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Children Track Probabilistic Information in Speech Differently from Adults

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Abstract

Language learning is a sophisticated process as learners need to detect and extract rich regularities embedded in the continuous speech inputs. Children, compared to adults, appear to learn languages more effortlessly. Nevertheless, early studies in implicit statistical learning revealed little developmental differences between children and adults. Recent work has found the speed of statistical learning in adults is associated with their neural sensitivity to probabilistic information in speech. It is not well understood, however, whether children share similar or different underlying neural processes for probabilistic information compared to adults. Specifically, are children similar to faster or slower adult statistical learners, or neither of them? In the current study, children aged between 5 and 12 completed a passive auditory oddball task, where they listened to syllables at different local and global frequency of occurrence. We used two neurophysiological measures, auditory mismatch responses (MMR) and late discriminative negativity (LDN) to compare children's sensitivity to distributional probabilities in speech with adults. We found that children were more sensitive to probabilistic information in speech inputs at both the local and the global level than both faster and slower adult statistical learners. Moreover, unlike adults who integrate probabilistic information across global and local hierarchies, children seem to process different levels of probabilistic information in parallel.

Keywords: Statistical Learning; Language Development; Mismatching Response; Late Discriminative Negativity; EEG

Introduction

The From the moment we are born, our sensory organs are continuously being bombarded with information that varies in its' consistency across time. Importantly, this information is not simply a series of random events, but rather contains a regular and probabilistic structure that makes it possible to recognize and predict upcoming information. Remarkably, humans possess an exceptional ability to perceive and detect temporal regularities and variabilities in continuous speech both on a local scale (e.g., milliseconds) and across a longer time scale (e.g., minutes) as they take place. This skill, also known as Statistical Learning (SL), is particularly critical in language acquisition, as it allows us to acquire key properties of language such as phonemic and syntactic categories (Werker et al., 2007; Maye et al., 2002). As we hear a continuous stream of acoustic signals, we start computing multiple levels of frequency information that exist within speech – from lower level information that forms speech sound categories to higher level information that shapes lexical, semantic, and syntactic regularities. By doing so, we can parse the continuous stream of acoustic speech signals into linguistic units, such as phonemes, syllables, words, and sentences (Johnson & Tyler, 2010), and ultimately, understand what these signals mean. Therefore, the process of detecting distributional regularities from the environment helps us to learn the basic building blocks of language, which we can then use to construct more complex and hierarchical linguistic structures.

Infants, children, and adults are sensitive to these distributional statistics in the environment, such as frequency of occurrence and co-occurrence, using them to learn various aspects of language, including word boundaries in continuous speech (Saffran, Aslin, & Newport, 1996; Saffran, 2001), speech categories (Maye, Weiss, & Aslin, 2008), phonotactic structures (Chambers, Onishi, & Fisher, 2003), and abstract representations of sequential patterns (Gomez & Gerken, 1999). For example, Maye, Weiss, and Aslin (2008) found that 8-month-old infants' ability to recognize patterns in speech plays a role in how they learn to perceive their native language. They observed that as infants learned to categorize sounds that were important in their language, they became better at distinguishing between phonetic differences that were initially challenging for them. Gómez and Gerken (1999) also suggested that 12-month-old children could distinguish new grammatical from non-grammatical sequences after brief exposure to an artificial grammar, indicating that they are capable of detecting distributional regularities from the input statistics to acquire language structures. However, it remains unknown whether SL ability remains constant over the course of a lifetime. Individuals at

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different developmental stages may process different types of probabilistic patterns in different ways, which may result in distinct representations of information (Forest, Schlichting, Duncan, & Finn, 2023).

The developmental account aligns with a well-known phenomenon in the language acquisition field – the success of acquiring a new language declines as age increases, with younger children achieving native-like fluency at much higher rates than older children and adults (Johnson & Newport, 1989; Newport, 1990; Hartshorne et al., 2018). Since SL has been proposed to play a key role in language acquisition (Bates & Elman, 1996; Romberg & Saffran, 2010), children's advantage for language learning may be partially accounted for by age-related changes in SL ability. Unlike the clear developmental advantage of adults in visual SL that has been attribute to more mature domain-general cognitive capacity (Arciuli & Simpson, 2011; Raviv & Arnon, 2017; Fortenbaugh et al., 2015; see Forest et al., 2023 for an review), surprisingly, the few existing studies examining the developmental differences in SL in the auditory speech domain suggested a lack of or a weak age-related effect (e.g., Saffran et al., 1997; Raviv & Arnon, 2017; Moreau et al., 2022; Ren et al., 2023). The fact that adults and older children, with more mature cognitive capacity and more prior language experiences, are not performing necessarily better than younger children in auditory linguistic SL, suggest certain underlying processing mechanisms are advantageous in children than adults. Indeed, the latest behavioral work suggest children are faster than adults in learning the embedded triplet structure in a continuous speech stream, despite similar offline recognition accuracy (Hu et al., 2022). However, little is known how children differ from adults *during* the processing of frequency-sensitive statistical information in speech.

Recent work has highlighted that statistical learning is not a unified construct. Instead, empirical evidence has shown abilities to learn linguistic and non-linguistic statistical patterns vary within individuals (e.g., Siegleman et al., 2015; Erickson et al., 2016). Dissociations between linguistic and nonlinguistic statistical learning in the developmental work (e.g., Shufania & Arnon, 2018; Hu et al., 2023) also supported the possibility that human brains process linguistic and nonlinguistic statistical patterns differently, which may result in different developmental trajectories.

Electrophysiological measures provide a valuable and tool for monitoring how children and adults detect and encode distributional probabilistic information without the cognitive demands of an explicit task. By measuring electrical signals that occur in the brain in response to repeated auditory stimuli, researchers can examine the integrity of early stages of neural processing up to the brain (Bishop, 2007). Numerous studies have found that the presence of a mismatching response (MMR) in the brain is linked to the ability to discriminate between frequent and rare stimuli, especially in response to locally rare stimuli (i.e., shorter time scale) in some infants and younger children, making it a useful tool for studying developmental differences in auditory speech sound discrimination. The MMR is often followed by a late negative component, also known as Late Discriminative Negativity (LDN), around 300 – 600 ms after the onset of deviants (Korpilahti, Krause, Holopainen, & Lang, 2001; Cheour, Korpilahti, Martynova, & Lang, 2001; Martynova, Kirjavainen, & Cheour, 2003). Although the functional significance of the LDN remains inconclusive, existing evidence suggests that it seems to be (1) language-specific (Korpilahti et al., 2001), (2) triggered by auditory rule extraction processes, (3) reflects a process of transferring rules into long-term memory (Zachau et al., 2005). A recent study validated MMR and LDN as indices of auditory sensitivity to probabilistic information in speech. In adults, MMR and LDN have been found to be sensitive to local (P(deviant) within 3-10 syllables) and global (P(deviant) within hundreds of syllables) frequency of occurrences, respectively, in a continuous stream of syllables (Schneider et al., 2022). The same group of adults also completed an auditory statistical learning task, where the acceleration of response time was used to index implicit learning of embedded triplet patterns (Schneider et al., 2020). Those who showed faster learning also displayed greater integration of probabilistic information across the local and global levels during passive listening, implicated by a shift from an LDN response to a P3a-like response, whereas the slower learners showed a relatively consistent LDN pattern.

In the current study, we aim to examine differences between children and adults in their underlying neural processes to track distributional probabilities of speech inputs across local and global levels and across syllabic (linguistic) and acoustic (nonlinguistic) domains. By comparing children to two groups of adults (faster learners vs. slower learners), we ask the following two questions: (1) Do children process global and local probability differently from adults? (2) If so, are the developmental differences specific to phonemic processing or speech acoustic processing in general?

Methods

Participants

The current study involved sixty-seven participants, divided into three groups. The Child Group consisted of twenty-two school-aged neurotypical children ($M_{\text{age}} = 10.2$, $SD_{\text{age}} = 1.99$, 5 males). The adult participants were the same sample reported in Schneider et al. (2022) but divided into the faster and the slower learner groups. The grouping in adults was based on adults' behavior performance during a target detection task when listening to a speech stream with embedded triplet structure. The target stimuli were the third element of a given triplet. As learning continued, faster RT acceleration (i.e., more negative RT slope) indicated faster implicit learning, while slower RT acceleration (i.e., more positive RT slope) indicated slower implicit learning. The Faster Learner Group included twenty-two adults with negative RT slope ($M_{\text{RT slope}} = -22.76$, $SD_{\text{RT slope}} = 1.95$, 6 males) and the Slower Learner Group included twenty-three adults with positive RT slope ($M_{\text{RT slope}} = 21.03$, $SD_{\text{RT slope}} = 2.02$, 11 males). All participants were right-handed, native English speakers, with no history of neurological or psychiatric disorders, or brain damage. All had average or above-average non-verbal intelligence (age-based standard score > 85) as measured by the Matrices subtest (Faster Learner Group: $M = 107.84$, $SD = 12.89$; Slower Learner Group: $M = 109.37$, $SD = 14.15$; Child Group: $M = 105.6$, $SD = 33.38$) of the Kaufman Brief Intelligence Test (KBIT-2; Kaufman & Kaufman, 2004). Adult groups and children were matched on gender distribution, and there were no significant differences between groups in their non-verbal intelligence ($ps > .05$). All participants were compensated for their participation. Participants provided written informed consent before the experiment.

Auditory Oddball Paradigm

The auditory oddball paradigm was adopted from Schneider et al. (2022). In this task, two female English native speakers produced sounds of "bog" and "dog" 100 times for each word in a picture-naming task. The naturalistic /ba/ and /da/ sounds were then manually cut from the original recordings. 100 tokens for each word were digitally recorded using a SHURE SM58 microphone and Edirol UA-25EX sound card, sampling at 44.1 kHz. 50 tokens with better recording quality were then chosen for the experiment. The duration of each sound file was 180 ms with ramping at the beginning and the end each syllable. The intensity of each sound was normalized to 70dB. Two auditory streams of 1500 stimuli (SOA = 0.7 seconds) were created consisting of standard and deviant conditions (see Figure 1 for visualization of paradigm). The standard condition included repeated presentations of the /ba/ syllable spoken by one female speaker. To understand listeners' sensitivity to the linguistic domain, we manipulated the deviants as linguistic and non-linguistic deviants. The linguistic deviant was a different syllable, /da/, spoken by the same speaker as in the standard condition. The non-linguistic deviant was the same syllable, /ba/, spoken by a different female speaker, suggesting the only difference between /ba/ sounds was related to non-linguistic voice acoustics rather than linguistic qualities. To examine listeners' sensitivity to global probability, we manipulated the frequency of deviant stimuli across two experimental 6-minute blocks. In both blocks, standard stimuli were presented 1200 times, resulting in a global probability of 0.80 (1200 standards /1500 total stimuli). In one block, the linguistic deviant occurred at a high frequency (global probability = 0.13; 200 deviants/1500 total stimuli), while the non-linguistic deviant occurred at a low frequency (global probability = 0.07; 100 deviants /1500 total stimuli). In the other block, the non-linguistic deviant occurred at a high frequency (global probability = 0.13), while the linguistic deviant occurred at a low frequency (global probability = 0.07). The block order was counterbalanced across participants. Moreover, to investigate listeners' sensitivity to local probability, we manipulated the number of standard stimuli preceding deviant stimuli within each global probability condition. In the low local probability condition, two standard stimuli were presented before a linguistic or non-linguistic deviant (i.e., /STANDARD/ − /STANDARD/ − /DEVIANT/). In the high local probability condition, six standard stimuli were presented before a linguistic or non-linguistic deviant (i.e., /STANDARD/ − /STANDARD/ − /STANDARD/−/STANDARD/−/STANDARD/−/DEVIANT/). High frequency and low frequency conditions were randomly interspersed in each auditory stream. The local probability conditions were randomly ordered within each auditory stream.

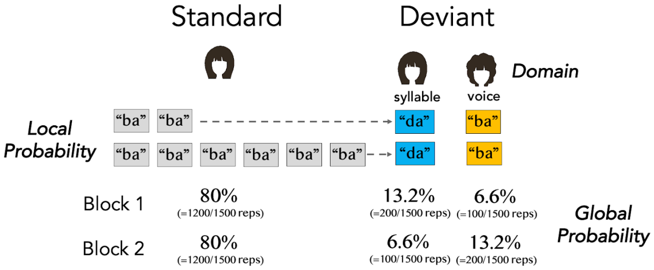

Figure 1: Schematic illustration of the EEG Paradigm. The global probability was manipulated across the two blocks. In the first block there were greater repetitions (reps) of the linguistic deviant, as compared to the non-linguistic deviant, and this pattern switched in the second block. The local probability was manipulated within each block. In the high condition two standard stimuli were presented before the linguistic or non-linguistic deviant and in the low condition six standard stimuli were presented before the deviant. Block order was counterbalanced across participants.

EEG Recording Procedure

The EEG recording procedure follows that of Schneider et al. (2022) study. Participants were instructed to watch a silent animation movie while listening to the auditory streams through a pair of noise-attenuating Cortech ER-2 earphones. Each experimental block lasted for 17.5 minutes. All the visual and auditory stimuli were presented using Presentation® software (Version 18.0, Neurobehavioral Systems, Inc., Berkeley, CA, www.neurobs.com). EEG was recorded with a 24-channel mobile EEG system (SMARTING, mBrainTrain, Belgrade, Serbia) which features a sampling rate of 500 Hz, a resolution of 24 bits, and a bandwidth from 0 to 250 Hz (SMARTING, www.mbraintrain.com). The amplifier used in this study includes a 3D gyroscope and power supply for several hours use (weight 64 grams; size 82 × 51 × 14 mm). Data is transmitted wirelessly via Bluetooth (v2.1) to a nearby paired laptop. Electrode impedances were kept below 10 kΩ. Recordings were online referenced to electrode FCz and grounded to electrode AFz. All data was saved using Labrecorder software, which is part of the Lab Streaming Layer (LSL).

Data Preprocessing

All continuous raw data was high-pass filtered at 0.1 Hz, low-pass filtered at 30 Hz, and re-referenced to the mastoids. An Independent Components Analysis (ICA; Delorme, Makeig, & Sejnowski, 2001) was carried out for artifact removal. The components related to eye-movements or muscle activity were identified and removed from the data on the basis of their time-courses, frequency spectra and topographies. The data was then epoched from 100 msec before to 600 msec after stimulus onset and baseline corrected to the 100 msec before stimulus onset. Trials were removed from analysis if the peak-to-peak voltage between 100 ms pre-stimulus and 600 ms post-stimulus exceeded 100 µV for any of the 24 EEG channels. On average, the Child Group had 5.01 components (*SD* = 3.16) and 32.01 trials (*SD* = 15.35) removed. In addition, there were 3.48 components (*SD* = 1.3) and 28.98 trials (*SD* = 10.41) were removed in the Faster SL Adult Learner Group. The same pattern was observed in the Slower SL Adult Learner Group, where 3.69 components (*SD* = 1.1) and 27.34 trials (*SD* = 11.87) were removed.

To ensure the time windows and electrodes of interest for the MMR and LDN components are suitable for the developmental samples we investigated, our choices follow a previous developmental study that examined the developmental changes of these components across children, adolescents, and adults (Bishop et al., 2011). As a result, we measured the mean amplitude of the difference wave for the MMR between 100 and 250 ms after the onset of the stimulus, and for the LDN, we focused on 300 – 550 ms after the onset of the stimuli. We kept all the electrodes for our analyses, the mean amplitudes were then averaged across electrodes for each deviant condition and extracted for each participant using the ERPLAB toolbox in MATLAB (Lopez-Calderon & Luck, 2014). The ERP mean amplitudes were then submitted to a linear mixed-effect modeling using the *lmer* package (version 1.1-33) in R (RStudio Team, 2016). The model included fixed effects for Domain (Syllable vs. Voice), Local Probability (High vs. Low frequency), Global Probability (High vs. Low frequency), Group, and their interactions, with by-subject random intercepts and random slopes for the interaction for Domain, Local and Global probability. The Group contrast was set up as dummy coding, with the Child Group as the baseline. Group contrast 1: Children vs. Faster Learner Group. Group contrast 2: Children vs. Slower Learner Group. Each contrast represents the comparison between the Child Group and the Faster or the Slower Learner Group

Results

Analysis 1. Developmental differences in MMR and LDN responses as indices of auditory discrimination

In the MMR Time Window (100 – 250 ms) we did not observe any significant interactions between Group and Stimulus Type (Standard vs. Deviant), children and the two adult groups did not differ in their MMR responses (*ps* > .05). However, in the LDN Time Window (300 – 550 ms), we found a significant interaction between Group (Child vs. Slower Learner) and Stimulus Type ($\beta = 0.72$, $SE = 0.29$, $t = 2.47$, $p = .017$), suggesting a larger LDN magnitude in children than Slower Adult Learners. There was no interaction between Children and Faster Learners in the magnitude of LDN ($p > .05$). Post-hoc analyses within each group indicated that only children ($\beta = -0.63$, $SE = 0.33$, $t = -2.10$, $p = .048$) and faster SL adult learners ($\beta = -0.36$, $SE = 0.17$, $t = -2.15$, $p = .047$) displayed significant LDN, but not slower SL adult learners ($\beta = -0.16$, $SE = 0.12$, $t = -1.32$, $p = .20$).

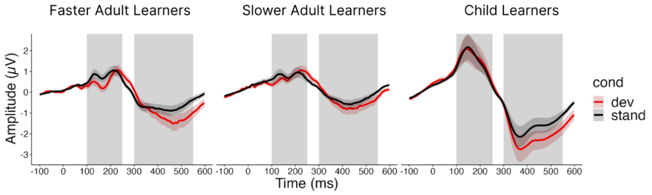

Figure 2: Waveforms recorded in response to all standards (stand) and all deviants (dev) in the three groups. The grey-shaded areas represent our analysis windows for MMR (100 – 250 ms) and LDN (300 – 550 ms).

Analysis 2. Developmental differences in MMR and LDN responses as indices of probabilistic sensitivity

We compared children with the two adult groups in how their MMR and LDN responses were modulated by the Domain (Syllable vs. Voice), Local Probability (Low frequent vs. High frequent), and Global Probability (Low frequent vs. High frequent) of the deviant stimuli.

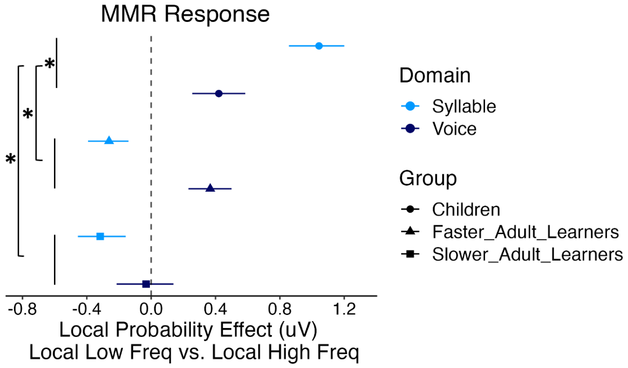

Figure 3: The interaction for Group × Local × Domain Probability in the MMR time window. Error bars represent the standard errors of the mean.

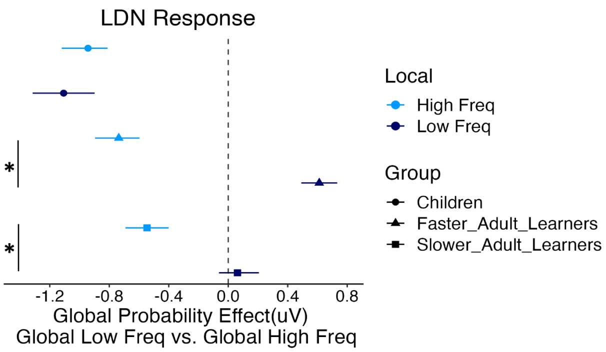

Figure 4: The interaction for Group × Local × Global Probability in the LDN time window. Error bars represent the standard errors of the mean.

MMR Time Window (100 – 250 ms) We observed a significant main effect of Local Probability (β = 0.73, SE = 0.24, t = 3.05, p = .003), confirming that this early ERP component is sensitive to Local Probability, as suggested by previous studies. As shown in Figure 3, comparing higher versus lower local probability, children showed a strong MMP response, whereas adults showed an overall mild MMN response. We also observed a significant two-way interaction between Local Probability and Group (Children vs. Slower Learners; β = -0.90, SE = 0.35, t = -2.61, p = .01). The post-hoc analysis revealed that the mismatching positivity responses were elicited for low frequent deviants comparing to the high frequent deviants only in the Children (β = 1.09, SE = 0.31, p = .002) but not in the Slower Learners. Importantly, we found a significant three-way interaction between Local probability, Domain, and Group (Children vs. Faster Learners; β = 1.25, SE = 0.50, t = 2.49, p = .02), suggesting such developmental differences were not homogenous across the syllable and the voice deviants. The results of post-hoc pairwise comparisons for the three-way interaction suggested that there was a similar magnitude of local probability effect across linguistic and non-linguistic domains in Faster Learners (p = .05), but a stronger local probability effect in linguistic stimuli compared to non-linguistic stimuli in children, in which mismatching positivity responses were elicited for Local probability in the linguistic deviants only (β = 1.09 , SE = 0.31, p = .002) but not in the non-linguistic inputs (p = 0.18).

LDN Time Window (300 – 550 ms) We observed a main effect of Global probability across the three groups (β = -1.02 , SE = 0.27, t = -3.75, p = .0004), confirming LDN is sensitive to global probability, as suggested by previous studies. As shown in Figure 4, children showed strong LDN responses to Global probability, whereas adults' LDN responses vary across Local probability conditions. We found a significant two-way interaction for Global probability and Group contrast 1 (Children vs. Faster Learners; β = 0.78 , SE = 0.40, t = 1.98, p = .05). Children showed a significant LDN effect in response to Global probability manipulation (β = -1.03, SE = 0.37 , p = .01). However, faster learners showed an overall much reduced LDN response for the Global probability effect (p > .05). A similar marginal two-way interaction was found between Global probability and Group contrast 2 (Children vs. Slower Learners; β = 0.78, SE = 0.40 , p = .053). Importantly, we also found a significant three-way interaction between Global probability, Local probability, and Group contrast 1 (Children vs. Faster Learners; β = 1.51, SE = 0.69, t = 2.21, p = .03). Our post-hoc analyses suggest a consistent LDN responses in children, but an interaction between global and local probability in faster learners, such that the LDN global effect was significantly larger for locally high (β = -0.92 , SE = 0.39 , p = .02), as compared to the locally low frequent deviants (p = .19). There were no two-way interactions between Group and Domain or three-way interactions between Group, Global, and Domain (ps > .05).

General Discussion

This study aimed to examine how neural sensitivity to probabilistic information in speech differs between children and adults. Specifically, we asked whether children process global and local probability differently than adults with varying statistical learning (SL) abilities. To explore this, we reanalyzed adult ERP data from Schneider et al. (2022), dividing it into faster and slower SL learner groups based on the performance of the word segmentation task, and then compared the data with children's ERP data. Overall, the results suggested intriguing differences between children and adults in processing and predicting probabilistic information in speech locally and globally. First, in the early processing stage (100 – 250 ms), children displayed stronger positive-going MMRs to syllable than voice deviants at the local level compared to both adult groups, indicating greater sensitivity to less frequent local speech deviants. In addition, in the later processing time window (300 – 550 ms), children's processing of global probabilistic information appeared independent of their local-level processing, whereas adults, especially faster SL learners, computed prediction errors across both global and local hierarchies, attending to extremely infrequent deviants. This result aligns with previous findings that adults transition from a LDN to a P3a response as auditory anomalies become less frequent and more surprising. In sum, these results suggest developmental differences in how the brain tracks statistical regularities in speech, with children process various levels of distributional information simultaneously, while adults integrate of probabilistic information across multiple levels.

Use In the early processing stage (100 – 250 ms), a time window specifically sensitive to local probabilistic information, we found children showed greater sensitivity to perturbations in local probability than both groups of adults, reflected as a positive-going MMR. It is particular interesting that this advantage in children is more evident for the syllable than the voice deviants, indicating that children's auditory system might automatically tune into subtle probabilistic changes particularly for the content of speech as their language system continues to mature. The polarity of children's MMR responses, however, are opposite to adults (MMN). Previous literature suggests the p-MMR represents an "immature MMN" (He et al., 2007, 2009a, 2009b; Lee et al., 2012; Mueller et al., 2012; Schaadt, 2015) that will invert polarity with development, or a distinct response. Chen et al. (2016) suggested the p-MMR may be a precursor to the P3a, reflecting attentional orienting (Escera et al., 1998). Lee et al. (2012) proposed that positive difference waves arise from stimulus factors like short inter-stimulus intervals or difficult discriminations. Finally, some studies report two simultaneous discriminative components: a slow positive and a fast negative wave from different cortical layers (Shafer et al., 2010; Trainor et al., 2003). Our MMR findings are broadly consistent with previous literature suggesting that infants initially learn to segment words from speech by tracking transitional probabilities at the local level, i.e., between syllables (e.g., Thiessen & Saffran, 2003, 2007; Aslin, Saffran & Newport, 1998). According to these studies, probabilities between neighboring syllables are critical cues in that their use enables children to bootstrap all other speech cues to word boundaries, providing a potentially language-general strategy for the acquisition of language-specific segmentation cues.

In addition, our research points out that during these early and pre-attentive stage of auditory processing, there's no significant engagement with the global probabilistic information, in agreement with literature showing that the memory trace represented by the MMR is transient, causing the MMR to be insensitive to global patterns (Näätänen et al., 2007). Previous studies have documented that the MMR does not respond to deviants that violate global distributional statistics patterns, such as when a deviant sequence of AAAAA is presented after a standard sequence of AAAAB. Our findings support these earlier studies, revealing that both adults and children do not process global probabilistic information in this early processing phase, thereby implying a selective sensitivity to different temporal regularities in the continuous sound stream.

In the later processing time window (300 – 550 ms), we found that adults' LDN responses, especially faster SL learners, were modulated by intertwined local and global probabilistic information while children maintain their focus to global distributional information. The interaction between local and global effects within the adult's LDN responses suggests that attention mechanisms play a pivotal role in processing distributional information embedded in speech patterns, as shown in one of our earlier studies highlighted that adults undergo a transition from an LDN to a P3a response as auditory anomalies become less frequent and more surprising. Children, on the other hand, children seemed to process global probabilistic information in a more parallel manner with local probabilistic information. The presence of a global effect aligns with previous studies indicating that global probabilistic information is processed at a later stage (Bishop, 2007; Wetzel & Schröger, 2014), which posited that both children and adults exhibit a LDN response when faced with verbal stimuli, pointing to an automatic processing mechanism for intricate auditory, and possibly linguistic-related inputs. Such findings extend our understanding of how humans, across different age groups, manage to interpret and integrate complex patterns of probabilistic information from their auditory environment. For adults, the nuanced interplay between attention and the processing of probabilistic cues reflects a sophisticated auditory processing capability, likely honed over years of linguistic and cognitive development. For children, the distinct processing of global information highlights their developing cognitive abilities and suggests a foundational mechanism through which linguistic knowledge and processing skills are built and refined.

Taken together, our findings suggest that children appear to process global and local probability in speech streams differently, compared to adults with varying SL skills. Especially, there are significant differences in the sensitivity to detect different temporal scales of distributional cues specific to linguistic cues. By using MMR, children's advantage in detecting local probabilistic information appears to be more sensitive than adults in response to local probabilistic information, specifically for linguistic inputs (syllables) as opposed to non-linguistic inputs (voice). Our results further indicate that children may have a more generalized ability to process distributional probability information in speech, which may provide a potential advantage for acquiring linguistic categories, such as speech sounds, morphosyntactic markers, and verb biases during language development. In conclusion, our study provides insight into how SL ability changes with development and how this may inform research investigating the mechanisms underlying the sensory period hypotheses of language acquisition. For future research, we suggest extending research focus to younger population for a thorough investigation of developmental trajectories during earlier years in children's life. By delving into the developmental trajectories of SL skills, we aim to enhance our understanding of the fundamental processes that underpin language acquisition. This not only contributes to the theoretical knowledge in the field but also has the potential to influence practical approaches in early education, speech research, and language teaching methodologies, paving the way for strategies that align with the natural developmental progressions in language learning.

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