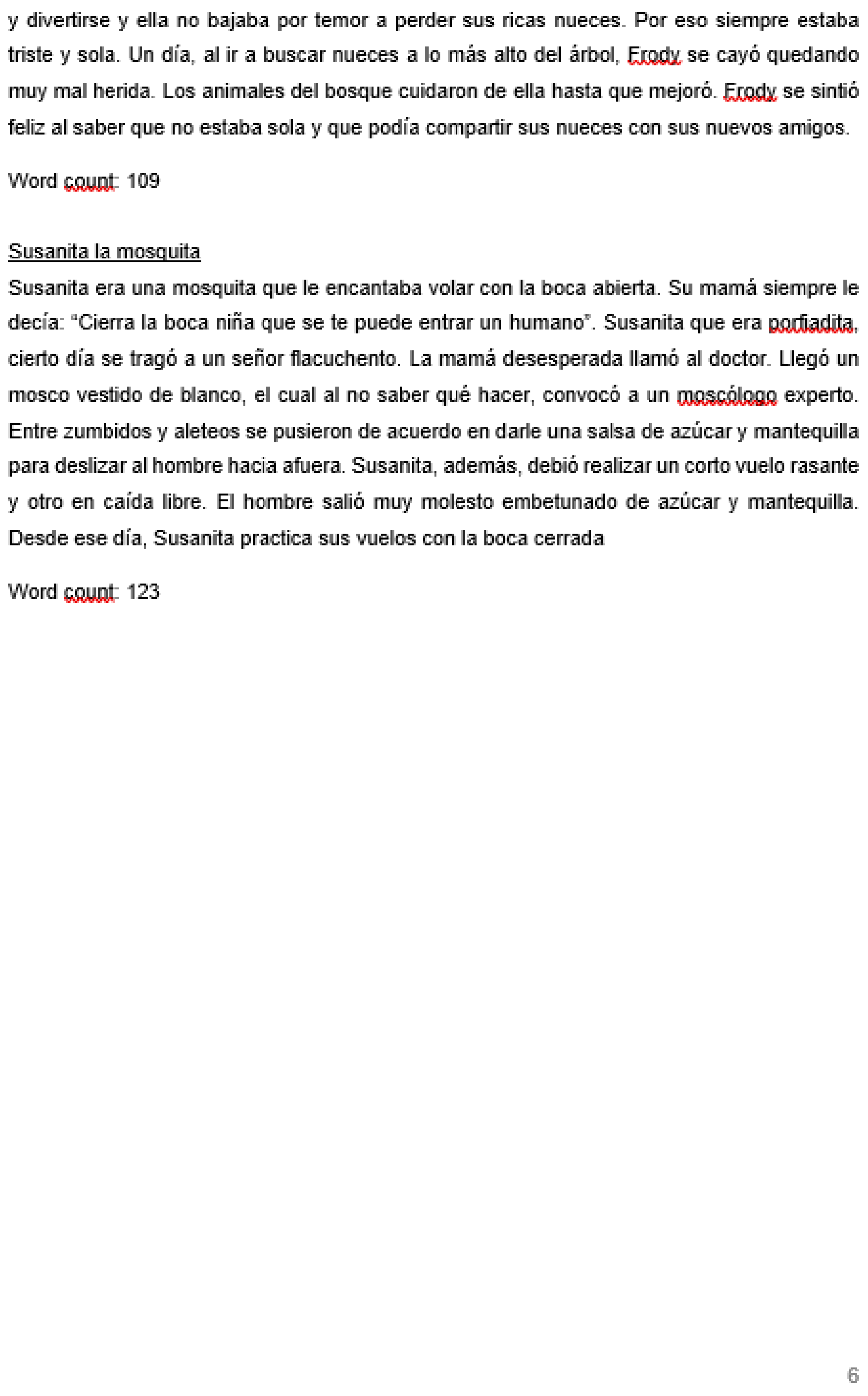
El que guarda siempre tiene

¡Mamá! gritaba alegremente Felipe, "mira cuántas monedas me trajo el ratoncito de los dientes", al tiempo que dejaba ver un puñado de monedas en sus manitos. "Con estas monedas te haré un regalo", dijo el pequeño niño. La madre agradecida, dijo al niño, "mientras eso ocurre, te voy a explicar que siempre es bueno ahorrar". ¿Ahorrar?, ¿qué es eso?, dijo el niño. "Ahorrar es guardar un poco de lo que tienes, para cuando no tengas", contestó la mamá, mientras formaba dos grupos de monedas. Felipe miró a su madre y le preguntó "¿cuál de los dos montoncitos vamos a guardar?" La mamá contestó con dulce voz, "el que quieras, lo importante es ahorrar, porque el guarda siempre tiene".

Word count: 123

La ardilla Frody

En un gran árbol de nueces vivía la ardilla Frody. Frody era muy egoísta y no dejaba que nadie subiera al árbol. Todos los días ella miraba desde lo alto al resto de los animales jugar



y divertirse y ella no bajaba por temor a perder sus ricas nueces. Por eso siempre estaba triste y sola. Un día, al ir a buscar nueces a lo más alto del árbol, Frody se cayó quedando muy mal herida. Los animales del bosque cuidaron de ella hasta que mejoró. Frody se sintió feliz al saber que no estaba sola y que podía compartir sus nueces con sus nuevos amigos.

Word count: 109

Susanita la mosquita

Susanita era una mosquita que le encantaba volar con la boca abierta. Su mamá siempre le decía: "Cierra la boca niña que se te puede entrar un humano". Susanita que era porfiadita, cierto día se tragó a un señor flacuchento. La mamá desesperada llamó al doctor. Llegó un mosco vestido de blanco, el cual al no saber qué hacer, convocó a un moscólogo experto. Entre zumbidos y aleteos se pusieron de acuerdo en darle una salsa de azúcar y mantequilla para deslizar al hombre hacia afuera. Susanita, además, debió realizar un corto vuelo rasante y otro en caída libre. El hombre salió muy molesto embetunado de azúcar y mantequilla. Desde ese día, Susanita practica sus vuelos con la boca cerrada

Word count: 123

Appendix 5.2

Data Amount per Participant

		Story (S) duration (sec)																		Total data per participant			
Group	SubjID	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16	S17	S18	Total secs	Minus1sec(*)	Min Sec(dec)	Time (min:sec)
Adults	AdCH01	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92		50.99	48.58		53.55	47.44	52.49	52.5	47.2	52.56	810.23	809.23	13.49	**13:29**
	AdCH02	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5	47.2	52.56	916.99	915.99	15.27	**15:16** max
	AdCH05	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49				764.73	763.73	12.73	**12:44**
	AdCH06	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5	47.2	52.56	916.99	915.99	15.27	**15:16**
	AdCH07	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5	47.2	52.56	916.99	915.99	15.27	**15:16**
	AdCH08	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5	47.2	52.56	916.99	915.99	15.27	**15:16**
	AdCH09	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5	47.2	52.56	916.99	915.99	15.27	**15:16**
	AdCH10	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5	47.2	52.56	916.99	915.99	15.27	**15:16**
	AdCH11	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5	47.2	52.56	916.99	915.99	15.27	**15:16**
	AdCH12	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5	47.2	52.56	916.99	915.99	15.27	**15:16**
	AdCH13	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5	47.2	52.56	916.99	915.99	15.27	**15:16**
	AdCH14	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5	47.2	52.56	916.99	915.99	15.27	**15:16**
	AdCH15	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58		53.55	47.44		52.5	47.2	52.56	813.96	812.96	13.55	**13:33**
	AdCH16	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5	47.2	52.56	916.99	915.99	15.27	**15:16**
	AdCH17	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5	47.2	52.56	916.99	915.99	15.27	**15:16**
	AdCH18	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5	47.2	52.56	916.99	915.99	15.27	**15:16**
	AdCH20	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5	47.2	52.56	916.99	915.99	15.27	**15:16**
TLD	TLD03	49.99		54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49				717.74	716.74	11.95	**11:57**
	TLD04			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5			720.25	719.25	11.99	**11:59**
	TLD05	49.99		54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5			770.24	769.24	12.82	**12:49**
	TLD06			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5			720.25	719.25	11.99	**11:59**
	TLD07			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44					615.26	614.26	10.24	**10:14**
	TLD11			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54							514.27	513.27	8.55	**08:33**
	TLD14			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55						567.82	566.82	9.45	**09:27**
	TLD15			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44					615.26	614.26	10.24	**10:14**
	TLD16			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5			720.25	719.25	11.99	**11:59**
	TLD17	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5			817.23	816.23	13.60	**13:36**
	TLD18			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44					615.26	614.26	10.24	**10:14**
	TLD19	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5	47.2	52.56	916.99	915.99	15.27	**15:16**
DLD	DLD01			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44					615.26	614.26	10.24	**10:14**
	DLD03			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44					615.26	614.26	10.24	**10:14**
	DLD04			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44					615.26	614.26	10.24	**10:14**
	DLD05			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44					615.26	614.26	10.24	**10:14**
	DLD06			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44					615.26	614.26	10.24	**10:14**
	DLD07			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5			720.25	719.25	11.99	**11:59**
	DLD08			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55						567.82	566.82	9.45	**09:27**
	DLD09			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49				667.75	666.75	11.11	**11:07**
	DLD11			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44					615.26	614.26	10.24	**10:14**
	DLD12			54.15	53.74	48.13	52.08	49.92	49.92											307.94	306.94	5.12	**05:07** min
	DLD14			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44					615.26	614.26	10.24	**10:14**
	DLD15			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5			720.25	719.25	11.99	**11:59**
	DLD16	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5	47.2	52.56	916.99	915.99	15.27	**15:16**
	DLD17			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49				667.75	666.75	11.11	**11:07**
	DLD18	49.99	46.99	54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5	47.2	52.56	916.99	915.99	15.27	
	DLD19			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44	52.49	52.5			720.25	719.25	11.99	**11:59**
	DLD21			54.15	53.74	48.13	52.08	49.92	49.92	56.22	50.99	48.58	50.54	53.55	47.44					615.26	614.26	10.24	**10:14**

Appendix 5.3

Normality and Variance Homogeneity Tests for Experiment 4 (Neural Tracking)

r values								
	Homogeneity of Variance[a]				Normality[b]			
Neural Tracking Measure	Levene Statistic	df1	df2	*p*	Group	Shapiro-Wilk Statistic	df	*p*
Acoustic Envelope	2.257	2	43	.117	Adults	.873	17	.025
					TLD	.972	12	.934
					DLD	.910	17	.101
Lexical Frequency Envelope	1.505	2	43	.234	Adults	.981	17	.969
					TLD	.875	12	.077
					DLD	.964	17	.699

Within Subjects Effect								
	Equality of Covariance Matrices[c]				Sphericity[d]			
	Box's M	df1	df2	*p*	Mauchly's W	Approx. Chi^2	df	*p*
Factor: Tracking Measure	9.42	6	23610	.188	1.0	.000	0	**.**

Note. Significant tests are indicated in bold fonts.

[a] Tests the null hypothesis of equal variances across groups

[b] Tests the null hypothesis of a normal data distribution

[c] Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.

[d] Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.