UNIVERSITY OF PADOVA

Department of General Psychology

Master Degree in Developmental and Educational Psychology

Final dissertation

The Development of Hemispheric Lateralization to Repetition-Based Rule-Learning With Linguistic Stimuli: A Meta-Analysis of Infant and Adult fNIRS Studies

Supervisor

Professor Judit Gervain

Co-supervisor

Dr. Jessica Gemignani

Candidate: Victoria Taylor Johnston

Student ID number: 2105903

Academic Year 2024/2025

Table of Contents

Abstract

In most adults, language processing is lateralized to the left hemisphere of the brain, but what are the developmental origins of this lateralization? To address this question, we conducted a comprehensive meta-analysis combining 27 fNIRS studies examining brain responses to repetition-based artificial grammar sequences across 5 age groups: 0m, 6m, 7m, 9m and Adults. Our meta-analysis included 525 infants (0-9 months) and 42 adults, focusing on hemispheric activation patterns in temporal and frontal regions of interest. We examined the effects of age, hemisphere (left vs. right), and brain region (temporal vs. frontal) on hemodynamic responses measured via fNIRS. We employed random-effects meta-analytic models to estimate subgroup-level effect sizes and conducted moderated analyses to examine interactions between developmental and neural factors. While our hypothesis anticipated progressive hemispheric specialization, hemisphere effects were consistently non-significant across all analyses ($p > 0.05$). Instead, robust age-related effects emerged as the dominant pattern, consistently approaching or achieving statistical significance (HbO all-data: $p = 0.0532$; HbR speech-only: $p = 0.0284$). Developmental trajectory analysis revealed peak activation at 6-7 months across both hemispheres, followed by declining activation toward adulthood. Adults demonstrated significant effects in both hemispheres rather than the predicted left-temporal specialization, with unexpected subtle right-lateralization patterns (lateralization index = -0.3) that remained statistically non-significant. Regional analyses showed temporal areas exhibited slightly stronger developmental patterns than frontal regions, though these differences did not reach significance either. The absence of significant lateralization effects suggests that repetition-based rule-learning may engage bilateral neural networks rather than the strongly lateralized language systems typically observed in higher-order linguistic processing.

1. Introduction

The brain's capacity for learning languages is a complex phenomenon that begins before birth and evolves throughout infancy and into adulthood. One important aspect of this is our ability to learn abstract linguistic rules: through a process called “rule-learning” (Carral et al., 2005; Dehaene-Lambertz et al., 2002; Gervain et al., 2008; Gervain et al., 2012; Koulaguina & Shi, 2013; Opitz & Friederici, 2003, 2004; Kepinska et al., 2017). For instance, infants can readily learn simple linguistic rules when exposed to two repeating syllables in a tri-syllabic sequence (e.g., ABB: “mu-ba-ba”, “pe-na-na”, and “ta-lu-lu”), compared to non-repetition tri-syllabic sequences (e.g., ABC: “mu-ba-ge”, “ta-lu-pi”, “pe-na-ku”) as shown by Gervain et al. (2008). Rule learning is a fundamental process in language acquisition, and still, little is known about how infants begin to learn and process these grammatical rules, especially regarding which neural mechanisms are specifically involved.

The present work, therefore, analyzes hemispheric activation across development during linguistic pattern-based rule-learning stimuli, in both infants and adults. Specifically, focusing on whether and, if yes, how rule learning gets lateralized in young infants’ brains, similarly to how language processing becomes lateralized to the left temporal cortex in adults (Hickok & Poeppel, 2007). Indeed, many adult studies have uncovered left hemispheric (LH) dominance during linguistic processing, and similarly initial temporal LH involvement has also been shown in infants (newborns) when exposed to speech stimuli (Dehaene-Lambertz et al., 2002; Gervain et al., 2008; Peña et al., 2003). However, it has also been uncovered that 6-month-old infants exhibit greater responses to repetition-based stimuli in the bilateral frontal areas, indicating an increase of right hemispheric (RH) involvement (Gemignani & Gervain, 2024). This suggests a developmental change of hemispheric activation during the neural processing of linguistic repetition-based stimuli throughout infancy and into adulthood. It is, thus, important to investigate further, when and why these developmental changes occur in order to best understand the cognitive trajectory of language acquisition. We, thus, preformed a meta-analysis to further explore these lateralization processes of brain activity, in both infants and adults, during repetition-based rule-learning language stimuli, using functional near-infrared spectroscopy (fNIRS) to measure brain activity in both the temporal and frontal regions.

1.1 Lateralization

Lateralization refers to the functional specialization of activity to one hemisphere of the brain, as certain cognitive processes are thought to occur predominantly in either the LH or the RH (Seghier, 2008). Lateralization processes related to linguistic rule-learning and pattern recognition change significantly from birth throughout adulthood, with changes in hemispheric dominance as well as involvement of specific brain regions (Gemignani & Gervain, 2024, Kuhl, 2010, Sato et al., 2010). Past neuroimaging studies on adults seem to support the dominance of the left temporal areas during speech processing tasks (Hickok & Poeppel, 2000, Seghier, 2008, Wise et al., 2001, Binder et al., 2000) associating it with our ability to learn, recognize and process language. While the LH might be dominant for language in adults, it is not as established at birth. This developmental shift towards left temporal dominance is suggested to occur as infants mature from 0 – 9 months of age (Sato et al., 2010, Gemignani & Gervain, 2024, Pena et al., 2003). Further infant research using fNIRS has detected left temporal activation in newborns when exposed to repetition-based structures, indicating a possible innate ability to discriminate not only linguistic-stimuli, but also repetition-based sequences (e.g., ABB) (Gervain et al., 2008, Gervain et al., 2012, Pena et al., 2003). However, these lateralization processes seem to change throughout development as, at around 6 months of age, while left temporal activity continues to increase, we begin to see increased bilateral frontal lobe involvement, indicating increased RH involvement (Gemignani & Gervain, 2024, Gemignani et al., 2023). This activation is further supported by similar functional near infrared spectroscopy (fNIRS) findings which tested infants' ability to discriminate repetitions vs. non-repetitions using repetition-initial (AAB) and repetition-final (ABB) rule-learning stimuli (Gemignani & Gervain, 2024).

How language functions get lateralized during infancy is thus still not fully understood. The previously mentioned neurological differences are important to investigate as current research is not only limited and contradictory, but the lateralization processes behind linguistic pattern-recognition are crucial for investigating and understanding how language acquisition and processing functions throughout development (Gemignani & Gervain, 2024, Sato et al., 2010).

1.2 Neuroimaging Studies: Linguistic Rule-Learning and Artificial Grammar Learning

An important ability required for language learning is a newborn's sensitivity to patterns involving the repetition of sounds and syllables (Carral et al., 2005, Endress et al., 2009, Gemignani & Gervain, 2024, Gemignani et al., 2023). This demonstrates a predisposition for learning linguistic repetition-based rules, as well as an ability to discriminate patterns and regularities in spoken language (Dehaene-Lambertz et al., 2002). This rule-learning capacity allows infants to learn beyond the specific details of what they hear and get insights into the underlying structure behind language itself (Dehaene-Lambertz et al., 2002, Endress et al., 2007). The infant brain's capacity for linguistic rule-learning has become an important area of study in the field of psycholinguistics, allowing researchers to further examine how we acquire language.

This specific linguistic rule-learning capability has recently been investigated with artificial grammars: simplified, rule-based "languages" used to study how infants learn and process structural patterns (Gervain et al., 2020). They are often designed to be unfamiliar to participants, which allows researchers to control the learning environment while investigating repetition-based rule-learning mechanisms without the potential interference of pre-existing linguistic knowledge (Endress et al., 2007, Gervain et al., 2020, Gomez & Gerken, 1999). E.g., when exposed to artificial grammar learning (AGL) repetition-based ABB sequences (e.g. “mu-ba-ba") and non-repetition-based ABC sequences (e.g. "mu-ba-ge"), newborns showed a preference towards the repetition-based ABB sequences (Gervain et al., 2008). While more AGL research uncovered that infants possess not only the ability to recognize immediate repetitions during spoken language, but also a sensitivity to the position of the repetition within a sequence itself (Gervain et al., 2012). Current research also found that final-repetitions (ABB) may be easier to process than initial-repetitions (AAB), as per probable recency effects in memory. Regardless of this being quite weak (Endress, A. D et al., 2009), this suggests that infants can differentiate between tri-syllabic sequence-initial (AAB) and sequence-final repetitions (ABB) as well as between patterns (ABB) and non-patterns (ABC) (Gervain et al., 2012).

Furthermore, older infants seem to be able to generalize these learned patterns and apply them to new instances (Gervain et al., 2012, de la Cruz-Pavía & Gervain., 2023). For instance, research on 7-month-olds found that infants can learn tri-syllabic artificial grammars (ABB vs AAB) and once familiarized with these grammars, can discriminate novel items that conform to them from those that do not (Marcus et al., 1999). This rule-learning phenomenon thus indicates that infants are not just memorizing specific sequences but are actually learning linguistic rules by identifying abstract relationships between elements within specific sequences (Gervain et al., 2012, Marcus et al., 2007). By further examining neural trends of hemispheric activation, using fNIRS and these types of linguistic stimuli, we can better assess the lateralization processes behind language processing, across development.

1.3 Functional Near-Infrared Spectroscopy (fNIRS)

Several neuroimaging techniques have been used to study brain activity related to language processing in infants, including Functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), electroencephalogram (EEG), and functional near-infrared spectroscopy (fNIRS) (Gemignani & Gervain, 2024, Huberty et al., 2023, Kuhl, 2010, Sato et al., 2010, Dehaene-Lambertz et al., 2002). Each method has its own strengths and weaknesses regarding spatial resolution, temporal resolution, and suitability for use on infants (Dehaene-Lambertz et al., 2002, Gemignani & Gervain, 2024, Huberty et al., 2023, Kuhl, 2010). As such, infant fNIRS studies have provided valuable insights into the reliability as well as replicability of findings related to early language processing, with specific focus on rule-learning abilities (Gemignani & Gervain, 2024, Gemignani et al., 2023). It is for this reason that we will be focusing specifically on the use of fNIRS as a measurement for brain activation for the remainder of this meta-analysis.

fNIRS is non-invasive and uses near-infrared light to measure changes of oxygenated and deoxygenated hemoglobin (OxyHb / DeoxyHb) in the brain (Gemignani & Gervain, 2024, Gervain et al., 2008, Sato et al., 2010, Aslin & Mehler, 2005). These changes in concentration are typically indicators of brain activity, as when neurons are active, they consume more oxygen, leading to local changes in blood flow and thus, a change in oxygen levels in that area of the brain (Gemignani & Gervain, 2024, Gervain et al., 2008, Sato et al., 2010). Due to fNIRS' ability to provide information about the spatial distribution of brain activity (Dehaene-Lambertz et al., 2002, Pena et al., 2003, Henson et al., 2000), this neuroimaging technique best allows researchers to observe and compare LH and RH activity during rule-learning related language tasks (Seghier, 2008, Tervaniemi & Hugdahl, 2003, Sato et al., 2010).

Furthermore, while EEG is very powerful to detect brief linguistic processes in the range of 100 ms, fNIRS provides integration over a longer timeframe, provides better localization (Wallois et al., 2011) and is typically sufficient to distinguish brain activity using specific regions of interest (ROIs) during linguistic repetition-based stimuli in both infants and adults (Dehaene-Lambertz et al., 2002, Pena et al., 2003).

1.4 Regions of Interest (ROIs)

By around 6 months of age, an infant's ability to learn repetition-based regularities seems to trigger an increase in brain activity when exposed to diversity-based regularities compared to newborns (I. de la Cruz-Pavía & J. Gervain, 2021). These neurological responses to linguistic repetition-based stimuli have also shown to change from bilateral frontal activity at 6-months of age, to left temporal lobe dominance in adulthood (Gemignani & Gervain, 2024). Due to this, we can assume that one's ability to process and recognize linguistic patterns undergoes some amount of developmental change across infancy and into adulthood. In order to measure this, rather than analyzing the entire brain, which can lead to unclear results, researchers focus on specific brain regions that have already been suggested to be relevant for their area of interest (Gemignani & Gervain, 2024, Gemignani et al., 2023). This allows for a more targeted analysis of the brain's activity.

As mentioned above, regarding language and repetition-based stimuli, these specific brain regions are known to be the temporal and frontal lobes. Furthermore, these regions have previously been associated with auditory processing, language processing, as well as higher-order cognitive processing (Gervain et al., 2008, Gervain et al., 2012). Thus, focusing on these specific regions will allow us to better quantify hemispheric differences (by comparing specific areas: Temporal and frontal per hemisphere) as well as track developmental changes and make comparisons across multiple repetition-types **(**Gemignani & Gervain, 2024, Gemignani et al., 2023).

1.5 Meta-Analysis

To create a fuller image of how these neurological processes function, a meta-analysis can be a valuable tool as it allows researchers to assess the variability and reliability of findings across multiple studies (Gemignani et al., 2023, Gemignani & Gervain, 2024, Bergmann et al., 2018). A key benefit of meta-analyses is that it directly addresses the issue of reproducibility (Gemignani et al., 2023, Gemignani & Gervain, 2024); by combining results from multiple studies, researchers can determine whether effects are consistent across different labs, populations and experimental conditions (Gemignani et al., 2023, Valentine et al., 2010). Combining data from multiple studies increases the statistical power of the data and allows researchers to detect small, yet significant effects that might be missed in individual studies (Gemignani et al., 2023, Valentine et al., 2010). Furthermore, this approach provides researchers with the ability to synthesize complex findings through the examination of variability across studies as well as identify factors that might moderate the effects of interest (Braver et al., 2014, Goh et al., 2016), thus helping to improve future research methodologies (Gemignani et al., 2023).

In summary, a meta-analysis offers a powerful approach when studying the neural lateralization processes of linguistic pattern recognition throughout development. By combining results from multiple fNIRS studies, not only can we identify true differences between newborn, infant, and adult linguistic lateralization processes, but we can also enhance statistical power, quantify variability, assess reproducibility, identify the impact of additional moderators, provide methodological insights, as well as synthesize complex findings of already existing related research (Gemignani et al., 2023, Gemignani & Gervain, 2024, Valentine et al., 2010, Braver et al., 2014). This is particularly important as a meta-analysis will provide more reliable and accurate results, allowing us to take into consideration multiple populations, studies and research techniques to reach our goal of establishing potential hemispheric lateralization during linguistic stimuli.

1.6 Hypothesis

Overall, our goal is to assess hemispheric lateralization during linguistic pattern-recognition-based tasks throughout development, with the use of a neuroimaging tool: fNIRS. This hypothesis assumes that newborns will initially show a left-lateralized response to speech processing repetition-based stimuli (Pena et al., 2003), followed by an increase in RH activation shown through an increased response in the bilateral frontal area at around 6 months of age, all while the temporal lobe remains left-lateralized (Gervain et al., 2008, Dehaene-Lambertz et al., 2002) with effect size being lowest for repetition-sequences in the left frontal region (Gemignani & Gervain, 2024). The brain will become more specialized as we look into adulthood, with the LH temporal-lobe now becoming dominant for the majority of language-based functions, such as, repetition-based rule-learning (Hickok & Poeppel, 2000).

This hypothesis will be analyzed using a meta-analytic technique, which will consider data from previous neuroimaging studies focused on infants, as well as neuroimaging studies on adults, in order to investigate the specific neural lateralization processes that are involved in linguistic repetition-based rule-learning. With our research focusing specifically on brain activity in the temporal and frontal regions of both the LH and RH during exposure to linguistic pattern recognition tasks using repetition-based rule-learning stimuli, in order to measure hemispheric lateralization changes throughout development.

2 Methodology

Within this work, we will follow a meta-analytical methodological approach, where linguistic rules, such as: Repetition-based ("R") regularities will be used to compare hemispheric lateralization to baseline. Primarily, meta-analytic techniques will be used in order to estimate the overall and subgroup-level effect-sizes of neural responses within each hemisphere (LH / RH), age group and region of interest (Figures 3 & 4), with intercept-only random effects models. Secondly, moderated analyses are carried out to statistically assess the effect of hemisphere. The data analyses performed focus on measuring the effects of hemispheric activation during linguistic rule-learning, while considering our moderating variables (age, hemisphere & ROI), and repetition condition. As per previous meta-analytic research done by Gemignani et. al., (2023), we can disregard methodological sources of variability, such as that of cross-lab variability, as they have been found to be non-significant moderators of the effect.

2.1 Data

2.1.1 Studies

The current research combines 27 published and unpublished infant and adult fNIRS studies. Each study measured brain responses of typically developing infants through the use of two types of linguistic stimuli: Repetition-based sequences (R: ABA / ABB / AAB), e.g., "ba-mu-ba" "mu-ba-ba" "ba-ba-mu", and non-repetition-based sequences (N: ABC), e.g., "mu-ba-ge" (Gemignani & Gervain, 2024). All studies comprising our infant data were found through both PubMed as well as Google Scholar, using the following key terms: "Repetition-based regularity", "rule learning", "fNIRS", and "infants". Exclusion criteria included atypical populations as well as studies which used different neuroimaging methods than fNIRS

(Gemignani et. al., 2023). All papers that included more than one study were considered individual studies. Thus, out of 43 potential results, only 12 published studies met our inclusion criteria, and were therefore included. Additionally, 15 unpublished infant and adult-studies were added. Although these are not yet peer-reviewed articles, they are available online in PhD dissertations. Furthermore, some of the studies presented were useful for several comparisons, in that a specific study may have contributed to just one or several of the comparisons (e.g., Study 4 and Study 5 belong to the same experiment, but since this presented two types of repetition, each repetition was considered separately). The final sample is, thus, comprised of 525 infants between 0 and 9 months as well as 42 adults. Details on all included studies, such as the specific material they employed, their individual sample sizes and their bibliographic information, can be found below in Table 1.

All infant and adult studies used similar methods regarding stimuli and experimental designs. However, each addressed a different hypothesis (e.g., auditory VS. visual stimuli) and differ in whether or not they test repetition-based regularities, diversity-based regularities, or both. In the current research, we conducted multiple meta-analyses with the goal of measuring the effect sizes of 3 separate comparisons: Hemispheric lateralization (left hemisphere/LH vs. right hemisphere/RH), regional differences (frontal vs. temporal brain regions), as well as age effects. Each moderator was analysed across 3 different subgroups of data (combined speech/visual, Speech-only, and Speech-only data presenting tri-syllabic sequences, with adjacent repetitions occupying either the Initial or Final position). Lastly, we created a comprehensive visualization of these effect estimates across development for each above-mentioned subgroup (Figures 3 & 4).

As mentioned, cross-lab variability for the aforementioned datasets has been measured in previous research (Gemignani et. al., 2023). This is important to note, as it indicates that laboratory differences are not significant moderators of variation in effect sizes. Thus, our results rely solely on the theoretical variables in which we are interested, allowing us to accurately assess the development of hemispheric activity in specific ROIs, during exposure to linguistic repetition-based stimuli, across our infant and adult-samples.

Table 1: List of studies included in our meta-analyses (R versus 0). As described in Sec. 2.2.3, different sets of studies contributed to three comparisons of interest (All data, Speech-only, and Trisyllabic), indicated by the boldness of the last two columns (bold = included & NA = not included); the columns also report which pattern regularities were selected for each study. All of our data was included within our "all-data" analysis and was therefore excluded from this table.

											Included in which statistical analysis	
Study-ID	Study	Publication	Cond1	Cond2	Adjacency of the Repetition	Repetition Position	Input Modality	Type of Input	Age	Sample Size	Speech-only	Trisyllabic
1	A_A-A_C-0m-Speech	Gervain thesis	A_A	A_C	Adjacent	Bisyllabic	Auditory	Linguistic	0m	21	**A_A**	A_A
2	AA-AB-0m-Speech	Gervain thesis	AA	AB	Adjacent	Bisyllabic	Auditory	Linguistic	0m	22	**AA**	AA
3	AAB-ABC-0m-Speech-Exp1	Gervain et al. 2012	AAB	ABC	Adjacent	Initial	Auditory	Linguistic	0m	22	**AAB**	**AAB**
4	AAB-ABB-0m-Speech-AltNonAlt-Exp2-R=AAB	Gervain et al. 2012	AAB	ABB	Adjacent	Initial	Auditory	Linguistic	0m	20	**AAB**	**AAB**
5	AAB-ABB-0m-Speech-AltNonAlt-Exp2-R=ABB	Gervain et al. 2012	AAB	ABB	Adjacent	Final	Auditory	Linguistic	0m	20	**AAB**	**AAB**
6	AAB-ABB-0m-Speech-SimpleBlocks-Exp3-R=AAB	Gervain et al. 2012	AAB	ABB	Adjacent	Initial	Auditory	Linguistic	0m	24	**AAB**	**AAB**
7	AAB-ABB-0m-Speech-SimpleBlocks-Exp3-R=ABB	Gervain et al. 2012	AAB	ABB	Adjacent	Final	Auditory	Linguistic	0m	24	**AAB**	**AAB**
8	AAB-ABC-0m-Speech-ReplicationNIRx	unpublished	AAB	ABC	Adjacent	Initial	Auditory	Linguistic	0m	24	**AAB**	**AAB**
9	AAB-ABC-0m-Tones	unpublished	AAB	ABC	Adjacent	Initial	Auditory	Non-Linguistic	0m	20	ABA	**AAB**
10	ABA-ABC-0m-Speech	Gervain et al. 2008	ABA	ABC	Non-Adjacent	Non-Adjacent	Auditory	Linguistic	0m	22	**ABB**	ABA

Table 1: List of studies included in our meta-analyses (R versus 0). As described in Sec. 2.2.3, different sets of studies contributed to three comparisons of interest (All data, Speech-only, and Trisyllabic), indicated by the boldness of the last two columns (bold = included & NA = not included); the columns also report which pattern regularities were selected for each study. All of our data was included within our "all-data" analysis and was therefore excluded from this table.

											Included in which statistical analysis	
Study-ID	Study	Publication	Cond1	Cond2	Adjacency of the Repetition	Repetition Position	Input Modality	Type of Input	Age	Sample Size	Speech-only	Trisyllabic
11	ABB-ABC-0m-Speech	Gervain et al. 2008	ABB	ABC	Adjacent	Final	Auditory	Linguistic	0m	22	**ABB**	**ABB**
12	ABB-ABC-0m-Speech-CorV-RepeatedContext-R=C	Bouchon thesis (Exp 3)	ABB	ABC	Adjacent	Final	Auditory	Linguistic	0m	24	**ABB**	**ABB**
13	ABB-ABC-0m-Speech-CorV-RepeatedContext-R=V	Bouchon thesis (Exp 3)	ABB	ABC	Adjacent	Final	Auditory	Linguistic	0m	24	**ABB**	**ABB**
14	ABB-ABC-0m-Speech-CorV-VariableContext-R=C	Bouchon thesis (Exp 2)	ABB	ABC	Adjacent	Final	Auditory	Linguistic	0m	21	**ABB**	**ABB**
15	ABB-ABC-0m-Speech-CorV-VariableContext-R=V	Bouchon thesis (Exp 2)	ABB	ABC	Adjacent	Final	Auditory	Linguistic	0m	21	**ABB**	**ABB**
16	ABB-ABC-0m-Speech-CV	Bouchon et al. 2015	ABB	ABC	Adjacent	Final	Auditory	Linguistic	0m	24	**ABB**	**ABB**
17	AA-AB-6m-Cartoon	de la Cruz-Pavia et al. under review	AA	AB	Adjacent	Bisyllabic	Visual	Non-Linguistic	6m	21	AA	AA
18	AA-AB-6m-Sign	de la Cruz-Pavia et al. under review	AA	AB	Adjacent	Bisyllabic	Visual	Linguistic	6m	23	AA	AA

Table 1: List of studies included in our meta-analyses (R versus 0). As described in Sec. 2.2.3, different sets of studies contributed to three comparisons of interest (All data, Speech-only, and Trisyllabic), indicated by the boldness of the last two columns (bold = included & NA = not included); the columns also report which pattern regularities were selected for each study. All of our data was included within our “all-data” analysis and was therefore excluded from this table.

											Included in which statistical analysis	
Study-ID	Study	Publication	Cond1	Cond2	Adjacency of the Repetition	Repetition Position	Input Modality	Type of Input	Age	Sample Size	Speech-only	Trisyllabic
19	AA-AB-6m-Speech	unpublished	AA	AB	Adjacent	Bisyllabic	Auditory	Linguistic	6m	15	**AA**	AA
20	AAB-ABC-6m-Speech-Entropy	Radulescu et al. in preparation	AAB	ABC	Adjacent	Initial	Auditory	Linguistic	6m	21	**AAB**	**AAB**
21	ABB-ABC-6m-Speech-AltNonAlt	de la Cruz-Pavia & Gervain in prep	ABB	ABC	Adjacent	Final	Auditory	Linguistic	6m	24	**ABB**	**ABB**
22	RuleLearning5-8months	Lucarini et al (in prep)	ABA	ABC	Non-Adjacent	Non-Adjacent	Auditory	Linguistic	6m	23	**ABA**	ABA
23	ABB-ABC-7m-Speech	Wagner et al. 2011	ABB	ABC	Adjacent	Final	Auditory	Linguistic	7m	13	**ABB**	**ABB**
24	RuleLearning5-8months	Lucarini et al (in prep)	ABA	ABC	Non-Adjacent	Non-Adjacent	Auditory	Linguistic	7m	15	**ABA**	ABA
25	ABB-ABC-9m-Speech	Wagner et al. 2011	ABB	ABC	Adjacent	Final	Auditory	Linguistic	9m	15	**ABB**	**ABB**
26	RuleLearningAdults-Italian	Lucarini et al (in prep)	ABA	ABC	Non-Adjacent	Non-Adjacent	Auditory	Linguistic	Adults	27	**ABA**	ABA
27	RuleLearningAdults-non-Italian	Lucarini et al (in prep)	ABA	ABC	Non-Adjacent	Non-Adjacent	Auditory	Linguistic	Adults	15	**ABA**	ABA

2.1.2 Stimuli used in the included studies

All studies included in our analysis used two different bi- or tri-syllabic artificial grammar sequences as rule–learning stimuli, as illustrated before. Table 1 reports the specific characteristics of each study and includes both our hemispheric subgroups of data. Other stimuli used can be found within their respective publications and were highly similar across studies.

2.1.3 Procedure

In all studies, participants were tested using fNIRS devices with auditory stimuli that were administered through loudspeakers. 8-10 sources as well as 8 detectors were placed bilaterally on the participants' heads (with a distance of 2.5-3cm from source to detector), thus, creating 10 - 12 channels per hemisphere. The anatomical localization of the above-mentioned array is further described in research by Abboub et al. (2016). Given the current literature's hypothesis and as per relevant research regarding the involvement of these areas during linguistic processing, we decided to focus our attention on the left and right temporal and frontal lobes, shown in Figure 1 as the cluster of channels 3, 6 and 17, 19 as well as 2, 5 and 13, 15, respectively. With both anatomical and functional localization methods now readily available in literature, choosing the most relevant regions of interest (ROIs) can be quite difficult (Yücel et al., 2021). However, we have decided to use the predefined ROIs mentioned above (left and right temporal / frontal lobes), as both of these areas were found to be activated within the majority of research included within this meta-analysis (See table 1). These ROIs will allow for a more accurate measurement of hemispheric involvement during exposure to linguistic repetition-based stimuli.

Figure 1: ROI Cluster channels
Figure 1 illustrates the spatial arrangement of near-infrared spectroscopy (NIRS) optodes and channels used to define regions of interest (ROIs) in the current study. The figure displays bilateral brain views showing the left hemisphere (left panel) and right hemisphere (right panel) with our frontal (LH channels: 2, 5 & RH channels: 13, 15) and temporal (LH channels: 3, 6 & RH channels: 17, 19) ROIs circled in red.

2.2 Data-Analysis

2.2.1 fNIRS Preprocessing

fNIRS data was preprocessed using similar methods for all studies (Gemignani et. al., 2023). This method was validated independently in synthetic data, and it closely matches the original analysis pipelines used in the published studies (Gemignani and Gervain, 2021). Light intensities were converted into optical densities and hemoglobin concentration changes were measured using the modified Beer–Lambert Law with absorption coefficients: μ_a, $\text{mm}^{-1} \times \text{mM}^{-1}$: μ_a (HbO_2 695 nm) = 0.0955, μ_a (HbO_2 760 nm) = 0.1496, μ_a (HbO_2 830 nm) = 0.2320; μ_a (HbO_2 850 nm) = 0.2526; μ_a (HbR, 695 nm) = 0.4513, μ_a (HbR, 760 nm) = 0.3865, μ_a (HbR, 830 nm) = 0.1792; and μ_a (HbR, 850 nm) = 0.1798. The product of the optical pathlength and the differential pathlength factor was set to 1, allowing concentration changes to be communicated in mM × mm. A bandpass filter between 0.01 and 0.7 Hz was also applied to hemoglobin concentration changes through the use of an FFT digital filter. Blocks of single-trial data were rejected if they contained motion artifacts or if the light intensity reached the saturation value, where motion artifacts are described as signal changes larger than 0.1 mM × mm, over 0.2 s , this is further shown in research by Gemignani and Gervain, (2021).

Furthermore, as mentioned in Gemignani et. al., (2023), detection and trial rejection procedures were performed separately for each channel, and those with less than two valid blocks were removed from the analysis. The trial inclusion rate for each study included ranged from 52% to 100% (M: 65.1%, SD: 12.8%) and for each all-non-rejected block, a baseline was linearly fit between the mean of the 5s before the onset of the block and the mean of the 5s before the onset of the following block (Gemignani et. al., 2023). Lastly, all blocks were averaged within each participant to obtain channel-wise block averages for each condition and across all participants in order to acquire study-level grand averages and thus, study-level effect sizes (Figure 2, below). This preprocessing method was chosen as per its reliability to successfully and accurately measure hemodynamic responses in response to linguistic rule-learning stimuli (Gemignani and Gervain, 2021).

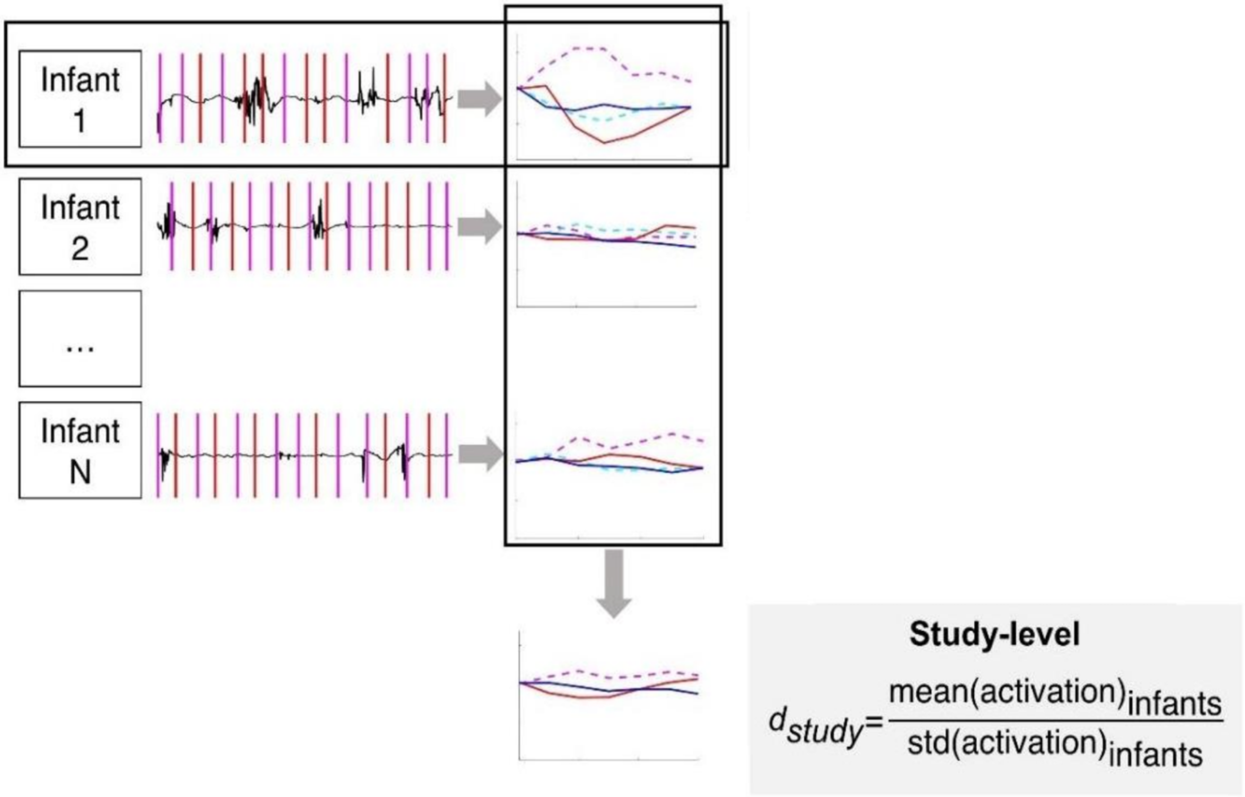

Figure 2: fNIRS Preprocessing Method
Figure 2 illustrates the hierarchical data processing method used to calculate study-level effect sizes for this meta-analysis. The diagram demonstrates study-level summary statistics suitable for meta-analytic synthesis

2.2.2 Calculation of Effect Sizes

Effect sizes were computed as standardized mean differences, which is an approach to be preferred compared to using raw mean differences when the source data is a neuroimaging measure, to ensure complete comparability between studies (Borenstein, 2009). Therefore, for each study, the meta-analytic effect size was computed by averaging a participant's responses in all trials of the repetition condition (Figure 2). These individual means were then averaged and divided by their standard deviation, to obtain the effect size *d*. The corresponding sampling variance was then computed as $V_d = {}^{2}/_{n} + {}^{d^2}/_{4n}$, with *n* being the number of participants, i.e., effect sizes were weighted by the number of participants in a study (Borenstein et al., 2021, Bergmann et al., 2018).

Effect sizes were computed for both HbO and HbR and analyzed separately., using random-effects models to examine subgroup-level effect sizes across age groups, hemispheres, and ROI (Figures 3 & 4). This approach combines findings across multiple studies, while providing effect estimates and accounting for any between-study differences. We also conducted moderated meta-analyses to examine the impact of any of the aforementioned variables (age, hemisphere, and ROI) on the estimates. This approach allows us to identify potential patterns of hemispheric lateralization during linguistic repetition-based stimuli, across specific age groups.

2.2.3 Statistical analysis

Meta-Analysis Modeling

Subgroup-level effect sizes were analyzed through the use of meta-analytic random-effects models with package "metafor" in Rstudio.34, all models were fit using restricted maximum likelihood (REML) estimation. These analyses were conducted across 2 subgroups of data (LH & RH data, as shown in Table 1). This allowed us to study the effect sizes of our moderators: Hemisphere, age, as well as region, independently, within each hemisphere, and to build the forest plots shown below in Figures 3 & 4. Within-age group effect sizes allowed us to examine the developmental trajectory. Additionally, moderated meta-analyses were carried out, in order to statistically assess the impact of our aforementioned moderators of interest, and the extent to which they explain heterogeneity in the effect sizes: Hemisphere, Age and Region of Interest across all five different age groups.

Application of Analyses to Study Comparisons

We created three subsets of the studies included in the analysis on the basis of shared characteristics (Table 1): the entire dataset (1: 27 studies), set of studies that use speech stimuli (2:24 studies, excluding studies 9, 17, 18), and lastly, a set of studies that use speech stimuli with adjacent, trisyllabic repetitions (3:17 studies, excluding studies 1, 2, 9, 10, 17, 18, 22, 24, 26, 27). The previously mentioned groupings allow us to more accurately measure the development of hemispheric activation within each respective ROI (temporal & frontal) during exposure to different types of repetition-based linguistic-stimuli: allowing us to depict any potential lateralization patterns that might occur during linguistic rule-learning.

Age- Related Developmental Trajectory Analysis

In order to visualize developmental patterns in hemispheric lateralization across development, we constructed 2 developmental trajectory plots (one for each ROI) using the effect size estimates derived from our intercept-only meta-analytic models mentioned above, as shown in Figure 5. These visualizations integrate results from our subgroup analyses across different age groups (newborns, 6-month-olds, 7-month-olds, 9-month-olds, and adults), for each comparison. This analysis allowed us to further examine linguistic rule-learning developmental changes in lateralization patterns.

3 Results

3.1 Overview of Meta-Analytic Findings

Forest plots demonstrate consistent effect size patterns across the 27 included studies, with visual confirmation of age-related effects and overlapping hemispheric confidence intervals supporting the statistical analyses (Figures 3 & 4, below).

Overall, hemisphere was not significant (HbO: $p > 0.05$ & HbR: $p > 0.05$). Rather, we see age-related effects on overall brain activation that approach significance in our HbO all–data analysis ($p = 0.0532$), in our speech-only analysis ($p = 0.0890$) as well as in our HbR all-data analysis ($p = 0.0693$) and reach significance in our HbR speech-only analyses ($p = 0.0284$).

Developmental trajectory plots revealed similar developmental patterns for left and right hemispheres, both peaking at 6-7 months (particularly in frontal regions) and declining toward adulthood. While our lateralization indices showed gradual activation of the left temporal lobe, from near-zero at birth (CIs crossing zero), to modest right-lateralization in adults (-0.3).

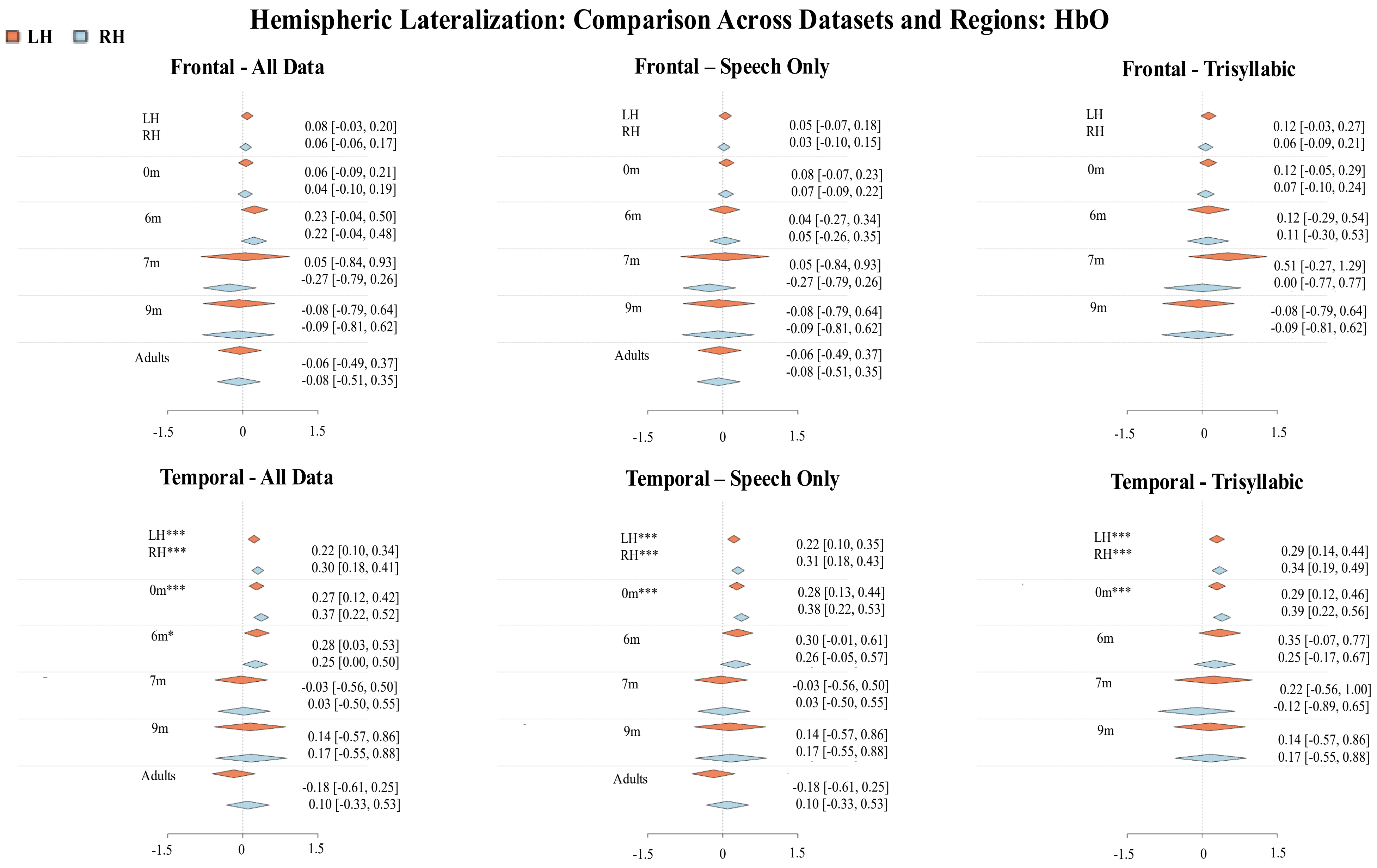

Figure 3: HbO Forest Plots

Figure 3 presents HbO forest plots comparing hemispheric lateralization across three datasets (All Data, Speech Only, and Trisyllabic) and two brain regions (Frontal and Temporal). Each plot displays effect sizes with 95% confidence intervals for both left hemisphere (LH, coral) and right hemisphere (RH, light blue) responses across different age groups (0 months, 6 months, 7 months, 9 months, and Adults), as well as overall meta-analytic estimates for each hemisphere, with asterisks used to indicate significance (*= $p<0.05$, **= $p< 0.01$, *** = $p<0.001$) .

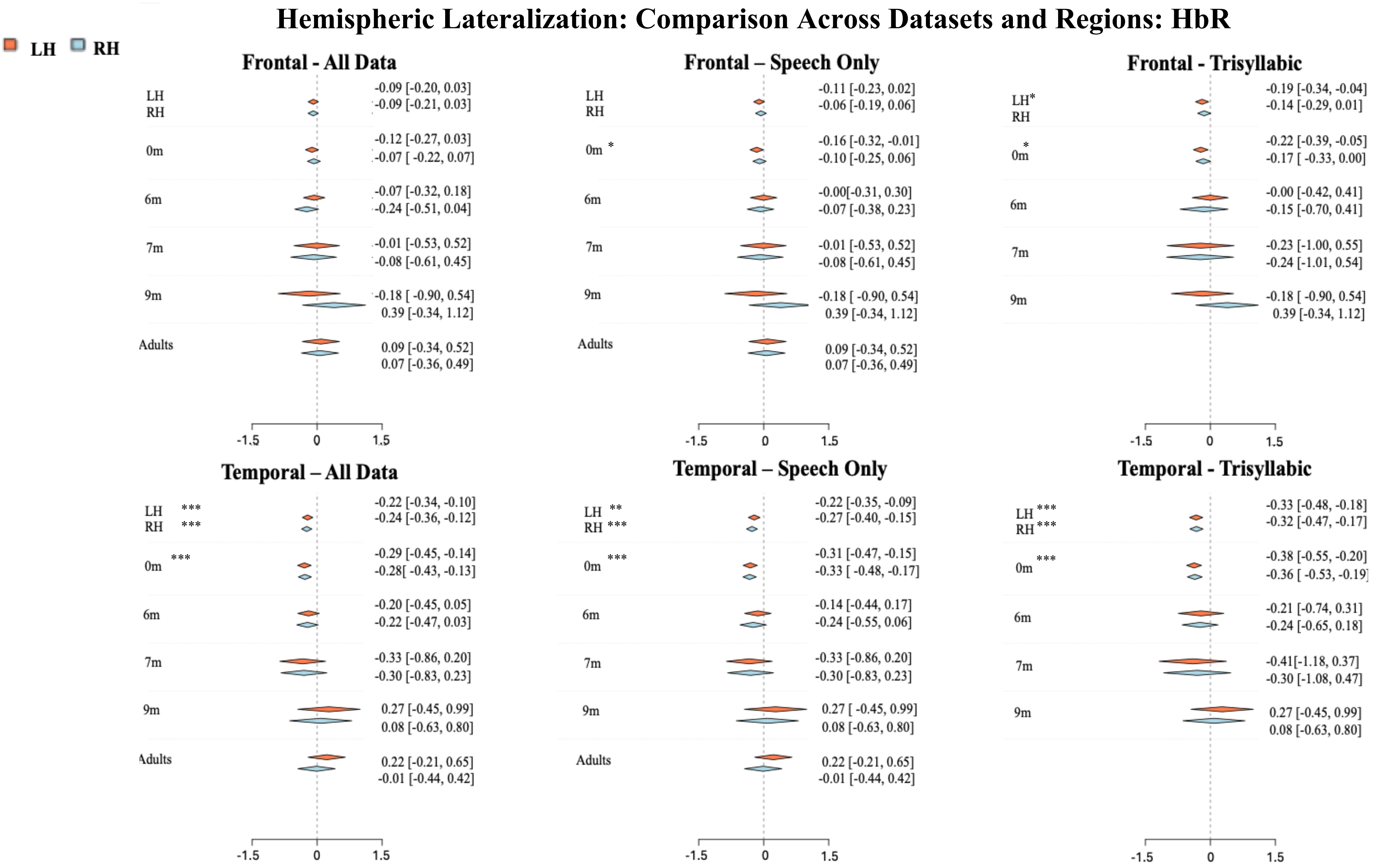

Figure 4: HbR Forest Plots

Figure 4 presents HbR forest plots comparing hemispheric lateralization across three datasets (All Data, Speech Only, and Trisyllabic) and two brain regions (Frontal and Temporal). Each plot displays effect sizes with 95% confidence intervals for both left hemisphere (LH, coral) and right hemisphere (RH, light blue) responses across different age groups (0 months, 6 months, 7 months, 9 months, and Adults), as well as overall meta-analytic estimates for each hemisphere, with asterisks used to indicate significance (*= $p<0.05$, **= $p< 0.01$, *** = $p<0.001$) .

3.2 Hemispheric Lateralization Effects

3.2.1 Hemisphere Main Effects

Our moderated HbO hemispheric analyses revealed non-significant main effects (All data:, $p = 0.7016$; Speech-only: $p = 0.6573$), indicating that both hemispheres follow similar developmental trajectories. Our HbR hemisphere effects were also non-significant (All data: $p = 0.8528$; Speech-only: $p = 0.9406$), further confirming the complementary developmental trajectory across LH and HR. While Age × Hemisphere interactions approached significance in our HbO all-data analysis ($p = 0.0912$) and in our HbR speech-only analysis ($p = 0.0546$), these effects were driven primarily by age-related changes affecting both hemispheres rather than true hemispheric specialization.

3.2.2 Regional Lateralization Patterns

No Hemisphere X Region interaction reaches statistical significance for HbO data across our subsets (all-data: Temporal: $p = 0.37$; Frontal: $p = 0.73$; speech-only: Temporal: $p = 0.36$; Frontal: $p = 0.79$), and the combination of wide confidence intervals (~ ± 0.15 to ± 0.18, all crossing zero) with consistently small effect sizes (Cohen's $d < 0.2$) prevents explicit confirmation of these lateralization patterns. Age × Region interactions for HbO data were not significant either (all-data: frontal: $p = 0.25$, temporal: $p = 0.13$; speech-only: frontal: $p = 0.77$, temporal: $p = 0.11$). Similar analyses over HbR generally supported the HbO findings of non-significant hemispheric effects. This lateralization index can be visualized below in Figure 5.

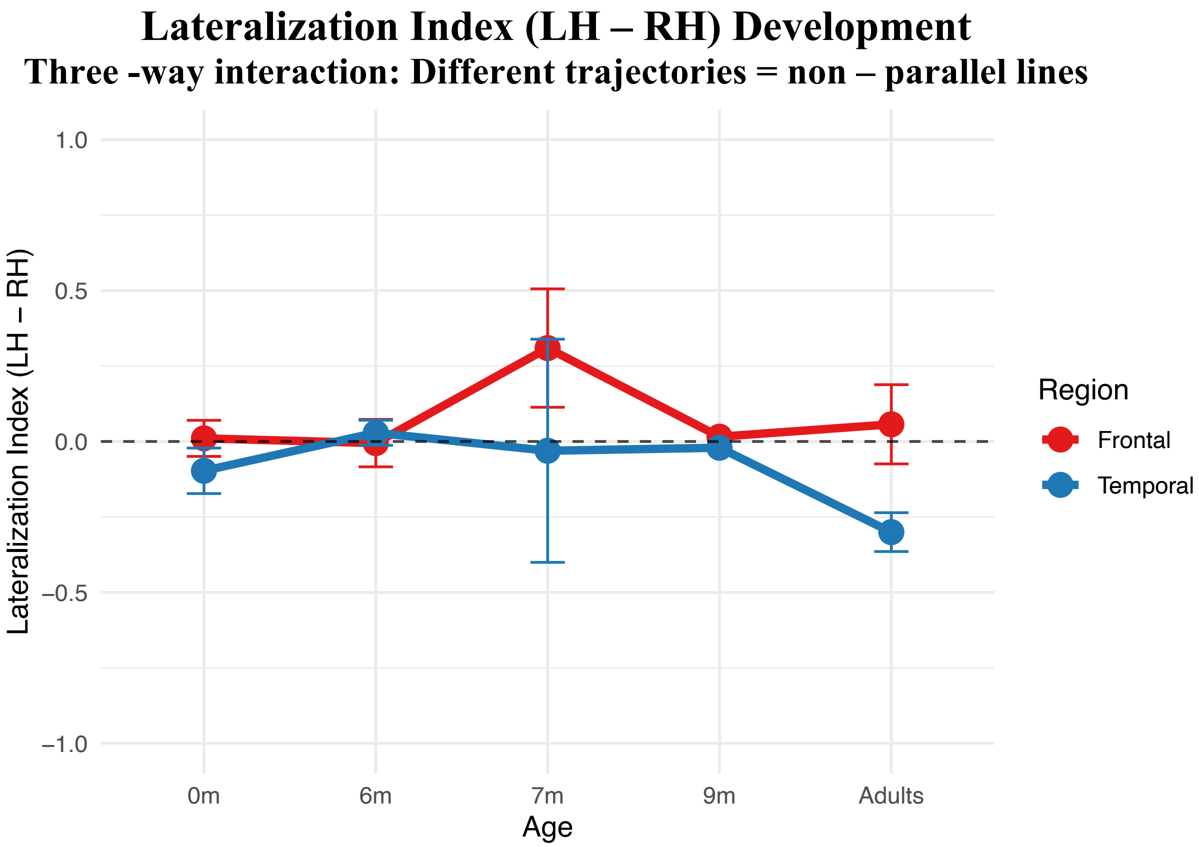

Figure 5: Lateralization Index HbO

Figure 5 displays the developmental trajectory of hemispheric lateralization for HbO, across age groups, showing the lateralization index (LH - RH) for both frontal (red) and temporal (blue) regions. The lateralization index represents the difference between left and right hemisphere activation, where positive values indicate left hemisphere dominance and negative values indicate right hemisphere dominance.

3.3 Age-Related Developmental Effects

In the comprehensive dataset (all data), Age effects approached significance over our HbO analysis ($p = 0.0532$), while our HbR speech-only analyses revealed weaker Age effects ($p = 0.0890$), indicating meaningful developmental differences in neural engagement. Furthermore, individual age group analyses reveal that adults show significant effects in our all-data ($p = 0.0369$) as well as speech-only ($p = 0.0275$) analyses. Additionally, HbR measures generally support these findings, showing even stronger age-effect significance in speech-only analyses (p

= 0.0284), with adults consistently demonstrating significant effects (p = 0.0071) and 9-month-olds approaching significance (p = 0.0532).

3.3.1 Developmental Trajectory Patterns

When visualizing the developmental trajectory analyses (Figures 6 and 7), we can see that HbO data reveals distinct patterns across age groups. Compared to newborns, 6-month-old infants show the largest HbO effects, particularly in speech-only analyses (estimate = -0.3389), 7-month-olds and adults demonstrated medium HbO effects (estimate: 7m: -0.2619, adults: -0.2559), while 9-month-olds consistently displayed the smallest effects across all analyses (HbO estimates: all data: 0.3309, speech-only: -0.1649, trisyllabic: -0.1809. HbR estimates: all data: -0.1506 , speech-only: 0.3631, trisyllabic: 0.4196). These measures support peak activation in both hemispheres at 6-7 months followed by progressively reduced activation into adulthood. Notably, adults reached statistical significance in both HbO all-data (p = 0.0369) and HbO speech-only analyses (p = 0.0275), while other age groups showed meaningful effect sizes without reaching significance. This pattern is further supported by our HbR speech-only analyses, which confirm significant age effects (p = 0.0284), though with different developmental timing.

Regional and Hemispheric Developmental Trajectories of HbO Lateralization Effects

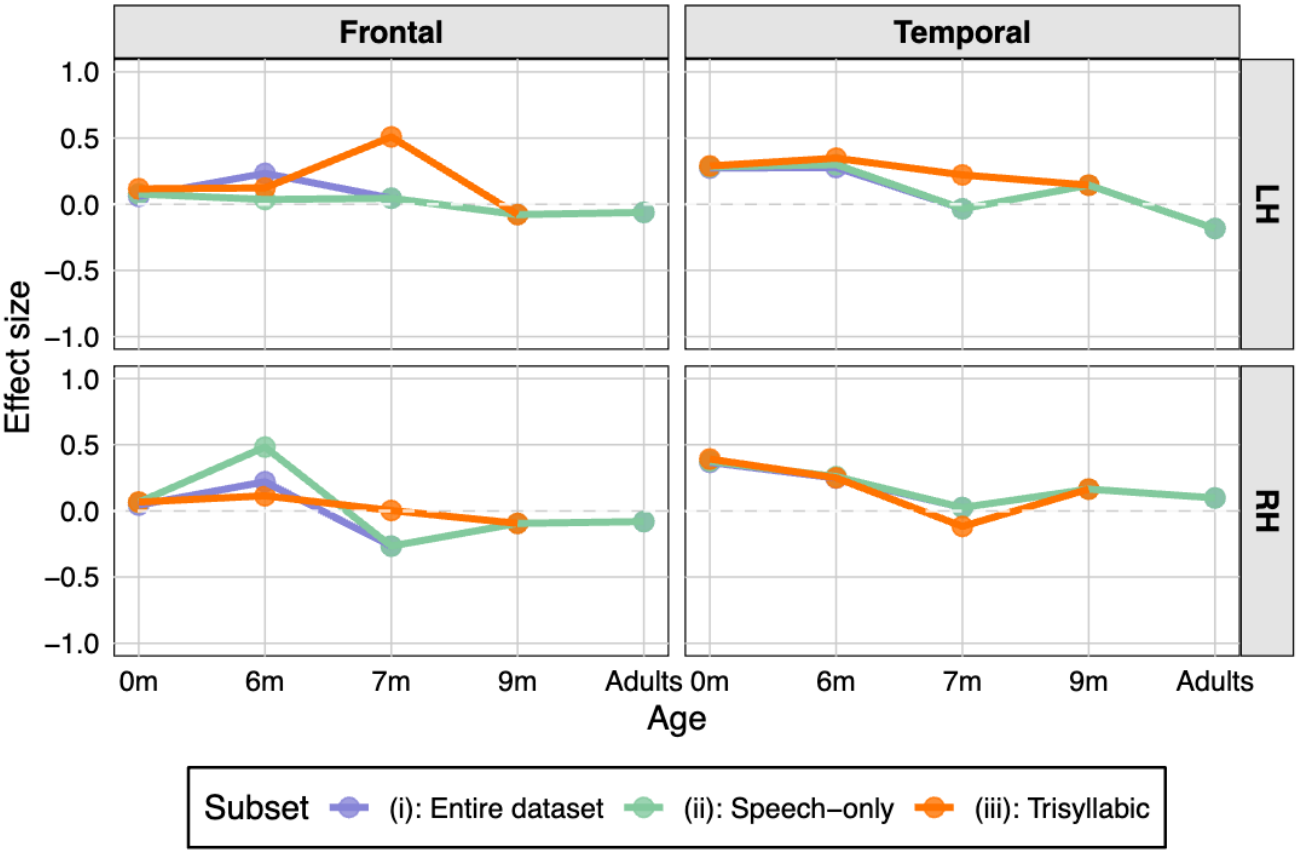

Figure 6: Regional and Hemispheric Developmental Trajectory Plots HbO

Figure 6 presents the developmental trajectories of hemispheric lateralization effects (HbO) across age groups, separated by brain region (Frontal and Temporal) and hemisphere (LH and RH) analyzed by dataset and hemisphere. Effect sizes are plotted for All Data (purple), Speech Only (green), and Trisyllabic (orange) conditions.

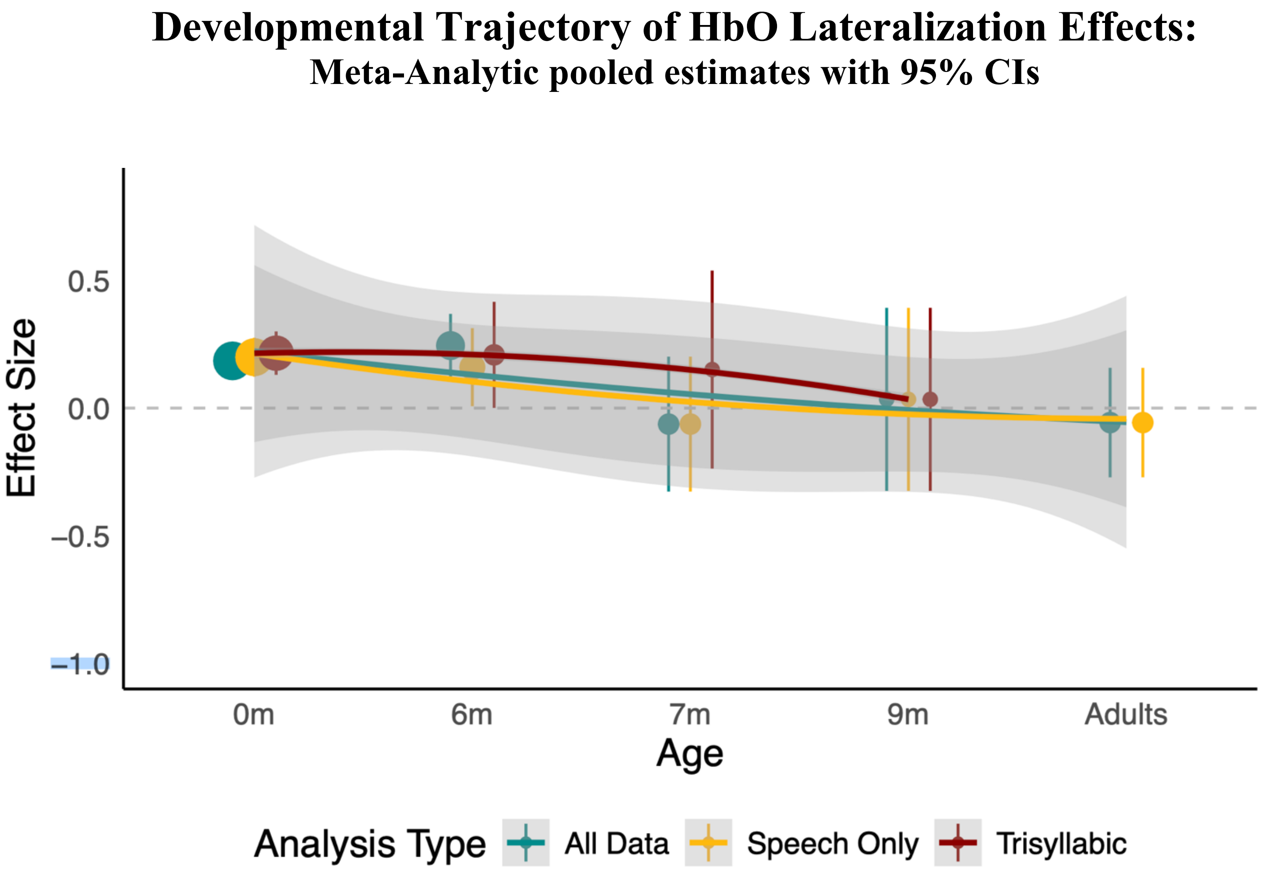
Developmental Trajectory of HbO Lateralization Effects:
Meta-Analytic pooled estimates with 95% CIs

Figure 7: Developmental Trajectory of Lateralization Effects HbO

Figure 7 illustrates the developmental changes in hemispheric lateralization effect sizes for oxygenated hemoglobin (HbO) across three distinct meta-analytic subsets from birth to Adulthood. Each colored line represents a different analysis: All Data (green), Speech Only (gold), and Trisyllabic (dark red). Data points show the mean effect size at each age with error bars representing 95% confidence intervals. Smooth trend lines with confidence bands were fitted using quadratic regression ($y \sim x + I(x^2)$) to capture potential non-linear developmental patterns.

4 Discussion

In this research, we conducted meta-analytic mixed-effects models in order to measure lateralization effects across development associated with linguistic pattern-recognition. We used these models to estimate the overall subgroup-level effect-sizes of neural responses across each Hemisphere (LH / RH), as well as across possible moderating factors Age (0m, 6m, 7m, 9m, Adults) and Region of Interest (Frontal & Temporal). Our fNIRS data consisted of 27 published and unpublished studies including, 525 infants (from 0m – 9m) and 42 adults. The purpose of our research is theoretical: to test the developmental trajectory of hemispheric lateralization during linguistic rule-learning, addressing a gap in current linguistic research. These analyses were computed across 3 different comparisons (All-data, Speech-only data, & Trisyllabic data), for both HbO and HbR fNIRS data.

4.1 Observed Effect Sizes

4.1.1 Age Effects

Our most important finding was that age had the most consistent significant or almost significant effect sizes across all of our analyses. The developmental trajectory of our age-effects (shown in Figure 7) revealed distinct patterns across age groups: six-month-olds showed the largest effects, followed by a notable decline at nine months where effects dropped to near zero, before increasing again in adults who demonstrated significant effects specifically in the right-hemisphere for both all-data and speech-only analyses. Here it is important to mention that in developmental research, small to medium effect sizes (0.2 - 0.3) are typical (Rabagliati et al., 2018). Thus, these results partially align with previous developmental research, as they suggest that infant brain responses to repetitive-linguistic stimuli undergo changes throughout development (Gemignani & Gervain, 2024). However, it contradicts a large body of current research, which suggests that the temporal LH should be more dominant in adults (Opitz et al., 2004; Binder et al., 1999; Belin et al., 2002; Hickok, 2009), as well as our hypothesis, since hemisphere was not a significant effect (as seen in Figure 6).

4.1.2 Hemisphere Effects

As previously mentioned, hemisphere analysis never showed significant results for any of the comparisons in any of our analyses. These effect sizes were consistently small and statistically non-significant. These findings contradict our initial hypothesis, which predicted left-lateralization regarding the developmental trajectory of linguistic rule-learning (Opitz et al., 2004; Binder et al., 1999; Belin et al., 2002; Hickok, 2009). However, it is likely that these findings are due to small sample size. Alternatively, it may be the case that repetition-based regularities truly engage both hemispheres to the same extent.

4.1.3 Region of Interest Effects

Our analyses revealed no significant effects of ROI, indicating that developmental trajectories and lateralization did not differ between the temporal and frontal regions. This may be related to the fact that both of these regions are strongly involved in language processing from birth. Future studies could compare these regions to brain areas known not to be involved in speech processing, such as the occipital areas.

4.2 Factors of Variability

4.2.1 Theoretically Relevant Sources of Variability

Our analyses revealed theoretically meaningful developmental patterns that provide insights into the neural activity that underlies linguistic rule-learning throughout development. We found that age indeed modulated effect sizes regarding the developmental trajectory of hemispheric lateralization during repetition-based language processing. Specifically, we observed age-related decreases in HbO responses along with increases in HbR responses, suggesting a fundamental shift in the hemodynamic responses during language processing from infancy to adulthood. Although this developmental pattern was numerically present across all datasets, it achieved significance most consistently in the speech-only analyses, where stimulus variability was reduced, thus allowing the effect of age to surface more clearly. Within our mixed-effects models, we observed particularly robust age effects in the right hemisphere for adults, with effect sizes being significantly greater than those of infants across both HbO and HbR measures. This effect was marginal in the all-data analysis but became highly significant in the speech-only dataset.

Furthermore, our results show no evidence that hemisphere nor region modulate effect sizes across development. This absence of main hemispheric effects, while contradicting our hypotheses, may reflect the specific nature of repetition-detection tasks, which appear to engage bilateral neural networks rather than the strongly lateralized language systems typically observed in higher-order linguistic processing (Gervain et al., 2012; Opitz et al., 2004).

These findings, thus, revealed only one statistically significantly trend, a shift in hemodynamic response patterns from infancy to adulthood for each dataset across both our HbO and HbR analyses.

4.3 Limitations & Future Implications

Our research sought to measure the developmental trajectories of hemispheric lateralization effects in linguistic rule-learning across multiple infants and adult fNIRS studies. Consequently, we needed to make several methodological choices that may have influenced our findings and, thus, should be considered when interpreting our results.

4.3.1 Measurement Reliability

There are several methodological factors that may be influencing the interpretation of our findings. First being, the relatively small adult sample size (n=42) compared to the larger infant sample (n=525). This is because typically, larger sample sizes yield more accurate results, as they allow for greater statistical power which controls for Type II errors (false negatives) (Biau et al., 2008). Furthermore, our standardized dataset is dominated mainly by high-activation infant responses, as opposed to adult responses, which typically have lower activation levels. Thus, while allowing for cross-study comparison, our standardized dataset may be affecting the precision of our adult effect estimates and contribute to the unexpected right-hemisphere effects observed in temporal regions as it can allow us to miss potential left-hemispheric effects (Fukui et al., 2003).

Secondly, regarding the headgears and optode configurations used throughout the 27 studies, the channels in which they were overlaid on the temporal areas seemed to vary less in respect to the underlying brain activity when compared to other channels (Gemignani et al., 2023). Unfortunately, this could not be controlled as the included studies used diverse optode configurations and headgear designs that were not originally designed for cross-study comparison, limiting our ability to define more precise ROIs. This may have contributed to our inability to detect the subtle left-lateralization typically observed in more targeted linguistic research. Additionally, by averaging across large bilateral regions, we may have obscured any subtle but theoretically important left-temporal specialization that has been consistently reported in adult language processing studies.

4.3.2 Analytical Limitations

Our decision to focus exclusively on repetition-based regularities compared to baseline (R vs 0) was theoretically motivated by previous research. R vs 0 comparisons have been shown to most directly reflect the infant brain's fundamental capacity to respond to repetition-based stimuli: the ability to represent repetition-based and non-repetition-based sequences do not emerge at the same developmental time, and therefore, represent two underlying abilities (Gemignani et al., 2024, Pavia de la Cruz et al., 2021). Thus, although our meta-analysis dataset included 24 studies with R vs N comparisons and 17 studies with N vs 0 comparisons, we chose to analyze the R vs 0 comparison to maximize statistical power within our largest sample (27 studies). However, whether similar developmental patterns extend to other linguistic processing paradigms, such as syntactic or semantic rule-learning, diversity-based regularities with respect to baseline (N vs 0) and direct comparisons between repetition- and diversity-based regularities (R vs N), remains to be determined. Future research incorporating the full range of comparisons would provide a more comprehensive understanding of hemispheric lateralization patterns across different aspects of linguistic rule-learning (Pavia de la Cruz et al., 2021).

Thus, several approaches would be beneficial regarding any future research on the development of lateralization throughout language development: First, researchers should also include N vs 0 and R vs N comparisons, as these are also required in order to best measure for lateralization across development as, more targeted analyses could reveal any process-specific effects that our broad method may have missed. Additionally, larger adult samples and more homogeneous stimulus protocols would enable for more reliable detection of subtle lateralization effects that our research also might have missed (Biau et al., 2008).

5 Conclusion

In conclusion, our meta-analysis addresses an important research gap in linguistic research by providing for the first time, a comprehensive developmental examination of hemispheric lateralization during linguistic rule-learning, demonstrating that age-related changes dominate over hemispheric effects. Our findings reshape the understanding of how language processing systems develop and mature over time. Where, instead of progressive hemispheric specialization, the development of linguistic repetition-based rule-learning initially appears to be characterized by bilateral patterns, though potential left-hemisphere specialization in adulthood may have been obscured by methodological limitations including small adult sample sizes and broad comparison analyses. These insights provide important foundations for future research in regard to understanding typical developmental language trajectories.

6 References

Abboub, N., Nazzi, T., & Gervain, J. (2016). Prosodic grouping at birth. *Brain and Language*, *162*, 46–59. https://doi.org/10.1016/j.bandl.2016.08.002

Belin, P., Zatorre, R. J., & Ahad, P. (2002). Human temporal-lobe response to vocal sounds. *Cognitive Brain Research*, *13*(1), 17–26. https://doi.org/10.1016/S0926-6410(01)00084-2

Bergmann, C., & Cristia, A. (2016). Development of infants' segmentation of words from native speech: A meta-analytic approach. *Developmental Science*, *19*(6), 901–917. https://doi.org/10.1111/desc.12341

Bergmann, C., Tsuji, S., Piccinini, P. E., Lewis, M. L., Braginsky, M., Frank, M. C., & Cristia, A. (2018). Promoting Replicability in Developmental Research Through Meta-analyses: Insights From Language Acquisition Research. *Child Development*, *89*(6), 1996–2009. https://doi.org/10.1111/cdev.13079

Biau, D. J., Kernéis, S., & Porcher, R. (2008). Statistics in brief: The importance of sample size in the planning and interpretation of medical research. *Clinical Orthopaedics and Related Research*, *466*(9), 2282–2288. https://doi.org/10.1007/s11999-008-0346-9

Binder, J. R., Rao, S. M., Hammeke, T. A., Frost, J. A., Bandettini, P. A., Jesmanowicz, A., & Hyde, J. S. (1995). Lateralized Human Brain Language Systems Demonstrated by Task Subtraction Functional Magnetic Resonance Imaging. *Archives of Neurology*, *52*(6), 593–601. https://doi.org/10.1001/archneur.1995.00540300067015

Borenstein, M., Hedges, L. V., Higgins, J. P. T., & Rothstein, H. R. (2009). *Introduction to Meta-Analysis* (1st ed.). Wiley. https://doi.org/10.1002/9780470743386

Braver, S. L., Thoemmes, F. J., & Rosenthal, R. (2014). Continuously Cumulating Meta-Analysis and Replicability. *Perspectives on Psychological Science*, *9*(3), 333–342. https://doi.org/10.1177/1745691614529796

Carral, V., Huotilainen, M., Ruusuvirta, T., Fellman, V., Näätänen, R., & Escera, C. (2005). A kind of auditory 'primitive intelligence' already present at birth. *European Journal of Neuroscience*, *21*(11), 3201–3204. https://doi.org/10.1111/j.1460-9568.2005.04144.x

Caruana, E. J., Roman, M., Hernández-Sánchez, J., & Solli, P. (2015). Longitudinal studies. *Journal of Thoracic Disease*, *7*(11), E537-540. https://doi.org/10.3978/j.issn.2072-1439.2015.10.63

Chen, Y., Green, H. L., Putt, M. E., Allison, O., Kuschner, E. S., Kim, M., Blaskey, L., Mol, K., McNamee, M., Bloy, L., Liu, S., Huang, H., Roberts, T. P. L., & Edgar, J. C. (2023). Maturation of auditory cortex neural responses during infancy and toddlerhood. *NeuroImage*, *275*, 120163. https://doi.org/10.1016/j.neuroimage.2023.120163

Collins-Jones, L. H., Cooper, R. J., Bulgarelli, C., Blasi, A., Katus, L., McCann, S., Mason, L., Mbye, E., Touray, E., Ceesay, M., Moore, S. E., Lloyd-Fox, S., Elwell, C. E., & BRIGHT Study Team. (2021). Longitudinal infant fNIRS channel-space analyses are robust to variability parameters at the group-level: An image reconstruction investigation. *NeuroImage*, *237*, 118068. https://doi.org/10.1016/j.neuroimage.2021.118068

De La Cruz-Pavía, I., & Gervain, J. (2021). Infants' perception of repetition-based regularities in speech: A look from the perspective of the same/different distinction. *Current Opinion in Behavioral Sciences*, *37*, 125–132. https://doi.org/10.1016/j.cobeha.2020.11.014

Dehaene-Lambertz, G., Dehaene, S., & Hertz-Pannier, L. (2002). Functional Neuroimaging of Speech Perception in Infants. *Science*, *298*(5600), 2013–2015. https://doi.org/10.1126/science.1077066

Endress, A. D., Dehaene-Lambertz, G., & Mehler, J. (2007). Perceptual constraints and the learnability of simple grammars. *Cognition*, *105*(3), 577–614. https://doi.org/10.1016/j.cognition.2006.12.014

Endress, A. D., Nespor, M., & Mehler, J. (2009). Perceptual and memory constraints on language acquisition. *Trends in Cognitive Sciences*, *13*(8), 348–353. https://doi.org/10.1016/j.tics.2009.05.005

Forkstam, C., Hagoort, P., Fernandez, G., Ingvar, M., & Petersson, K. M. (2006). Neural correlates of artificial syntactic structure classification. *NeuroImage*, *32*(2), 956–967. https://doi.org/10.1016/j.neuroimage.2006.03.057

Fukui, Y., Ajichi, Y., & Okada, E. (2003). Monte Carlo prediction of near-infrared light propagation in realistic adult and neonatal head models. *Applied Optics*, *42*(16), 2881. https://doi.org/10.1364/AO.42.002881

Gemignani, J., De La Cruz-Pavía, I., Martinez, A., Nallet, C., Pasquini, A., Lucarini, G., Cavicchiolo, F., & Gervain, J. (2023). Reproducibility of infant fNIRS studies: A meta-analytic approach. *Neurophotonics*, *10*(02). https://doi.org/10.1117/1.NPh.10.2.023518

Gemignani, J., & Gervain, J. (2021). Comparing different pre-processing routines for infant fNIRS data. *Developmental Cognitive Neuroscience*, *48*, 100943. https://doi.org/10.1016/j.dcn.2021.100943

Gemignani, J., & Gervain, J. (2024). Brain responses to repetition-based rule-learning do not exhibit sex differences: An aggregated analysis of infant fNIRS studies. *Scientific Reports*, *14*(1), 2611. https://doi.org/10.1038/s41598-024-53092-2

Gervain, J., Berent, I., & Werker, J. F. (2012). Binding at Birth: The Newborn Brain Detects Identity Relations and Sequential Position in Speech. *Journal of Cognitive Neuroscience*, *24*(3), 564–574. https://doi.org/10.1162/jocn_a_00157

Gervain, J., De La Cruz-Pavía, I., & Gerken, L. (2020). Behavioral and Imaging Studies of Infant Artificial Grammar Learning. *Topics in Cognitive Science*, *12*(3), 815–827. https://doi.org/10.1111/tops.12400

Gervain, J., Macagno, F., Cogoi, S., Peña, M., & Mehler, J. (2008). The neonate brain detects speech structure. *Proceedings of the National Academy of Sciences*, *105*(37), 14222–14227. https://doi.org/10.1073/pnas.0806530105

Goh, J. X., Hall, J. A., & Rosenthal, R. (2016). Mini Meta-Analysis of Your Own Studies: Some Arguments on Why and a Primer on How. *Social and Personality Psychology Compass*, *10*(10), 535–549. https://doi.org/10.1111/spc3.12267

Gomez, R. L., & Gerken, L. (1999). Artificial grammar learning by 1-year-olds leads to specific and abstract knowledge. *Cognition*, *70*(2), 109–135. https://doi.org/10.1016/S0010-0277(99)00003-7

Henson, R., Shallice, T., & Dolan, R. (2000). Neuroimaging Evidence for Dissociable Forms of Repetition Priming. *Science*, *287*(5456), 1269–1272. https://doi.org/10.1126/science.287.5456.1269

Hickok, G. (2009). The functional neuroanatomy of language. *Physics of Life Reviews*, *6*(3), 121–143. https://doi.org/10.1016/j.plrev.2009.06.001

Hickok, G., & Poeppel, D. (2000). Towards a functional neuroanatomy of speech perception. *Trends in Cognitive Sciences*, *4*(4), 131–138. https://doi.org/10.1016/S1364-6613(00)01463-7

Hickok, G., & Poeppel, D. (2007). The cortical organization of speech processing. *Nature Reviews Neuroscience*, *8*(5), 393–402. https://doi.org/10.1038/nrn2113

Huberty, S., O'Reilly, C., Carter Leno, V., Steiman, M., Webb, S., Elsabbagh, M., & The BASIS Team. (2023). Neural mechanisms of language development in infancy. *Infancy*, *28*(4), 754–770. https://doi.org/10.1111/infa.12540

Kemler Nelson, D. G., Jusczyk, P. W., Mandel, D. R., Myers, J., Turk, A., & Gerken, L. (1995). The head-turn preference procedure for testing auditory perception. *Infant Behavior and Development*, *18*(1), 111–116. https://doi.org/10.1016/0163-6383(95)90012-8

Kepinska, O., De Rover, M., Caspers, J., & Schiller, N. O. (2017). On neural correlates of individual differences in novel grammar learning: An fMRI study. *Neuropsychologia*, *98*, 156–168. https://doi.org/10.1016/j.neuropsychologia.2016.06.014

Koulaguina, E., & Shi, R. (2013). Abstract Rule Learning in 11- and 14-Month-Old Infants. *Journal of Psycholinguistic Research*, *42*(1), 71–80. https://doi.org/10.1007/s10936-012-9208-4

Kuhl, P. K. (2010). Brain Mechanisms in Early Language Acquisition. *Neuron*, *67*(5), 713–727. https://doi.org/10.1016/j.neuron.2010.08.038

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

Leppänen, P. H. T., Richardson, U., Pihko, E., Eklund, K. M., Guttorm, T. K., Aro, M., & Lyytinen, H. (2002). Brain Responses to Changes in Speech Sound Durations Differ Between Infants With and Without Familial Risk for Dyslexia. *Developmental Neuropsychology*, *22*(1), 407–422. https://doi.org/10.1207/S15326942dn2201_4

Lewis, M., Braginsky, M., Tsuji, S., Bergmann, C., Piccinini, P. E., Cristia, A., & Frank, M. C. (2016). *A Quantitative Synthesis of Early Language Acquisition Using Meta-Analysis*. PsyArXiv. https://doi.org/10.31234/osf.io/htsjm

Marcus, G. F., Vijayan, S., Bandi Rao, S., & Vishton, P. M. (1999). Rule Learning by Seven-Month-Old Infants. *Science*, *283*(5398), 77–80. https://doi.org/10.1126/science.283.5398.77

Opitz, B., & Friederici, A. D. (2003a). Interactions of the hippocampal system and the prefrontal cortex in learning language-like rules. *NeuroImage*, *19*(4), 1730–1737. https://doi.org/10.1016/S1053-8119(03)00170-8

Opitz, B., & Friederici, A. D. (2003b). Interactions of the hippocampal system and the prefrontal cortex in learning language-like rules. *NeuroImage*, *19*(4), 1730–1737. https://doi.org/10.1016/S1053-8119(03)00170-8

Opitz, B., & Friederici, A. D. (2004). Brain Correlates of Language Learning: The Neuronal Dissociation of Rule-Based versus Similarity-Based Learning. *The Journal of Neuroscience*, *24*(39), 8436–8440. https://doi.org/10.1523/JNEUROSCI.2220-04.2004

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

Rabagliati, H., Ferguson, B., & Lew-Williams, C. (2019). The profile of abstract rule learning in infancy: Meta-analytic and experimental evidence. *Developmental Science*, *22*(1), e12704. https://doi.org/10.1111/desc.12704

Rosenthal, R. (1979). The file drawer problem and tolerance for null results. *Psychological Bulletin*, *86*(3), 638–641. https://doi.org/10.1037/0033-2909.86.3.638

Sato, Y., Sogabe, Y., & Mazuka, R. (2010). Development of Hemispheric Specialization for Lexical Pitch–Accent in Japanese Infants. *Journal of Cognitive Neuroscience*, *22*(11), 2503–2513. https://doi.org/10.1162/jocn.2009.21377

Seghier, M. L. (2008). Laterality index in functional MRI: Methodological issues. *Magnetic Resonance Imaging*, *26*(5), 594–601. https://doi.org/10.1016/j.mri.2007.10.010

Sha, Z., Schijven, D., Carrion-Castillo, A., Joliot, M., Mazoyer, B., Fisher, S. E., Crivello, F., & Francks, C. (2021). The genetic architecture of structural left–right asymmetry of the human brain. *Nature Human Behaviour*, *5*(9), 1226–1239. https://doi.org/10.1038/s41562-021-01069-w

Shevtsova, N., & Reggia, J. A. (1999). A Neural Network Model of Lateralization during Letter Identification. *Journal of Cognitive Neuroscience*, *11*(2), 167–181. https://doi.org/10.1162/089892999563300

The ManyBabies Consortium, Frank, M. C., Alcock, K. J., Arias-Trejo, N., Aschersleben, G., Baldwin, D., Barbu, S., Bergelson, E., Bergmann, C., Black, A. K., Blything, R., Böhland, M. P., Bolitho, P., Borovsky, A., Brady, S. M., Braun, B., Brown, A., Byers-Heinlein, K., Campbell, L. E., … Soderstrom, M. (2020). Quantifying Sources of Variability in Infancy Research Using the Infant-Directed-Speech Preference. *Advances* *in Methods and Practices in Psychological Science*, *3*(1), 24–52. https://doi.org/10.1177/2515245919900809

Valentine, J. C., Pigott, T. D., & Rothstein, H. R. (2010). How Many Studies Do You Need?: A Primer on Statistical Power for Meta-Analysis. *Journal of Educational and Behavioral Statistics*, *35*(2), 215–247. https://doi.org/10.3102/1076998609346961

Viechtbauer, W. (2010). Conducting Meta-Analyses in *R* with the **metafor** Package. *Journal of Statistical Software*, *36*(3). https://doi.org/10.18637/jss.v036.i03

Virtala, P., Kujala, T., Partanen, E., Hämäläinen, J. A., & Winkler, I. (2023). Neural phoneme discrimination in variable speech in newborns – Associations with dyslexia risk and later language skills. *Brain and Cognition*, *168*, 105974. https://doi.org/10.1016/j.bandc.2023.105974

Wallois, F., Mahmoudzadeh, M., Patil, A., & Grebe, R. (2012). Usefulness of simultaneous EEG–NIRS recording in language studies. *Brain and Language*, *121*(2), 110–123. https://doi.org/10.1016/j.bandl.2011.03.010

Wise, R. J. S., Scott, S. K., Blank, S. C., Mummery, C. J., Murphy, K., & Warburton, E. A. (2001). Separate neural subsystems within `Wernicke's area'. *Brain*, *124*(1), 83–95. https://doi.org/10.1093/brain/124.1.83

Yücel, M. A., Lühmann, A. V., Scholkmann, F., Gervain, J., Dan, I., Ayaz, H., Boas, D., Cooper, R. J., Culver, J., Elwell, C. E., Eggebrecht, A., Franceschini, M. A., Grova, C., Homae, F., Lesage, F., Obrig, H., Tachtsidis, I., Tak, S., Tong, Y., … Wolf, M. (2021). Best practices for fNIRS publications. *Neurophotonics*, *8*(01). https://doi.org/10.1117/1.NPh.8.1.012101