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Exploring the neurodevelopment of visual statistical learning using event-related brain potentials

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ABSTRACT

Implicit statistical learning (ISL) allows for the learning of environmental patterns and is thought to be important for many aspects of perception, cognition, and language development. However, very little is known about the development of the underlying neural mechanisms that support ISL. To explore the neurodevelopment of ISL, we investigated the event-related potential (ERP) correlates of learning in adults, older children (aged 9–12), and younger children (aged 6–9) using a novel predictor-target paradigm. In this task, which was a modification of the standard oddball paradigm, participants were instructed to view a serial input stream of visual stimuli and to respond with a button press when a particular target appeared. Unbeknownst to the participants, covert statistical probabilities were embedded in the task such that the target was predicted to varying degrees by different predictor stimuli. The results were similar across all three age groups: a P300 component that was elicited by the high predictor stimulus after sufficient exposure to the statistical probabilities. These neurophysiological findings provide evidence for developmental invariance in ISL, with adult-like competence reached by at least age 6.

1. Introduction

Implicit statistical learning (ISL) refers to the automatic, incidental, and effortless acquisition of statistical patterns in the environment (Cleeremans et al., 1998; Conway and Christiansen, 2006; Eimer, Goschke, Schlaghecken, & Sturmer, 1996; Fiser and Aslin, 2002; Perruchet and Pacton, 2006). The use of ISL processes are believed to play an important role in language learning (Conway et al., 2010; Misyak et al., 2010; Saffran, 2003; Saffran et al., 1996) in addition to other aspects

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of cognitive development such as visual perception (Fiser and Aslin, 2002; Turk-Browne et al., 2010), motor skill learning (Robertson, 2007), and social intuition (Lieberman, 2000). These abilities are domain-general in the sense that the same general mechanisms appear to be used across multiple domains in parallel (Saffran and Thiessen, 2007). However, few studies have probed the neural mechanisms mediating ISL in adults, let alone in children, making it difficult to specify the neurocognitive development of these processes.

Reber (1993) suggested that implicit learning is developmentally invariant, a claim which has been supported by recent work examining saccadic eye movements in a behavioral learning paradigm (Amso and Davidow, 2012). However, other research has provided evidence of developmental differences (Barry, 2007; McNealy et al., 2010; Mecklenbräuker et al., 2003; Thomas et al., 2004). Perhaps not surprisingly, in most cases where developmental differences in implicit learning are found, adults out-perform children. However, the evidence is not straightforward. Some proposals take the somewhat paradoxical stance that cognitive limitations may confer a computational advantage for learning (Conway et al., 2003; Elman, 1993; Newport, 1990), which would indicate that ISL might be more efficient in childhood. Overall, relatively little is known about the

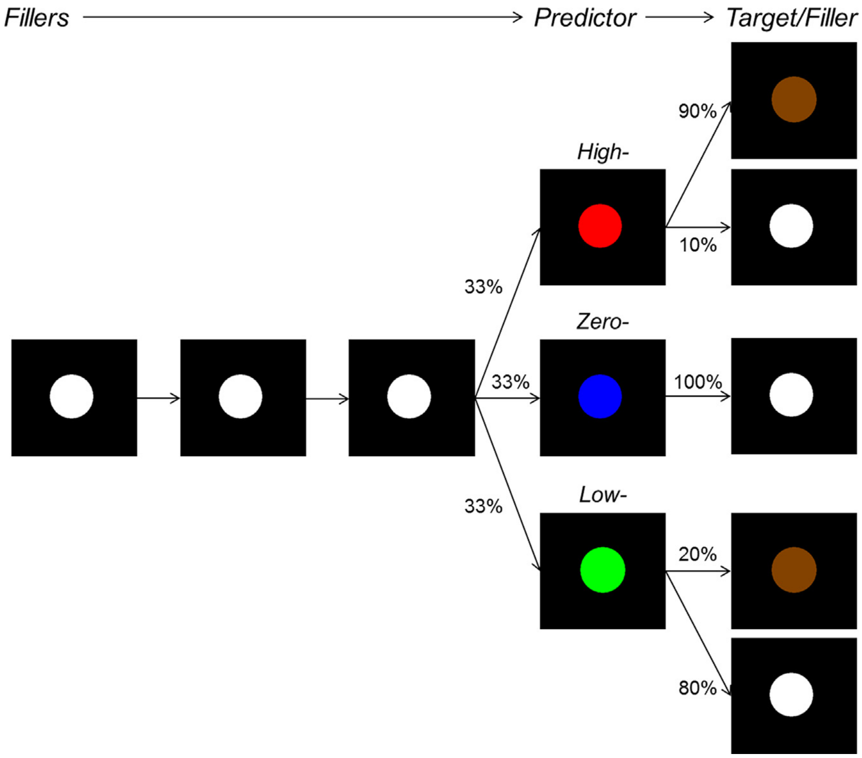

Fig. 1 – An example sequence of colored circles for each of the three stimulus types (high-, low-, and zero-probability predictor conditions). In the example three filler circles are used prior to the appearance of a predictor, but this number could vary from one to five. After the appearance of either the target or filler following a predictor, the process would repeat. In this example the target is brown, but circle color was randomly distributed across conditions for each participant.

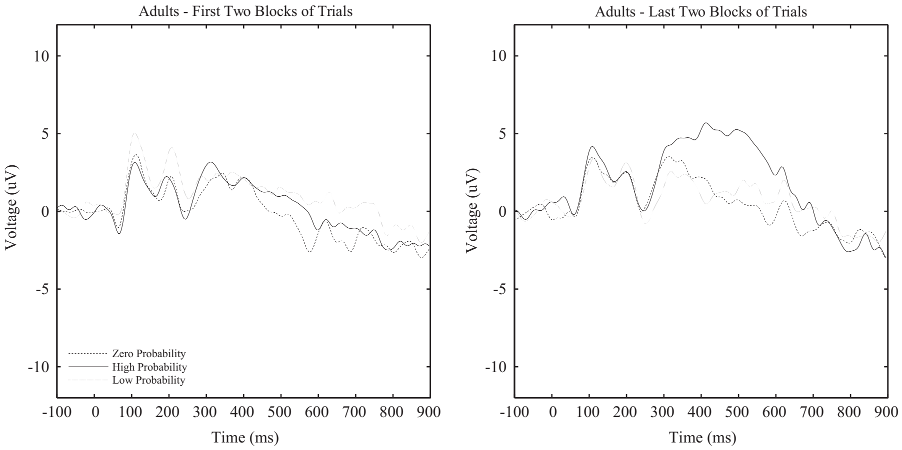

Fig. 2 – Averaged ERP waveforms in the centro-parietal region (POz) for the adult group, for first two blocks (left) and last two blocks (right).

development of ISL, especially in the visual modality. Even less is known about the development of the underlying neurobiological mechanisms that support such learning.

To investigate the neural mechanisms of ISL across development, the event related potential (ERP) technique is advantageous because it provides a direct neurophysiological measure of learning, making it potentially more sensitive to implicit (unconscious) learning mechanisms compared to behavioral measures. ERP also provides a precise temporal profile of neural information processing, which can reveal effects that other neuroscience techniques such as fMRI cannot. Only a handful of previous studies has used ERPs to investigate ISL in adults (Abla et al., 2008; Christiansen et al., 2012; Sanders et al., 2002). One ERP component that appears to be associated with the acquisition of statistical sequential patterns is the P300, a positive deflection in voltage potential that occurs approximately 300 ms after the presentation of a stimulus and may be a correlate of context-updating and stimulus discrimination (Patel and Azzam, 2005; Eimer et al., 1996; Ferdinand, Mecklinger et al., 2008; Schlaghecken et al., 2000). The P300 component has been suggested to reflect stimulus-evaluation processes (Rüsseler and Roesler, 2000), specifically the evaluation of incoming information and the updating of contextual representations (Ferdinand et al., 2008). Verleger (1988) has suggested interpreting the P300 as a correlate of “context closure”. This slightly more nuanced view of the context updating interpretation hypothesizes that the P300 is evoked by predictable, awaited events in highly structured tasks as subjects learn to associate and chunk adjacent elements.

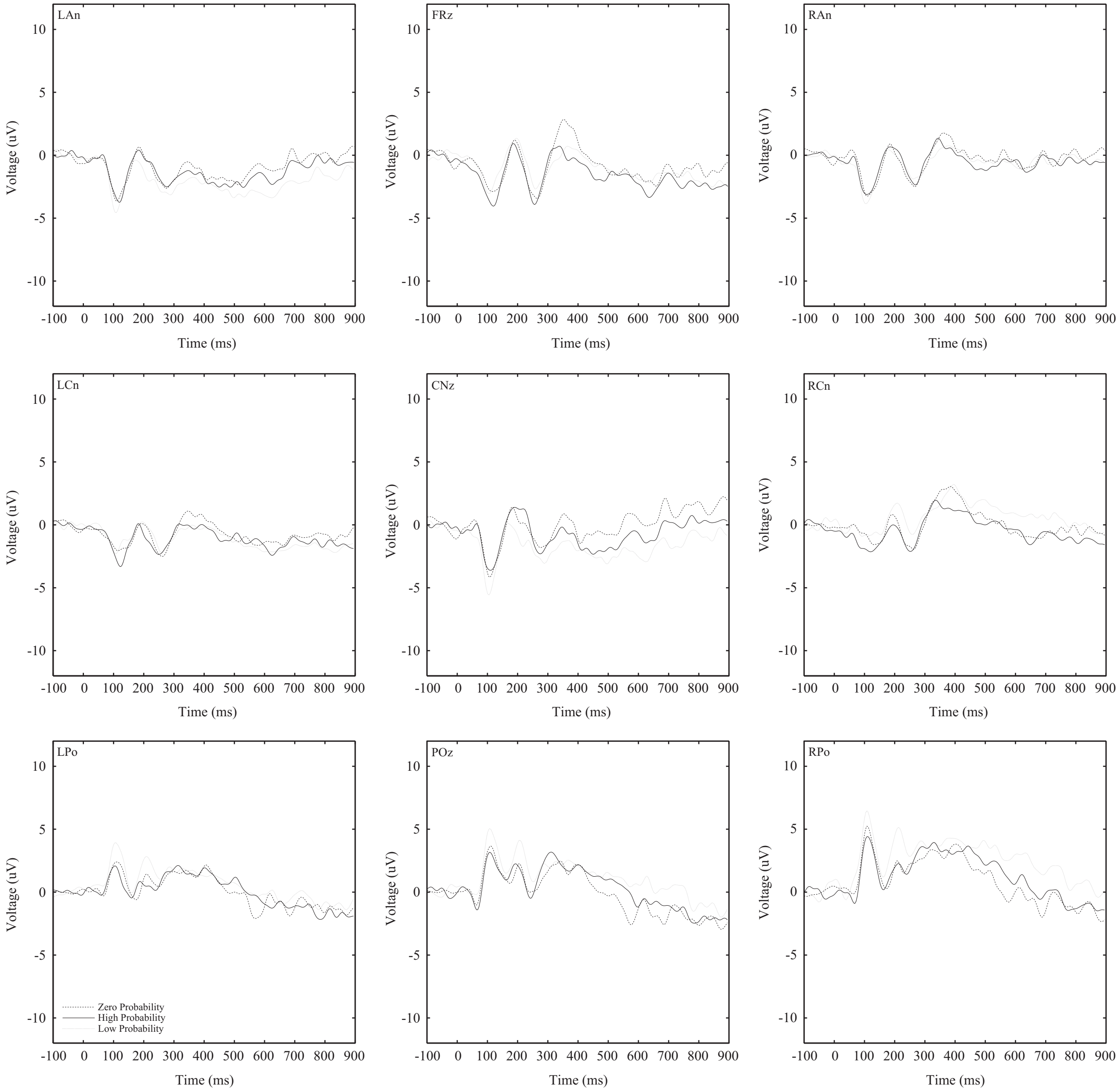

Fig. 3 – Waveform distribution for the first two blocks for the adult group. Regions of interest were created by averaging sets of sensors together at nine different regions, uniformly distributed across the scalp, as shown in Fig. 2.

Even fewer studies have investigated the ERP correlates of ISL in infants or children (e.g., Teinonen et al., 2009) and to our knowledge, no single study has used ERP to directly compare such learning across different ages. Thus, in order to investigate the neurodevelopment of ISL, we developed a novel ERP paradigm that is conducive for use with both adults and children. The task involved viewing a stream of visual stimuli containing covert statistical patterns governing the probability of a target stimulus' appearance (see Fig. 1). ERP responses to three different types of stimuli (a high-probability predictor, a low-probability predictor, and a zero-probability predictor) that reflected differing transitional probabilities for three groups of participants (adults, older children, and younger children) were compared. To ascertain how much exposure to the task was required before learning occurred, we compared ERP responses elicited early in the task versus later in the task.

2. Results

2.1. ERP results for adults

Fig. 2 shows the grand averaged centro-parietal ERP waveforms for the adults, time-locked to each of the three predictor types, for the first two blocks (left) and last two blocks (right) of the experiment. Visual inspection suggests that there are no clear differences between waveforms in the first two blocks of the experiment. On the other hand, in the last two blocks, there is a prominent late positivity – similar

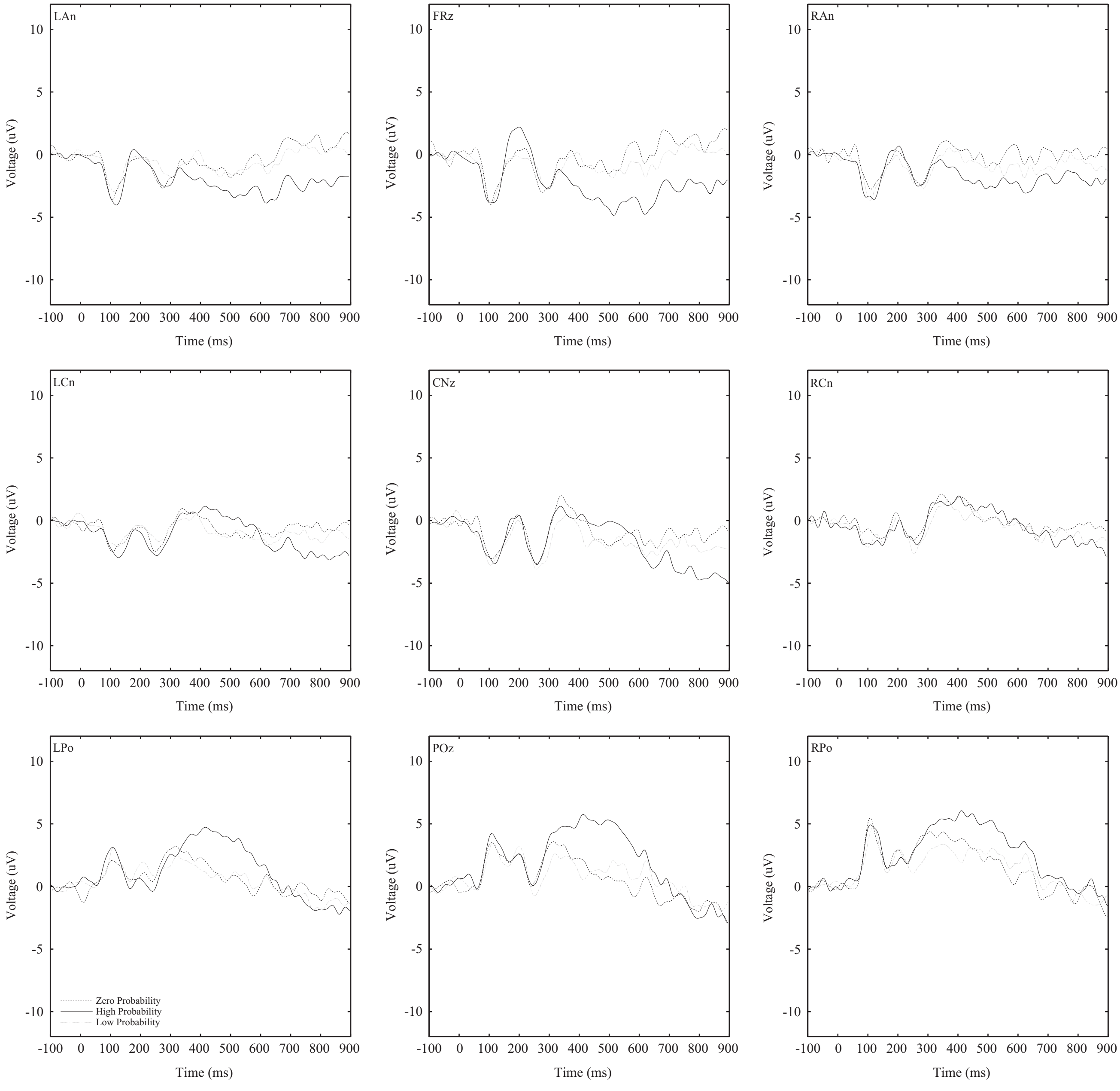

Fig. 4 – Waveform distribution for the last two blocks for the adult group.

in appearance to a P300 component – that is associated with the high-probability predictor condition specifically. Figs. 3 and 4 show the waveform distributions across the entire scalp for the first two and last two blocks, respectively.

In order to verify visual inspection, a 9 (region) x 3 (predictor) x 2 (block) repeated measures ANOVA was conducted using mean amplitude waveforms as the dependent variable, and the factors of region of interest (nine sensor sites distributed symmetrically across the array), predictor type (high-, low-, and zero-probability predictor conditions), and block (first two blocks vs. last two blocks). A 300–600 ms time window was selected to examine the P300 component for the adult participants. The Greenhouse-Geisser correction for nonsphericity of variance was applied in the calculation of reported p values for all ERP analyses reported.

The 9x3 $\times$ 2 ANOVA found a significant main effect for region ($F(2, 62)=15.22$, $p<.001$, $\eta_p^2=.559$). The interactions of region x predictor ($F(4, 43)=5.87$, $p=.001$, $\eta_p^2=.328$) and region x block ($F(3, 37)=5.27$, $p=.004$, $\eta_p^2=.305$) were also statistically significant. Importantly, pairwise comparisons in the POz region indicated significant differences between the high- versus low-probability predictor ($t(12)=3.53$, $p=.004$, $r=.484$) and the high- versus zero-probability predictor conditions ($t(12)=4.58$, $p=.001$, $r=.626$) in the last two blocks. This highlights the presence of a P300-like component in the adult data during the last two, but not the first two, blocks.

In sum, the adult ERP data suggests that ISL – learning that the high-probability predictor was a reliable predictor of the target – was reflected by a P300-like component that occurred in the last two blocks of the experiment.

2.2. *ERP results for older children*

Fig. 5 shows the grand averaged ERP waveforms for the older children. Visual inspection suggests that the last two blocks look very similar to the adults as there is a P300-like late positivity associated with the high-probability predictor condition. Due to the apparent latency of waveform onset, a time window of 400–700 ms was chosen for both groups of children for purposes of analysis. Figs. 6 and 7 show the waveform distributions across the entire scalp for the first two and last two blocks of the experiment, respectively.

A 9x3 $\times$ 2 repeated measures ANOVA was conducted for the 400–700 ms latency period as was done with the adults. The ANOVA found a marginal main effect for region ($F(1, 19)=3.66$, $p=.058$, $\eta_p^2=.220$). The interaction of region x predictor was significant ($F(4, 53)=4.10$, $p=.005$, $\eta_p^2=.240$). A relevant significant difference was found in the last two blocks between the high- and low-probability predictor conditions ($t(13)=2.78$, $p=.016$, $r=.301$), although the effect did not obtain for the comparison between the high- and zero-probability predictors in the last two blocks. These results demonstrate the adult-like appearance of a P300 component in the older child group by the end of the experiment.

These ERP data present neurophysiological evidence that just like the adults, older children exhibited a P300-like component that was elicited by the end of the experiment for the high-probability predictor condition, suggesting that learning did occur.

2.3. *ERP effects for younger children*

Fig. 8 shows the grand averaged ERP waveforms for the younger children. Visual inspection suggests that similar to both the adults and older children, there is a P300-like component in the last two blocks associated with the high predictor condition. Figs. 9 and 10 show the waveform distribution across the scalp in the first two and last two blocks, respectively.

To verify the visual inspection, a 9x3 $\times$ 2 repeated measures ANOVA was conducted for the 400–700 ms latency period as before. The ANOVA found a marginal main effect for region ($F(1, 19)=3.55$, $p=.06$, $\eta_p^2=.214$). The interaction of region x predictor was significant ($F(2, 29)=3.72$, $p=.033$, $\eta_p^2=.223$). The high-predictor was significantly different from the low-predictor ($t(13)=2.56$, $p=.024$, $r=.243$) and the zero-predictor ($t(13)=2.43$, $p=.03$, $r=.223$) in the last two blocks, but not in the first two blocks, suggesting that the P300-like component did not emerge until the end of the experiment.

In sum, like the adults and older children, the younger children displayed a P300-like component that was evoked by

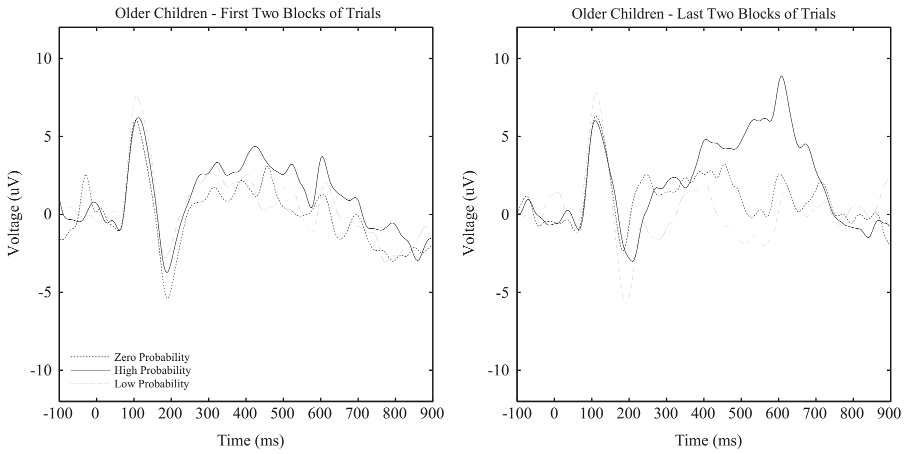

Fig. 5 – ERP waveforms in the centro-parietal region (POz) for the older child group, for first two blocks (left) and last two blocks (right).

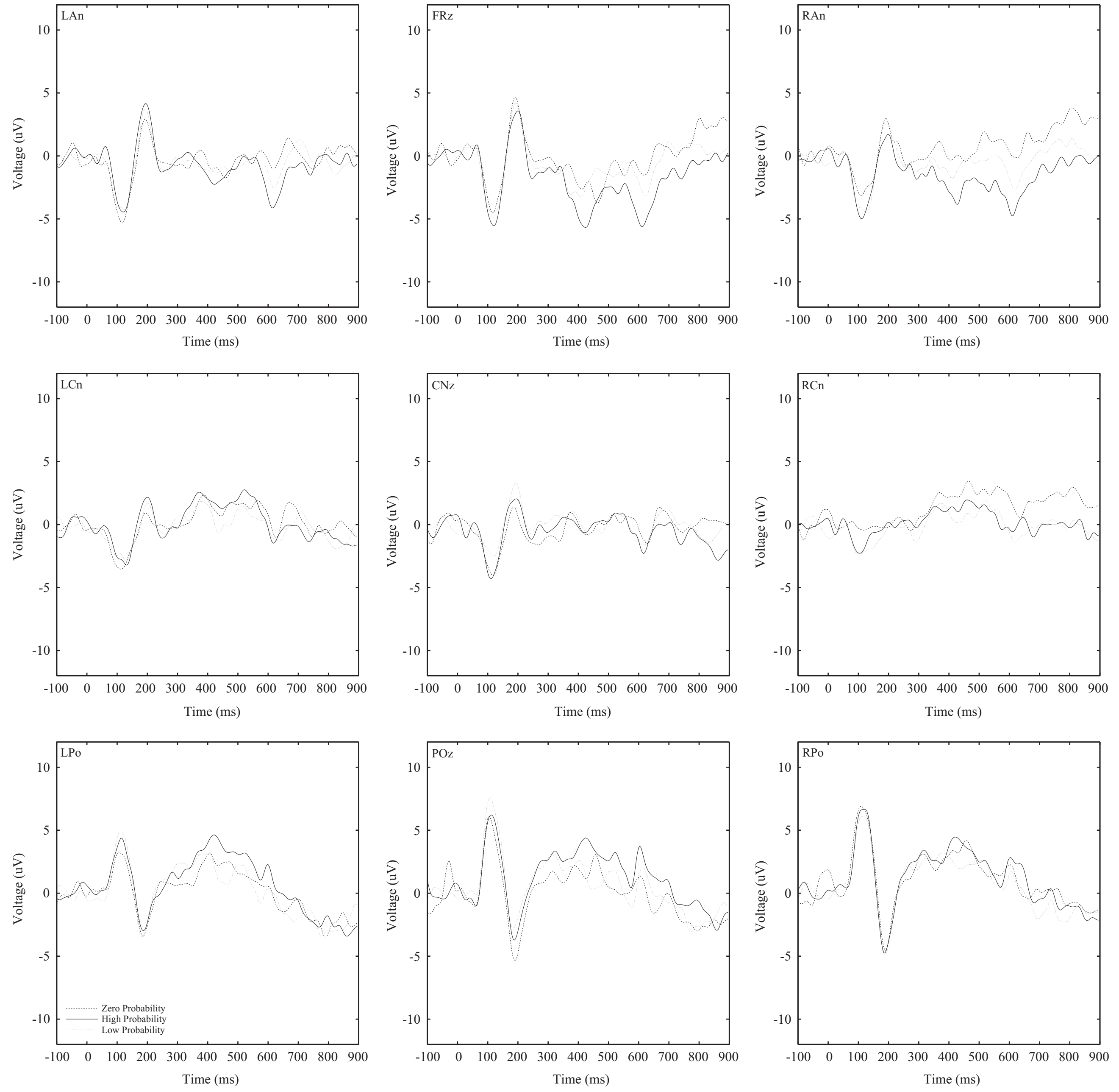

Fig. 6 – Waveform distribution for the first two blocks for the older child group.

the high-probability predictor and emerged only in the last two blocks of the experiment.

2.4. *Between groups analysis of ERP data*

To compare the ERP correlates of statistical learning across the three age groups (n=41), we computed difference waves between the high- and low-probability predictors as well as between the high- and zero-probability predictors for each of the three participant groups. We then submitted the difference waves to a 9 (region) x 2 (difference wave type) x 2 (block) x 3 (group) repeated measures ANOVA, with the age group included as a between subjects factor. The time windows used for each group in the previous sets of analyses were conserved. Conducting this analysis on the difference waves rather than the mean amplitude waveforms serves as a way to normalize potential group differences in overall waveform amplitudes.

The results revealed a main effect for region ($F(2, 68)=11.12$, $p<.001$, $\eta_p^2=.226$). The interaction of region x block was also significant ($F(3, 114)=3.84$, $p=.012$, $\eta_p^2=.092$). Critically, the test of between subjects' effects indicated a null result ($F(2, 38)=1.46$, $p=.244$, $\eta_p^2=.071$).

3. Discussion

The present study sought to explore the neurodevelopment of visual ISL using a novel paradigm in conjunction with ERP. The task was a modification of the standard “odd-ball”

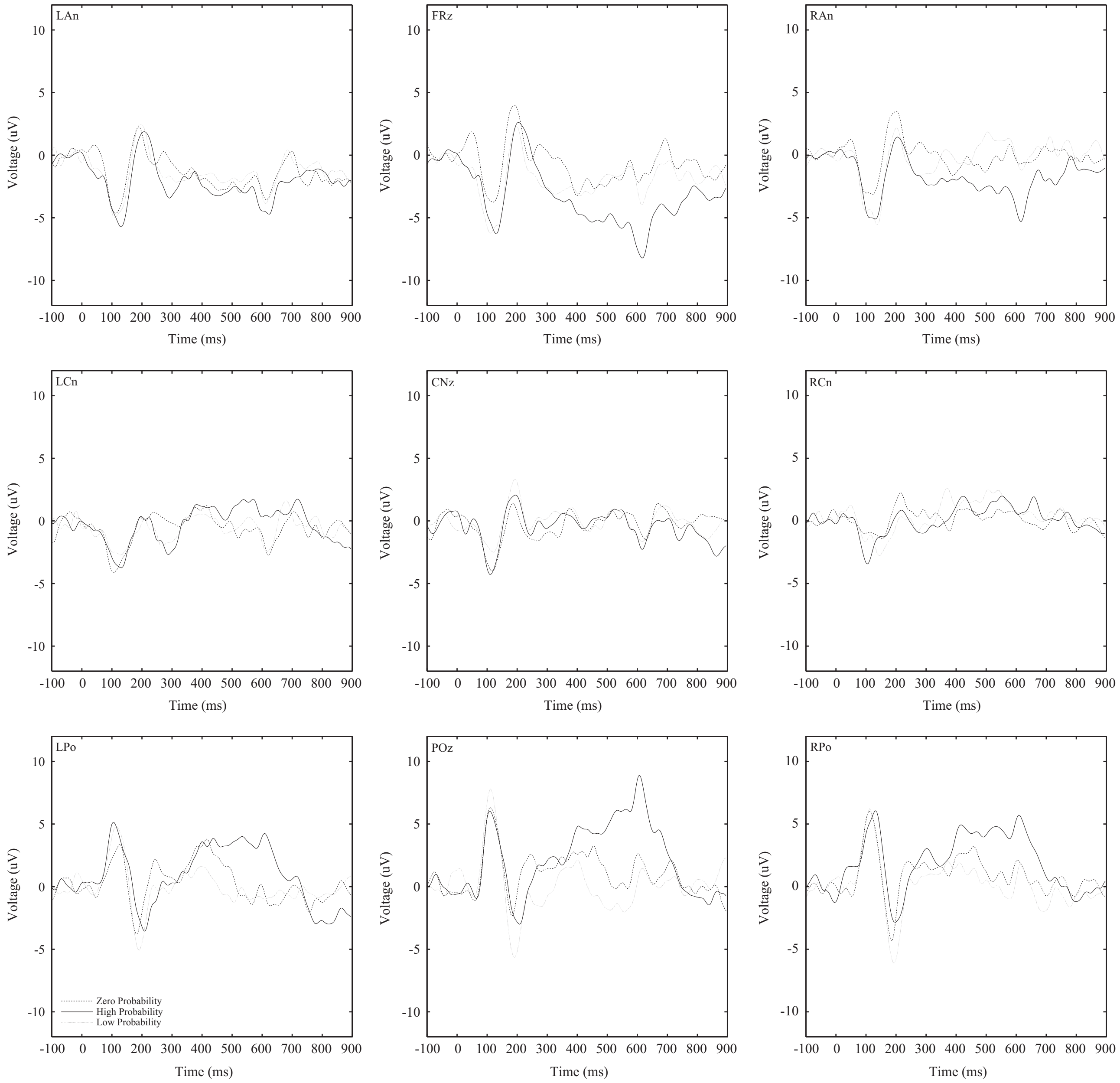

Fig. 7 – Waveform distribution for the last two blocks for the older child group.

paradigm that has been used extensively in ERP research (Huettel and McCarthy, 2004). However, instead of measuring ERPs to the appearance of a target stimulus, this new paradigm allowed us to investigate the ERP waveforms elicited in response to the occurrence of stimuli that predicted the target with varying probabilities. This allowed us to probe the neural responses in relation to learning simple sequential statistics embedded within the serial input stream. Advantages of this design are that it is a relatively simple task and thus amenable to use with children, it allows an online measure of learning by comparing learning effects at the beginning versus the ending of the task, and it can be easily "scaled up" in future studies by making the predictive statistics more complex.

The neurophysiological findings revealed that all three age groups (adults, older children 9–12 years old, and younger children 6–9 years old) displayed a late positivity in the centro-parietal region in response to the presentation of the high-probability predictor. The timing and topography of this waveform appear similar to the classic P300 component. The P300 is thought to be an index of target detection and evaluation (Van Zuijen et al., 2006), and also has been elicited in other types of ISL and sequence learning tasks (Baldwin and Kutas, 1997; Carrión and Bly, 2007; Rüsseler et al., 2003). This component was observed primarily during the last two blocks of trials, but not during the first two, suggesting that during the course of the experiment, participants gradually learned the statistical regularities governing the occurrence of the target, and only showed neural-related correlates of learning after a sufficient amount of exposure. In effect, the presence of the P300, normally elicited by the appearance of an infrequent target during the standard oddball task, was

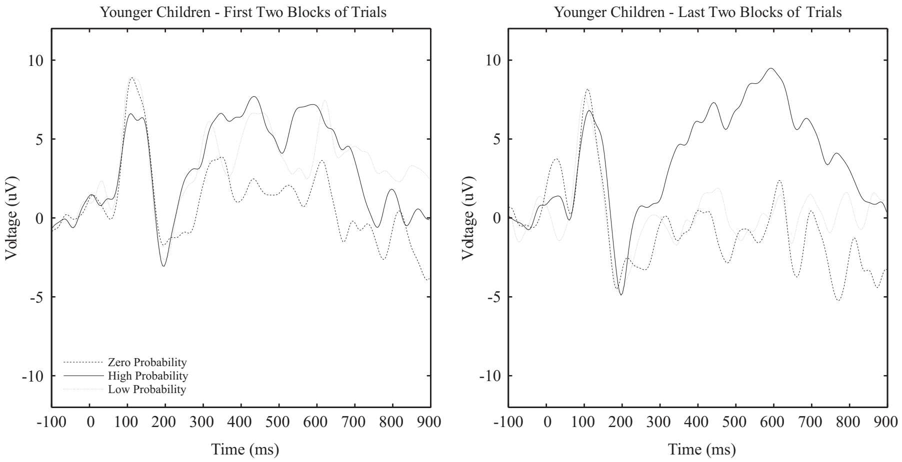

Fig. 8 – ERP waveforms in the centro-parietal region (POz) for the younger child group, for first two blocks (left) and last two blocks (right).

"shifted" earlier in the input stream so that it was elicited following the appearance of a stimulus that predicted the target with a high probability. To put it another way, following sufficient exposure to the statistical patterns, the participants' brains treated a stimulus that predicted the target similarly to the target itself, evidence of learning the predictive association between the two stimuli. This interpretation is consistent with the "context closure" interpretation of the P300 component that suggests that the P300 reflects a type of grouping or chunking operation (Verleger, 1988). That is, participants appeared to form an associative "chunk" between the high-probability predictor and the target stimulus, based on the strength of the underlying statistical association between the two stimuli. Importantly, the P300 for the high-probability predictor was elicited even though the three predictors were perfectly equated in terms of their frequency of occurrence.

A comparison of the ERP differences revealed no significant differences across age groups. This striking similarity in ERP waveforms in children and adults suggests that visual ISL might be developmentally invariant, an idea originally proposed by Reber for implicit learning skills more generally (Reber, 1993). Reber proposed that implicit learning was phylogenetically old (as compared to declarative memory, for example), and argued that therefore it is a robust mechanism characterized by invariance across development and across species. The present findings appear to support Reber's claim; however, before settling on this conclusion, a few caveats must be considered.

First, although we detected no group differences in the ERP responses, a null effect must, of course, be treated with caution. Null effects with ERP findings in particular are difficult to interpret because it is possible that there are effects in the brain that the ERP recordings are not able to detect (Otten and Rugg, 2005). Second, it is possible, given the relatively simple statistical probabilities used in this task that neurodevelopmental differences do exist but only with more complex types of input patterns. Third, it is possible that developmental differences might be more apparent in children younger than that used in the current study.

In contrast to the present findings, three other recent studies in fact have shown precocious learning abilities early in development. McNealy et al. (2011) found that younger children (5–7 years old) showed greater neural activation to weak statistical cues governing a novel stream of nonsense syllables, compared to older children (9–10 and 12–13 year olds) and adults. Similarly, Johnson and Wilbrecht (2011) found that juvenile mice required fewer trials than adult mice to reach criterion on a 4-choice reversal task, reflecting what the authors regarded as more efficient and more flexible learning abilities. Finally, using an implicit sequence learning task, Janacsek et al. (2012) found that children younger than 12 years old showed better learning compared to older children and adults. Clearly, it would seem advantageous for organisms to possess neural mechanisms that are highly adept at learning environmental patterns. Individual differences in visual ISL abilities have been shown to be associated with language processing skill in infants (Shafto et al., 2012), children (Conway et al., 2011), and adults (Conway et al., 2010; Misyak et al., 2010). Thus, having efficient information processing mechanisms for detecting statistical patterns early in development could help explain why young children are able to learn natural language so effectively.

Although the present findings do not establish developmental differences in ISL, they do point to adult-like levels of proficiency relatively early in development. The robust visual statistical learning skills that we observed in both groups of children are consistent with other research showing that children are highly skilled at learning structured statistical patterns in the environment (Fiser and Aslin, 2002; Kirkham et al., 2002; Saffran et al., 1996). The present findings are also consistent with Reber's (1993) claim of developmental invariance for implicit learning, suggesting that these learning mechanisms are highly conserved and may have a relatively old evolutionary origin. Future research determining the participants' awareness of the patterns underlying sequences such as those found in this study may be important, as there is increasing interest in understanding the manner in which explicit instruction and/or conscious awareness interacts with ISL (Arciuli et al., 2014). Using tasks such as this one

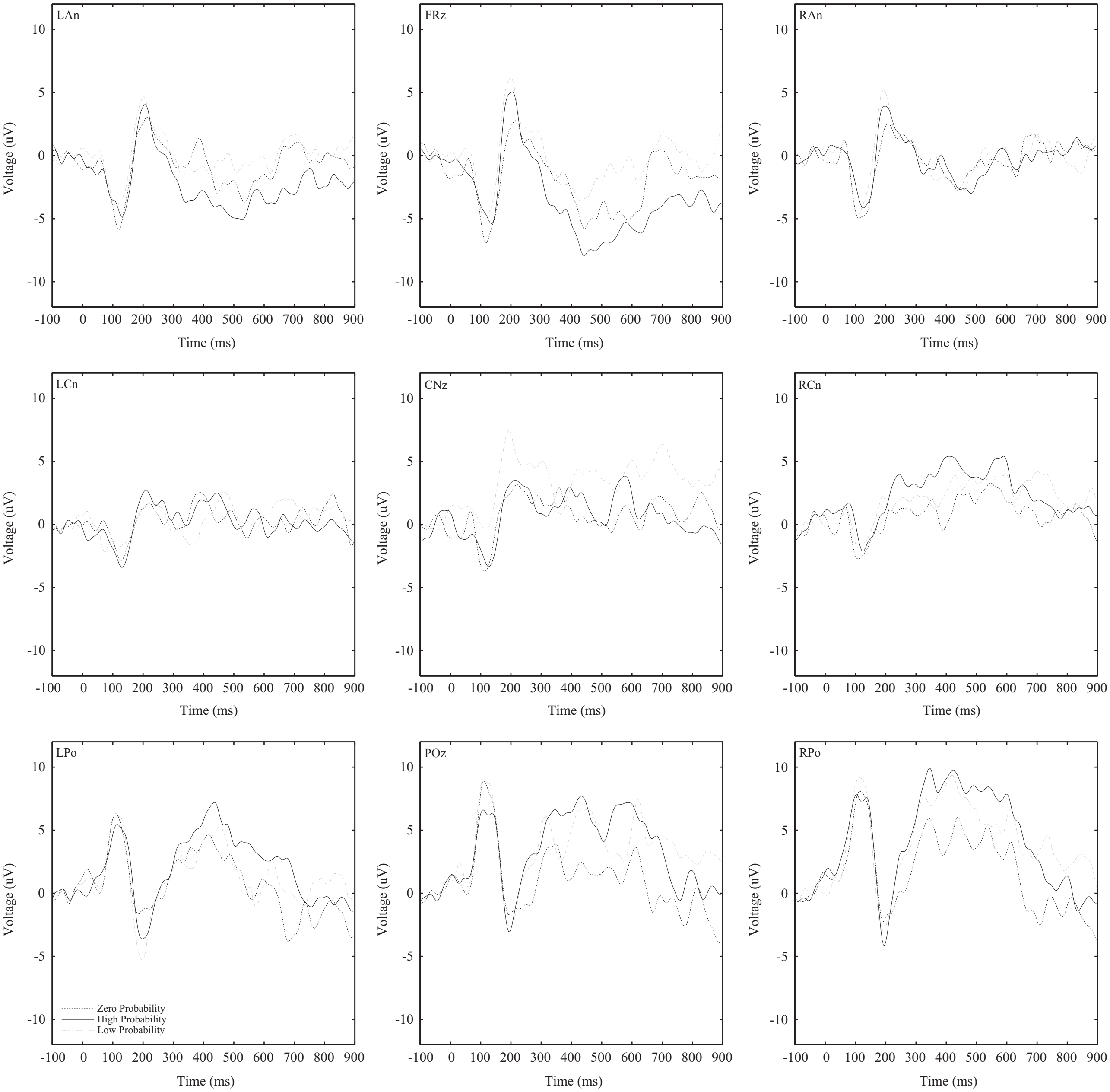

Fig. 9 – Waveform distribution for the first two blocks for the younger child group.

can also be used to probe learning abilities even earlier in development to ascertain whether the neural correlates of ISL truly are invariant across age.

4. Conclusion

In sum, this study investigated the development of the neurocognitive mechanisms underlying visual ISL. Adults and children displayed a P300 component associated with learning the statistical patterns embedded in the input stream. This pattern of ERP responses provides insight into the development of visual ISL abilities. Specifically, children appear to possess similar neural mechanisms as adults for learning serial statistical patterns. These learning abilities are present by at least six years of age and appear to be developmentally invariant through young adulthood. Future research can adapt this paradigm to incorporate more complex input patterns to further probe the nature of statistical learning mechanisms across development.

5. Experimental procedure

5.1. *Participants*

Adult participants ($n=13$, mean age$=20.69$ years; range 18–23 years; 9 female) were recruited from Saint Louis University. Child participants were recruited from the St. Louis metropolitan area and were divided into two age groups: older children ($n=14$, mean age$=10.92$; range 9–12 years;) and younger children ($n=14$, mean age$=8.25$; range 6–9 years;).

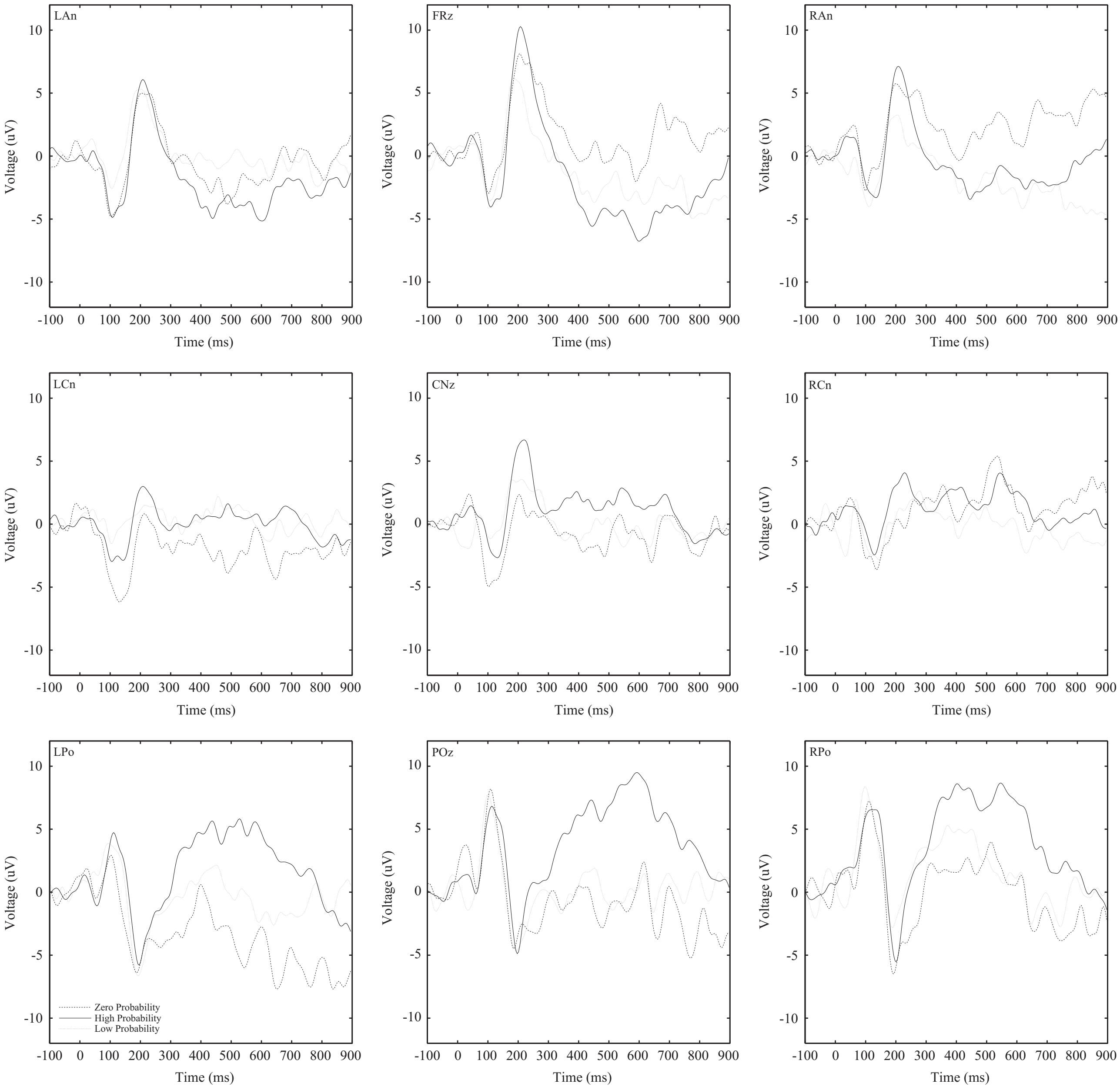

Fig. 10 – Waveform distribution for the last two blocks for the younger child group.

All participants (or their parents) self-reported no cognitive, neurological, or psychological conditions. Participants were compensated monetarily.

5.2. *Experimental paradigm*

The ISL task involved participants viewing a continuous stream of colored circles appearing in the center of the monitor, one circle at a time (Fig. 1). Participants were told to press a keypad whenever a target color appeared. The target was predictable to varying degrees by the color of the circle immediately preceding it. Each trial consisted of at least one and at most five "filler" circles, followed by one of three "predictor" circles, and then the possible appearance of the target. Filler circles were included so that the degree of target predictability could vary between predictor conditions while allowing for a continuous task structure. When the high-probability predictor appeared, the target and filler followed 90% and 10% of the time, respectively. When the low-probability predictor appeared, the target and filler followed 20% and 80% of the time, respectively. When the zero-probability predictor appeared, the target never followed. After the presentation of the predictor/target pair, the next trial began immediately with one to five filler circles preceding the appearance of the next predictor. The assignment of colors (red, blue, green, brown, white) to the three predictors, fillers, and target was determined randomly for each participant.

Each circle was presented on-screen for 500 ms on a black background, followed by an empty black screen for 500 ms. There were 50 trials of each predictor (for a total of 150 trials), which were divided into five blocks of 30 trials each (10 trials

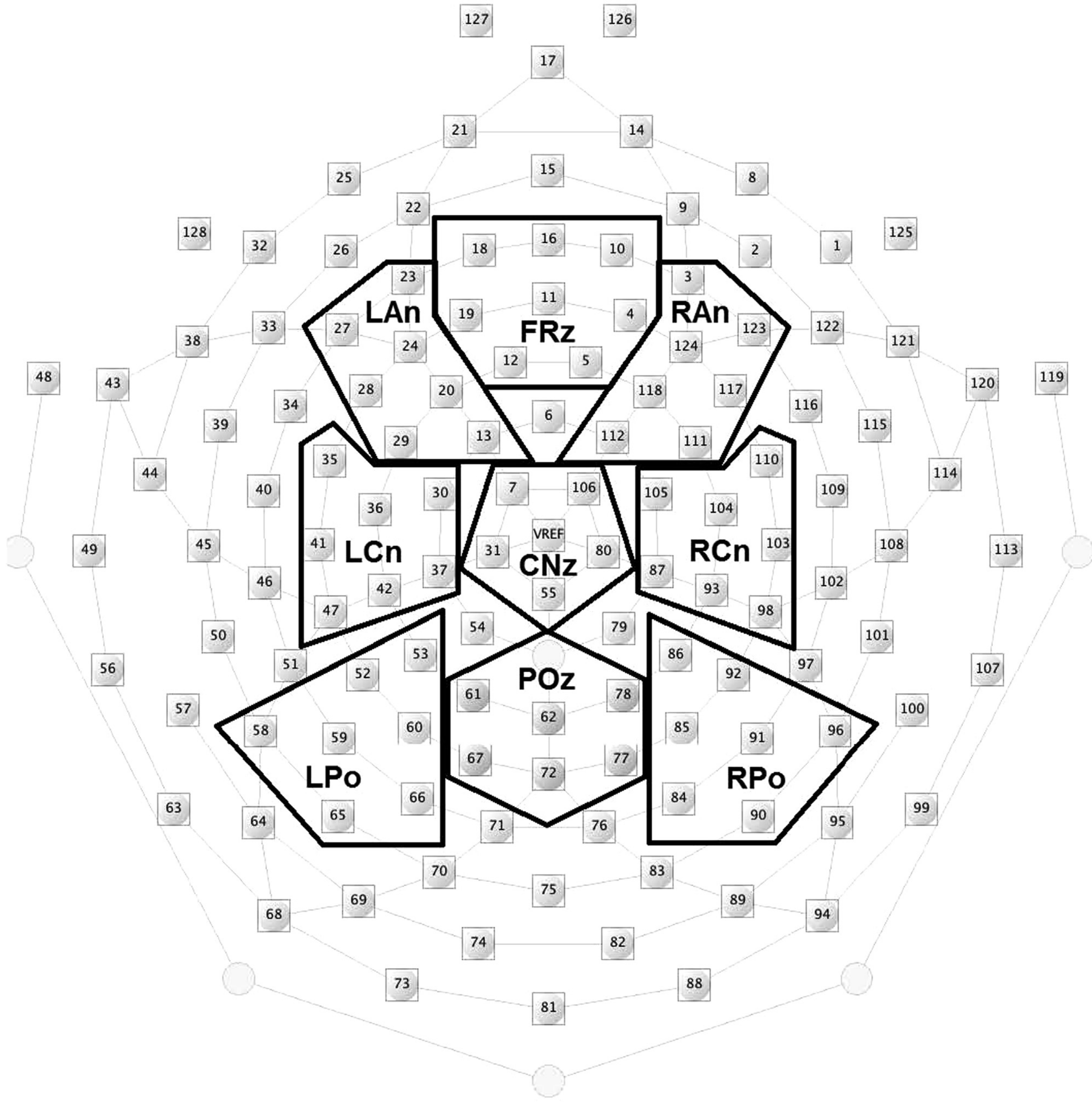

Fig. 11 – Illustration of sensor montages used for analyzing ERP data. The primary region of interest is the montage labeled POz – pairwise comparisons reported throughout the results are from these sensors, though data from all 9 montages are also presented.

of each predictor). Within each block, the trials were presented randomly.

5.3. *Recording technique*

EEG data associated with the experiment was collected using a 128-channel high-density sensor net (Electrical Geodesics, Eugene OR). Standard net-application techniques were followed. Impedances were kept below 50 kilo-ohms, and the data was digitized by NetStation acquisition software (Electrical Geodesics, Inc.).

Following data acquisition, the continuous raw EEG recording was filtered through a 0.1 Hz high-pass filter and a 30 Hz low-pass filter. ERP recordings were time-locked to the onset of each of the three predictor circles using a 100 ms pre-stimulus baseline, and continued for 900 ms after onset. This resulted in 50 trials for each of the three predictor conditions (high-, low-, and zero-probability) per participant. An artifact detection operation removed trials containing noise from eye blinks and other movements.

Based on previous ERP research, we expected that the P300 component would be elicited at the presentation of the high-probability predictor once participants had learned the statistical association between each predictor and the target. As this component appears in the centro-parietal region of the scalp, this is where we focused our analyses, using a montage of the six sensors closest to where the POz electrode is positioned in the 10–20 system (see Fig. 11).

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