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Statistical learning of orthography-semantics regularities: A developmental neurophysiological study

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ABSTRACT

Combining event-related potential (ERP) with an artificial orthography learning paradigm, this study examined how 7–11-year-old Chinese children from first to fifth grade implicitly acquired orthography-semantics regularities of artificial characters. We manipulated the semantic consistency levels of radicals embedded in artificial characters at high (100 %), moderate (80 %), and low (60 %). The behavioral results indicated that 8-year-olds in the second grade were able to acquire regularities of semantic radicals within a sequence of artificial characters. The ERP results revealed a N170-P300-N400 pattern. The N170 component in the occipitotemporal area indicated orthographic identification during the early stages of learning, while the P300 and N400 components reflected attentional allocation and semantic activation during the later stages of statistical learning of orthography-semantics connections. The interactions between neural activation of statistical learning and grade suggest a significant developmental change in 7-11-year-old children. These findings support the multi-component model of statistical learning and the age-related hypothesis.

1. Introduction

The human brain can automatically extract statistical regularities from environmental input (Thiessen, 2017). Known as statistical learning, this ability plays an important role in orthographic learning—the process of transitioning from decoding letters or logographic patterns and their associated constraints to fluent reading through rapid recognition of words or characters (Castles and Nation, 2010). Although behavioral studies have demonstrated the dependency of children's orthographic regularity acquisition on statistical learning in both alphabetic and nonalphabetic languages (Pacton et al., 2001; Tong and McBride, 2014), their reliance on reaction time or response accuracy as indicators of learning outcome limits outstanding of the specific neural mechanisms underlying statistical learning of orthographic regularities, particularly the temporal course of learning (Batterink and Paller, 2017; Tong et al., 2023). Moreover, as most studies have tested a narrow age range of children, the neurodevelopmental aspects of statistical learning have not been fully explored. Using event-related potentials (ERPs) for continuous and real-time recording of the brain's electrical activity during the learning process, this study investigates the neural indicators of statistical learning of semantic radical regularities embedded in artificial characters and the neurodevelopmental patterns of children in grades 1–5.

Understanding the neural mechanisms of statistical learning could offer objective biomarkers for orthographic learning and development. This is particularly important for Chinese because of its emphasis on ideographic characteristics and quasi-regularities. The Chinese writing system employs logographic characters as morpho-syllabic units, with semantic-phonetic compounds constituting approximately 85 % of characters (Shu et al., 2003). These compounds typically consist of semantic radicals, providing meaning cues, and phonetic radicals, offering pronunciation hints (Yeh and Li, 2002). This structure creates a complex distributional pattern of form-meaning relationships that learners must acquire. From a statistical learning perspective, the consistency and reliability of these relationships vary significantly (Tong and McBride, 2018). The semantic transparency of characters, or the degree to which a semantic radical predicts character meaning, follows a graded distribution. For example, in the Chinese character corpus (Tseng et al., 2018), the semantic radical 口 /kou3/ (indicating *mouth-related concepts*) is found in 247 characters, among which 155 possess meanings related to mouth (e.g., 吃 (*to eat*), 喝 (*to drink*), 唱 (to *sing*), 叫 (*to yell*)), yielding a semantic consistency of 62.75 %. Similarly, the semantic

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radical 车 /che1/ (denoting *vehicle or vehicle-like concepts*) occurs in 40 characters, with 28 of them related to vehicle (e.g., 轨 (*rail*), 载 (*to carry)*, 轮 (*wheel*), 输 (*to transport*)), yielding a semantic consistency of 70 %. This variability in form-meaning mappings presents a rich environment for statistical learning, where readers implicitly extract and internalize the probabilistic relationships between radicals and character meanings. Furthermore, previous developmental studies have shown that although Chinese children typically begin to acquire knowledge of character structure, position, sound, and semantic category of radicals at age 7 in Grade 1, they do not fully understand the function of semantic radicals until 9 years in Grade 3, indicating the late development of semantic radical knowledge compared to radical structural configuration (Ho et al., 2003; Tong et al., 2017).

Some behavioral studies have demonstrated the crucial role of statistical learning in the acquisition of regularities of semantic radicals in Chinese (He and Tong, 2017; Tong and McBride, 2014). However, few studies have investigated the neurophysiological mechanisms and neurodevelopmental aspects of statistical learning in children (Tong et al., 2023). To date, only one study has directly examined the neural markers of orthography-semantics connections in the Chinese language in adults (Tong et al., 2020b). Using ERPs, the researchers manipulated semantic consistency, i.e., the frequency of meaning associated with a target semantic radical, into three levels: low, moderate, and high. Across all conditions, three ERP components (N170, P200, and N400) were elicited, providing support for the multicomponent model of statistical learning proposed by Conway (2020).

In the study conducted by Tong et al. (2020b), the first elicited ERP component was the N170, a negative-going component that peaks within 170 ms after the onset of stimulus presentation (Maurer et al., 2005). Research has shown that this component is associated with the process of visual orthographic analysis and facial recognition (e.g., Maurer et al., 2008; Rossion et al., 2003; Simon et al., 2007). In Chinese, semantic radicals typically appear in a consistent position, usually at the left or top of a character (Shu et al., 2003). Thus, the N170 effect may reflect the process of analyzing positional information during statistical learning of semantic radicals (Tong et al., 2020b). The N170 has also been linked to the visual word form familiarity effect, which involves an enhanced N170 response when processing word stimuli with more orthographic representations (e.g., Bentin et al., 1999; Maurer et al., 2005). Tong et al. (2020b) found that the N170 amplitude was greater in the high-consistency condition compared to the low-consistency condition, suggesting enhanced orthographic identification for familiar and repeated inputs when consistency is high.

The second ERP component relevant to the current study is the P300, which is associated with attentional allocation, indexing the sequential processing of probability and expectancy at temporal-parietal regions and visual statistical learning at the parieto-occipital area (e.g., Jost et al., 2015; Polich, 2007; Singh et al., 2017). During statistical learning, this component is suggested to reflect both the allocation of attention to unexpected patterns and the updating of information as representations are integrated into larger patterns (Verleger, 1988). Furthermore, the increased P300 effect is often associated with the dynamic encoding of orthographic representations while learning Chinese characters and could predict long-term retention of orthographic representations (Chang et al., 2015). This component exhibits a positive deflection in the 210–280 ms time window for adults (Tong et al., 2020b) and in the 320–370 ms time window for children (Tong et al., 2023).

The third ERP component pertinent to our investigation is the negative-going N400-like/N400 component, a well-established neural indicator of word recognition (Beyersmann et al., 2014; Morris et al., 2007) and semantic processing in sentences (Hahne and Friederici, 2002; Kim and Osterhout, 2005). The N400/N400-like effect is also a crucial ERP component in studies of statistical learning across linguistic (e.g., Abla et al., 2008; Kooijman et al., 2005; Teinonen et al., 2009) and non-linguistic patterns (Abla and Okanoya, 2009). In speech processing, the N400 is thought to reflect three key phenomena: a familiarity effect, characterized by reduced amplitude for familiar words (e.g., Kooijman et al., 2005); a word-onset effect, with greater attenuation for initial syllables (Abla et al., 2008; Teinonen et al., 2009); and a training effect, involving decreased amplitude following learning (Sanders et al., 2002). These effects indicate easier lexical retrieval, anticipatory processing, and improved efficiency in word recognition, respectively. In visual statistical learning, the N400 also reflects online segmentation and learning processes. For example, high performers on a statistical learning task associated with word and tone segmentation showed larger N400 amplitudes at pattern onsets, particularly in the initial positions with lower transitional probabilities, with this effect diminishing over time as learning progresses (Abla and Okanoya, 2009). The N400's prominence in both auditory and visual tasks, typically maximal at middle frontal and central scalp sites, underscores its importance as a neural marker for statistical learning mechanisms in language acquisition and pattern learning.

Also noted is that the developmental trajectory of statistical learning remains a contentious issue (Arnon, 2019). According to the developmental invariance model, implicit statistical learning is a cognitive process not dependent on age (Reber, 1993). For instance, Jost and colleagues (2015) conducted an ERP study using a predictor-target task with adults, older children (aged 9–12), and younger children (aged 6–8) and found that high predictors elicited a similar P300 effect across all three age groups, indicating that visual statistical learning was age-independent. In contrast, the age-variant model suggests that children's statistical learning performance improves as they get older (Arciuli and Simpson, 2011). Using the visual triplet statistical learning paradigm on 5-12-year-olds, Arciuli and Simpson (2011) found that older children performed better than younger children. Nevertheless, no research has addressed the neurodevelopmental pattern of statistical learning of orthographic regularities, especially from Grade 1 to Grade 5, which is the second objective of our study.

In sum, to address the aforementioned research gaps, our study, first, investigates neural indicators of statistical learning of orthographic-semantics regularities embedded in artificial characters, and, second, examines how these neural indicators vary in children from Grade 1 to Grade 5. Based on previous EEG research (Tong et al., 2020b), we hypothesize that multiple neural markers could emerge at different stages of this learning process, specifically with N170 linking to statistical learning of positional regularities (e.g., Tong et al., 2023), P300 responsible for intermediate processing of orthography-semantics connections (Tong et al., 2020b, 2023), and N400 evoked later due to the integration of semantic information and visual patterns embedded in our artificial character stimuli. Furthermore, as this is the first study involving five age groups, we hypothesize developmental differences in the neural markers of statistical learning, with older children showing more efficient learning as potentially reflected in earlier or stronger ERP component modulations. However, we also acknowledge the possibility of age-invariant patterns, which would suggest that the basic mechanisms of statistical learning remain stable across development.

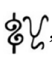
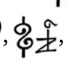
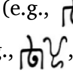
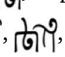
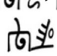
2. Methods

2.1. Participants

A total of 153 typically developing Chinese children participated in this study. The sample included first-graders (n = 26; 13 boys, 13 girls; Mean age = 7 years, 2 months, SD = 3.94 months), second-graders (n = 26; 11 boys, 15 girls; Mean age = 8 years, 2 months, SD = 3.40 months), third-graders (n = 40; 17 boys, 23 girls; Mean age = 9 years, 3 months, SD = 3.95 months), fourth-graders (n = 32; 20 boys, 12 girls; Mean age = 10 years, 2 months, SD = 4.81 months), and fifth-graders (n = 29; 15 boys, 14 girls; Mean age = 11 years, 3 months, SD = 3.89 months). All participants are monolingual Chinese speakers, although they are learning English as a second language in school as part of their regular curriculum. All of them were right-handed with normal or corrected-to-normal vision and no history of a learning disability or neurological disease.

ERP data for three children in Grade 1, three children in Grade 3, six in Grade 4, and one in Grade 5 were excluded from the final analysis due to artifact rejection. Additionally, the EEG data of one participant in Grade 4 was inaccessible because of a technological problem that appeared during data recording. Ethical approval was obtained from the Research Ethics Committee of the first author's university.

2.2. Materials and design

This study employed a single-factor design to manipulate semantic consistency across three levels: low (60 %), moderate (80 %), and high (100 %). The stimuli consisted of 15 left-right structured Geba pseudocharacters, which were previously used in a study by He and Tong (2017). To indicate the meanings of the pseudocharacters, three semantic radicals selected from Dongba characters were paired with five control radicals without semantic function selected from Geba characters. For each type of structured character, the three semantic radicals were paired with five sets of colored pictures, with each picture representing the meaning of one of the five pseudocharacters sharing the same semantic radical. In the high-consistency condition, the semantic radicals (e.g., ) represented sense organs in all five pseudocharacters (e.g., , , , , and ). In the moderate-consistency condition, the semantic radicals (e.g., ) represented animals in four pseudocharacters (e.g., , , , and ) and an animal body part in the fifth (e.g., ). In the low-consistency condition, the semantic radicals (e.g., ) represented types of food in three pseudocharacters (e.g., , , and ) and food-related containers in the other two (e.g.,  and ).

2.3. Procedure

Participants were tested on their ability to learn and recognize semantic radical regularities, with neural activity recorded during the learning phase. Response accuracy and reaction time were measured for both learning and recognition phases.

In the learning phase, a statistical learning paradigm, previously used in successful studies (He and Tong, 2017; Tong et al., 2020b), was adopted to examine participants' brain activity. E-Prime 2.0 software was used to present stimuli, with each learning trial consisting of a pseudocharacter on the left-side and a picture on the right-side of the monitor. The simultaneous presentation of pseudocharacters and associated pictures allowed us to examine how children process and learn the statistical regularities of semantic radical-meaning associations. The 15 pairs were displayed in a pseudorandomized sequence in four blocks, with each pair repeated 24 times for a total of 360 trials. Each trial began with a fixation at the center of the monitor for 500 ms, followed by a blank screen for 500 ms. A pseudocharacter-picture pair was then displayed for 2000 ms, followed by another blank screen for 1000 ms. Participants were instructed to press the SPACEBAR key when consecutive identical pairs of stimuli were presented.

During the recognition phase, participants were tested on all 15 pseudocharacters learned in the previous phase. Each pseudocharacter was presented with two pictures beneath it, one correct and the other unrelated. Participants were instructed to identify the picture that corresponded with the learned pseudocharacter by pressing the appropriate keyboard button.

2.4. Electroencephalography (EEG) recording and data analysis

The EEG data was only recorded during the learning phase. We used the Brain Product 32-channel Ag/AgCl system (Brain Products GmbH) to record participants' brain activity at a sampling rate of 500 Hz with the FCz electrode used as the online reference. The active electrodes were maintained with impedances below 15 kΩ.

The EEGLAB toolbox (Delorme and Makeig, 2004) was used to preprocess the EEG data. First, we rereferenced the data using the average reference. Second, we corrected artifacts (i.e., eye blinks, eye movements, and muscles) based on the guide by Chaumon et al. (2015) after applying independent component analysis with the Infomax algorithm (Makeig et al., 1995). The mean artifact component removal rates across grade levels were 3.73 % for Grade 1, 3.71 % for Grade 2, 3.47 % for Grade 3, 2.71 % for Grade 4, and 2.30 % for Grade 5. These removal rates are not very high for each grade although we simultaneously presented the pseudocharacter and the picture to children. Third, we segmented the continuous EEG data into epochs of −100–700 ms, then filtered the data using a notch filter of 50 Hz and a band-pass filter of 0.3–30 Hz. The ERP data were baseline-corrected at 100 ms pre-stimulus. Moreover, epochs with amplitudes exceeding ± 250 μV were excluded. The remaining proportions of epochs across grades were 89.45 % for Grade 1, 90.19 % for Grade 2, 84.41 % for Grade 3, 84.07 % for Grade 4, and 85.96 % for Grade 5. After averaging the ERPs within each condition, we used mean amplitudes to index the ERP components.

Given that the time courses of each ERP component in five grades were not completely overlapped, the successive time window analyses were conducted in five grades separately (see supplementary analysis). By segmenting the overall time range into consecutive short time intervals, this approach enables the analysis of ERP effects, allowing for the estimation of approximate time courses of various ERP components (Zou et al., 2019). Based on visual inspection, topographic map analysis, and successive time window analysis, three ERP components, i.e., N170 (180–280 ms), P300 (280–400 ms), and N400 (220–400 ms), were identified in this study.

For the N170 component, six occipitotemporal electrodes (i.e., TP9, TP10, P7, P8, O1, and O2) were selected based on the topographic maxima over both hemispheres across experimental conditions. In the subsequent analyses, the amplitudes of these electrodes were averaged for each hemisphere (LOT: TP9/P7/O1; ROT: TP10/P8/O2, see Fig. 1 A). For the P300 component, eight parietal-occipital-temporal electrodes were averaged for both left and right hemisphere (LPOT: P3/TP9/P7/O1; RPOT: P4/TP10/P8/O2, see Fig. 2 A). For the N400 component, the amplitudes of six frontal-central electrodes were averaged for each hemisphere (LFC: F3/C3; MFC: Fz/Cz; RFC: F4/C4, see Fig. 3 A).

The averaged amplitudes of each component were then analyzed using the linear mixed-effect model (LMM) fitted with the lme4 package (Bates et al., 2015) in RStudio. The model contains three fixed effects, i.e., consistency, grade, and laterality. Moreover, given that children's neural responses are subject to the repeated presentations of the items in the learning phase, the repetition was included as a covariate to adjust for the effect of repetition on the outcome of the LMM models. Participants and items were included as random effects with random intercepts. For all the models analyzed below, we used sum contrast coding for all the factors. The reference levels of factors Consistency, Grade, Laterality, and Repetition were the high level, the first grade, the right hemisphere, and the last repetition time, respectively. The function "contr.sum" was employed to apply sum coding to the aforementioned factors (Brehm and Alday, 2022). Within this model, we used the lmerTest package (Kuznetsova et al., 2017) with the Satterthwaites's method to perform an F test on fixed effects, and the emmeans package (Lenth, 2023) to analyze tests of simple effects and post hoc comparisons with Bonferroni correction.

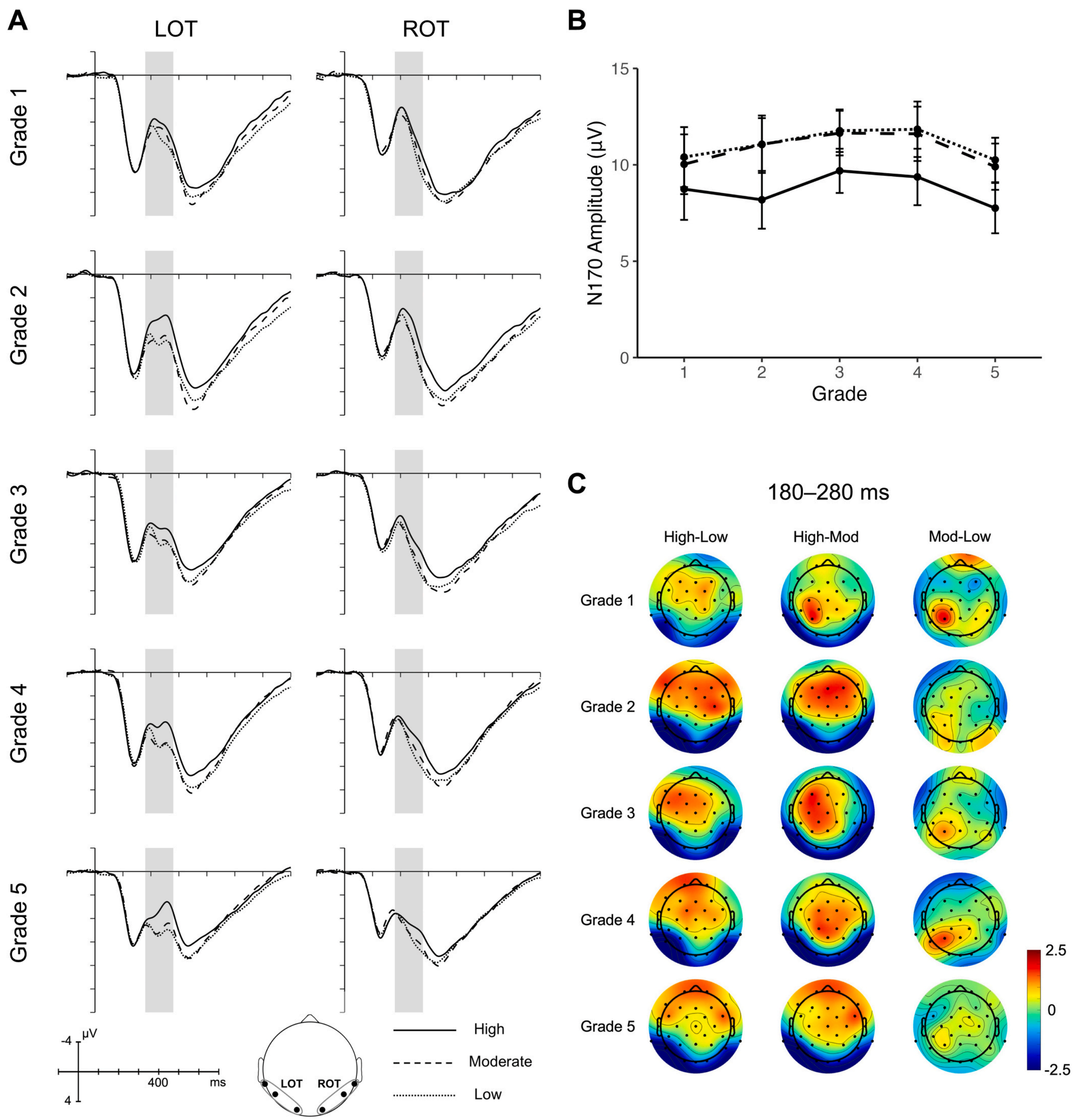


Fig. 1. (A) Grand averaged ERP waveforms of high-, moderate-, and low-consistency conditions in LOT and ROT for five grades. (B) Mean N170 amplitudes for the three consistency conditions in the occipitotemporal region for five grades. Error bars indicate the standard errors of the mean. (C) Topographical maps of different conditions across five grades in the 180–280 ms time windows.

3. Results

3.1. Behavioral results

Table 1 displays the reaction times, accuracy rates, as well as *t* and *p* values in one-sample *t*-tests from three conditions among five grades in the recognition phase.

In the learning phase, children's mean accuracy rates were 75.77 %, 85.90 %, 80.50 %, 86.82 %, and 84.31 % for Grade 1, Grade 2, Grade 3, Grade 4, and Grade 5, respectively. This indicates that all children had paid attention to the learning task.

In the recognition phase, one-sample *t*-test analyses were conducted to examine whether children in each grade could acquire different levels of orthography-semantics regularities by comparing the overall accuracy rates or accuracy rates of each consistency level for each grade with the chance level (50 %). As shown in Table 1, the results indicated that the overall accuracy rates for children from Grade 2 to Grade 5 were significantly higher than the chance level ($ps < .05$). However, no significant difference was observed in Grade 1 ($p = .516$). Specifically, the recognition accuracy in the moderate-consistency condition was

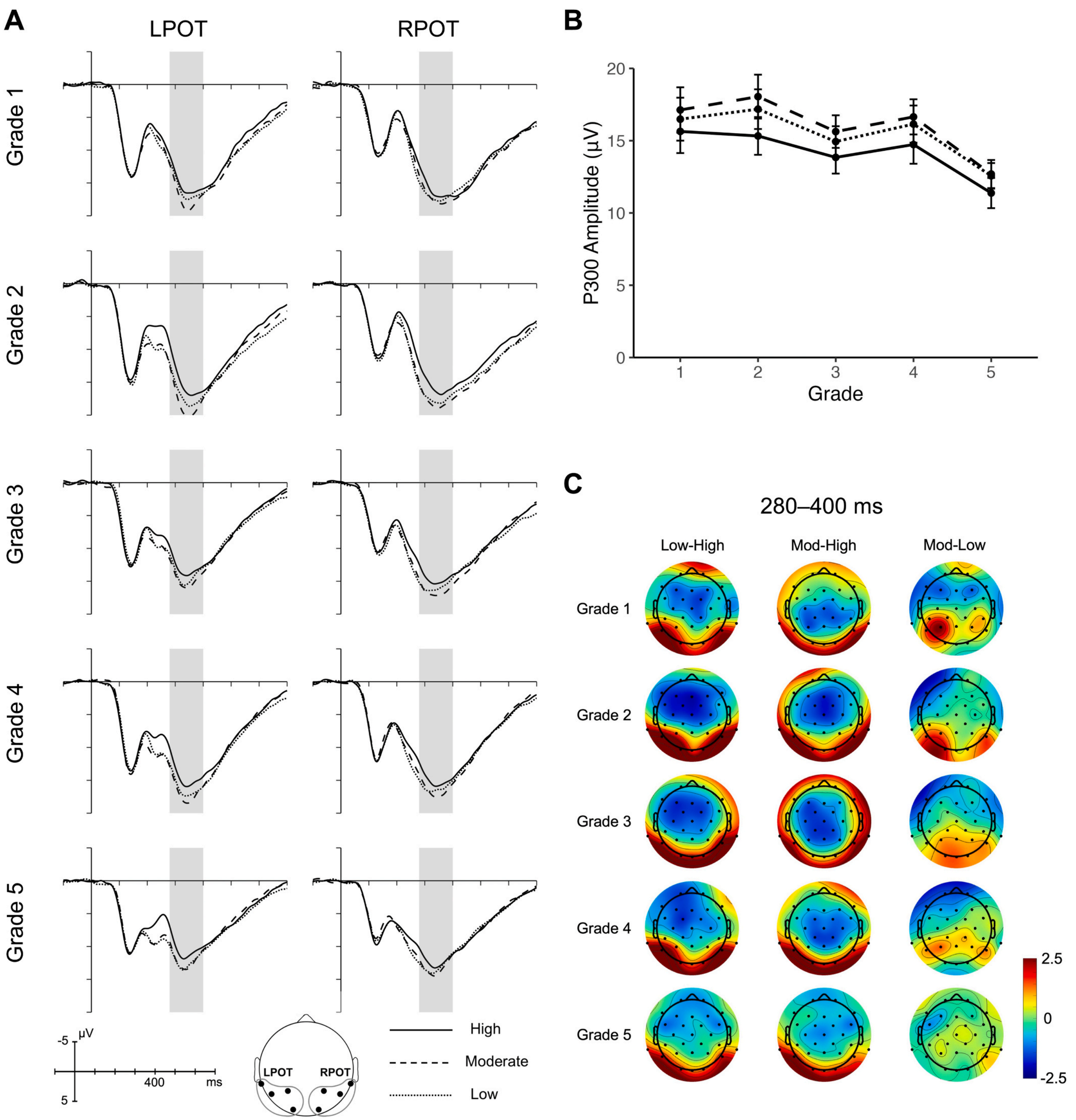


Fig. 2. (A) Grand averaged ERP waveforms of high-, moderate-, and low-consistency conditions in LPOT and RPOT for five grades. (B) Mean P300 amplitudes for the three consistency conditions in the parietal-occipital-temporal region for five grades. Error bars indicate the standard errors of the mean. (C) Topographical maps of different conditions across five grades in the 280–400 ms time windows.

significantly higher than the chance level for first and third graders ($ps < .05$). Fourth graders' recognition accuracy in the two conditions was significantly higher than the chance level for moderate- and low-consistency levels ($ps < .05$). Moreover, fifth graders' recognition accuracy in the three conditions was significantly higher than the chance level for high-, moderate-, and low-consistency levels ($ps < .05$).

We used the mixed-effect logistic regression model for the analysis of the response accuracy in the recognition phase. The model included fixed effects for consistency (sum coding) and grade (sum coding). Participants and items with random intercepts were entered as random effects in the model. The reference levels of factors Consistency and Grade were the high level and the first grade, respectively. The results in Type III Wald chi-square tests indicated that neither significant interaction effect between consistency and grade ($\chi^2(8) = 11.60$, $p = .170$), nor significant main effects (main effect of consistency: $\chi^2(2) = 1.66$, $p = .435$; main effect of grade: $\chi^2(4) = 8.06$, $p = .089$).

3.2. ERP results

The mean amplitudes of three ERP components for each condition in

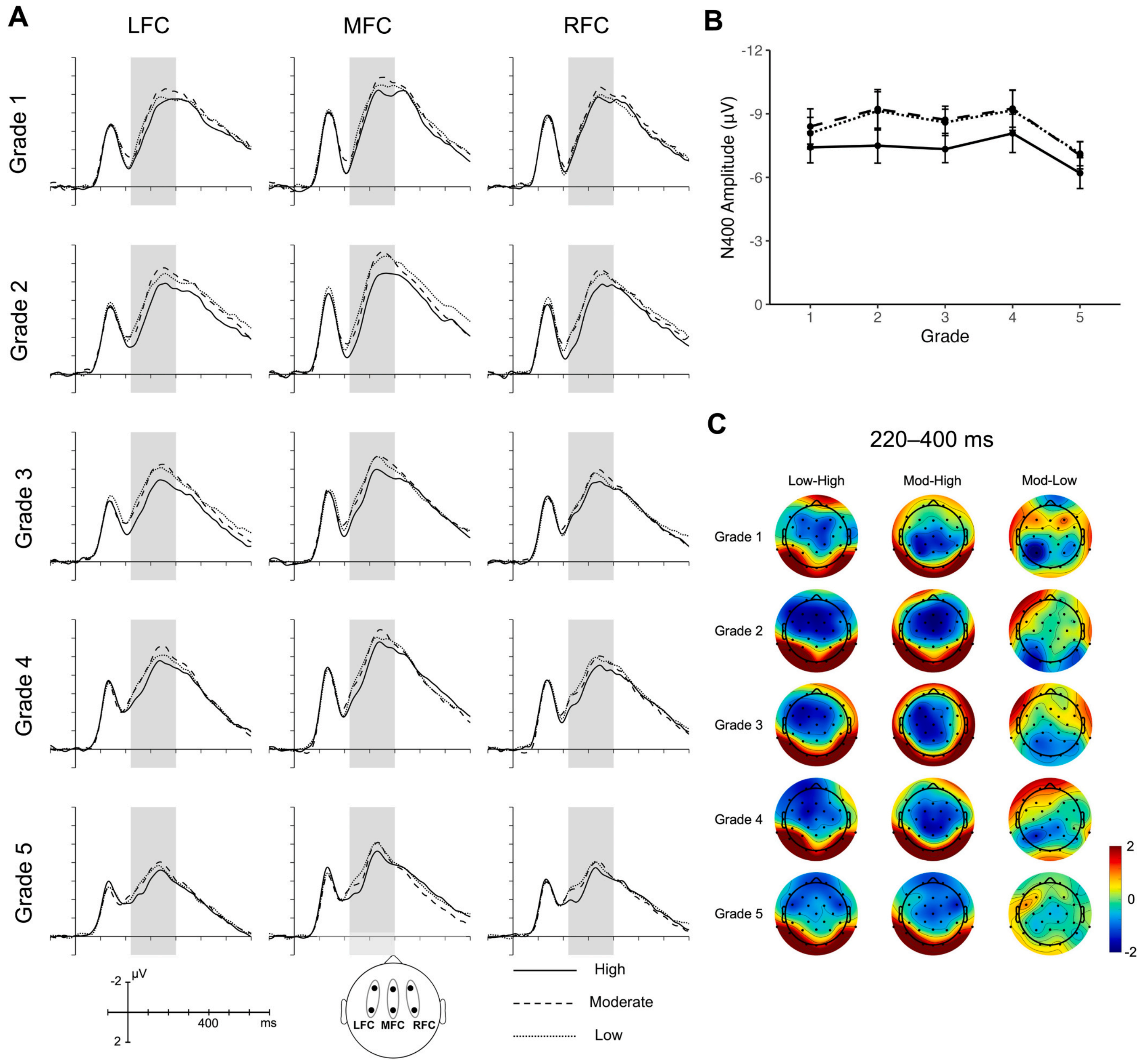


Fig. 3. (A) Grand averaged ERP waveforms of high-, moderate-, and low-consistency conditions in LFC, MFC, and RFC for five grades. (B) Mean N400 amplitudes for the three consistency conditions in the frontal-central region for five grades. Error bars indicate the standard errors of the mean. (C) Topographical maps of different conditions across five grades in the 220–400 ms time windows.

five grades are shown in Table 2. ERP waveforms of three conditions and topographical maps of different conditions for five grade groups in each time window are displayed in Figs. 1–3. The details of LMM for the three ERP components were described in Tables S5-7 (see the supplementary document).

3.2.1. N170 (180–280 ms)

The results of the LMM analysis for the N170 mean amplitude indicated a significant interaction between consistency and grade ($F_{(8, 72008)} = 2.13$, $p = .030$). Further analyses revealed that the mean amplitude for the high-consistency condition was more negative than for the moderate- and low-consistency conditions in second through fifth graders (second graders: for high vs. moderate, $\beta = -2.92$, $SE = 0.71$, $t = -4.13$, $p = .002$; high vs. low, $\beta = -2.90$, $SE = 0.71$, $t = -4.10$, $p = .003$; third graders: high vs. moderate, $\beta = -1.95$, $SE = 0.69$, $t = -2.82$, $p = .039$; high vs. low, $\beta = -2.06$, $SE = 0.69$, $t = -2.98$, $p = .029$; fourth graders: high vs. moderate, $\beta = -2.26$, $SE = 0.71$, $t = -3.16$, $p = .017$; high vs. low, $\beta = -2.51$, $SE = 0.71$, $t = -3.52$, $p = .008$; and fifth graders: for high vs. moderate, $\beta = -2.29$, $SE = 0.71$, $t = -3.25$, $p = .015$; high vs. low, $\beta = -2.58$, $SE = 0.71$, $t = -3.66$, $p = .006$). However, these differences were not significant for first graders (high vs. moderate, $\beta = -1.38$, $SE = 0.72$, $t = -1.93$, $p = .213$; high vs. low, $\beta = -1.66$, $SE = 0.72$, $t = -2.32$, $p = .100$).

The interaction between consistency and laterality was significant ($F_{(2, 72007)} = 5.39$, $p = .005$). Further analyses suggested that the high-consistency level elicited a larger N170 effect compared to the low and moderate conditions at LOT (high vs. moderate, $\beta = -2.57$, $SE = 0.67$, $t = -3.84$, $p = .006$; high vs. low, $\beta = -2.65$, $SE = 0.67$, $t = -3.97$, $p = .005$). At the ROT, the high-consistency condition elicited a greater N170 response than the low-consistency condition ($\beta = -2.03$, $SE = 0.67$, $t = -3.03$, $p = .029$) and a marginal greater N170 effect than the moderate-consistency condition ($\beta = -1.75$, $SE = 0.67$, $t = -2.61$,

Table 1
Reaction times, accuracy rates, and the results of one-sample t-tests by grade for three consistency conditions in the recognition phase. Standard deviations are in parentheses.

	Reaction time	Accuracy rate	*t*-value	*p*-value
Grade 1 (N = 26)			.66	.516
High	4483.609(1914.777)	.492(.242)	−.16	.872
Moderate	3956.646(2166.437)	.623(.221)	2.83**	.009
Low	4837.021(2585.685)	.439(.233)	−1.35	.191
Grade 2 (N = 26)			2.20*	.037
High	3630.113(1899.641)	.577(.290)	1.35	.189
Moderate	3061.210(1450.370)	.592(.280)	1.68	.105
Low	3624.742(1616.129)	.523(.294)	.40	.693
Grade 3 (N = 40)			2.70*	.010
High	3556.753(1790.931)	.545(.244)	1.17	.250
Moderate	3108.204(1464.052)	.585(.246)	2.19*	.035
Low	3511.117(1707.845)	.565(.248)	1.66	.105
Grade 4 (N = 32)			2.69*	.011
High	2984.887(1343.386)	.531(.295)	.60	.553
Moderate	3685.636(2327.794)	.606(.246)	2.44*	.021
Low	3586.247(1950.219)	.638(.256)	3.04**	.005
Grade 5 (N = 29)			4.10***	<.001
High	3667.055(2687.694)	.641(.304)	2.50*	.018
Moderate	3012.646(2034.432)	.635(.245)	2.95**	.006
Low	3694.691(2796.654)	.635(.251)	2.88**	.007

Table 2
Mean amplitudes of three ERP components (N170, P300, and N400) for three consistency conditions for each grade. Standard deviations are in parentheses.

	Grade				
	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5
N170					
High	8.739	8.186	9.689	9.371	7.753
	(6.249)	(6.243)	(5.706)	(5.981)	(5.642)
Moderate	10.030	11.068	11.646	11.608	9.904
	(6.071)	(6.198)	(5.758)	(5.757)	(5.192)
Low	10.401	11.054	11.768	11.845	10.251
	(6.098)	(5.706)	(5.479)	(5.878)	(4.985)
P300					
High	15.643	15.329	13.845	14.734	11.380
	(5.866)	(5.437)	(5.557)	(5.428)	(4.514)
Moderate	17.128	18.051	15.630	16.649	12.694
	(6.135)	(6.323)	(5.604)	(4.965)	(4.198)
Low	16.490	17.183	14.939	16.149	12.570
	(5.821)	(5.715)	(5.276)	(5.249)	(3.823)
N400					
High	−7.415	−7.496	−7.405	−8.075	−6.199
	(2.868)	(3.441)	(3.117)	(3.695)	(3.145)
Moderate	−8.400	−9.227	−8.713	−9.244	−7.039
	(3.252)	(3.820)	(3.100)	(3.583)	(2.762)
Low	−8.083	−9.138	−8.622	−9.163	−7.119
	(2.928)	(3.762)	(3.017)	(3.850)	(2.481)

$p = .064$). Moreover, we found a significant interaction between grade and laterality ($F_{(4,\ 72007)} = 8.45$, $p < .001$). Simple effect analyses showed that mean amplitudes at the LOT were more negative than those at the ROT in third and fifth graders (third graders, $\beta = -0.79$, $SE = 0.21$, $t = -3.82$, $p < .001$; fifth graders, $\beta = -0.85$, $SE = 0.24$, $t = -3.61$, $p < .001$). In contrast, the ROT elicited a greater N170 response than the LOT in first graders ($\beta = -0.56$, $SE = 0.26$, $t = -2.20$, $p = .028$).

A significant main effect of consistency was also found ($F_{(2,\ 12)} = 7.87$, $p = .007$). Follow-up analyses revealed that the mean amplitude for the high-consistency condition was more negative than for the moderate- and low-consistency conditions (high vs. moderate, $\beta = -2.16$, $SE = 0.66$, $t = -3.29$, $p = .019$; high vs. low, $\beta = -2.34$, $SE = 0.68$, $t = -3.57$, $p = .012$). No other significant interaction or effect was found (all $ps > .1$).

3.2.2. P300 (280–400 ms)

The results of the LMM analysis revealed a significant interaction between consistency and grade ($F_{(8,\ 72009)} = 2.11$, $p = .031$). Further analyses revealed that the mean amplitude for the low-consistency condition was more positive than for the high-consistency conditions in second graders ($\beta = 1.82$, $SE = 0.63$, $t = 2.89$, $p = .031$). The mean amplitude for the moderate-consistency condition was more positive than for the high-consistency condition across second to fourth graders (second graders, $\beta = 2.76$, $SE = 0.63$, $t = 4.38$, $p = .001$; third graders, $\beta = 1.77$, $SE = 0.61$, $t = 2.89$, $p = .033$; fourth graders, $\beta = 1.95$, $SE = 0.64$, $t = 3.06$, $p = .020$).

The interaction between grade and laterality was also significant ($F_{(4,\ 72007)} = 10.68$, $p < .001$). The subsequent analysis showed that the mean amplitudes at LOT for the first, second and fourth graders were significantly more positive than for the fifth graders (first vs. fifth graders, $\beta = 4.56$, $SE = 1.48$, $t = 3.08$, $p = .025$; second vs. fifth graders, $\beta = 5.16$, $SE = 1.43$, $t = 3.61$, $p = .004$; fourth vs. fifth graders, $\beta = 4.21$, $SE = 1.45$, $t = 2.91$, $p = .042$). The mean amplitude at ROT for the second graders was significantly more positive than for the fifth graders ($\beta = 4.11$, $SE = 1.43$, $t = 2.87$, $p = .048$).

We also observed a significant consistency effect on the P300 mean amplitude ($F_{(2,\ 12)} = 5.63$, $p = .019$). The follow-up analysis showed that the mean amplitude for the moderate-consistency condition was significantly more positive than for the high-consistency condition ($\beta = 1.89$, $SE = 0.58$, $t = 3.28$, $p = .020$). The grade effect was also significant ($F_{(4,\ 134)} = 3.39$, $p = .011$). Further analyses showed that the mean amplitudes for children in first and second grades were more positive than for it in fifth graders (first vs. fifth graders, $\beta = 4.20$, $SE = 1.47$, $t = 2.86$, $p = .049$; second vs. fifth graders, $\beta = 4.64$, $SE = 1.42$, $t = 3.26$, $p = .014$). Moreover, the laterality effect was found to be significant ($F_{(1,\ 72007)} = 44.06$, $p < .001$), with the mean amplitude more positive at ROT than it at LOT ($\beta = 0.70$, $SE = 0.11$, $t = 6.64$, $p < .001$). No other significant interaction was found (all $ps > .1$).

3.2.3. N400 (220–400 ms)

The LMM analysis of the N400 mean amplitude revealed an interaction between consistency and grade ($F_{(8,\ 108098)} = 2.28$, $p = .019$). Simple effect analyses showed that the mean amplitudes for low-consistency conditions were more negative than for the high-consistency condition from second to fifth graders (second graders, $\beta = -1.64$, $SE = 0.37$, $t = -4.48$, $p < .001$; third graders, $\beta = -1.22$, $SE = 0.35$, $t = -3.46$, $p = .009$; fourth graders, $\beta = -1.14$, $SE = 0.37$, $t = -3.08$, $p = .017$; fifth graders, $\beta = -0.96$, $SE = 0.36$, $t = -2.64$, $p = .048$). The moderate-consistency condition elicited a larger negative response compared to the high-consistency condition across first to fourth graders (first graders, $\beta = -1.02$, $SE = 0.37$, $t = -2.73$, $p = .037$; second graders, $\beta = -1.74$, $SE = 0.37$, $t = -4.76$, $p < .001$; third graders, $\beta = -1.29$, $SE = 0.35$, $t = -3.66$, $p = .006$; fourth graders, $\beta = -1.17$, $SE = 0.37$, $t = -3.15$, $p = .015$).

The interaction between grade and laterality was significant ($F_{(8,\ 108095)} = 3.19$, $p = .001$). The follow-up analysis showed that the mean amplitude at MFC was more negative than it at LFC and RFC for children across first through fifth grades ($ps < .001$). Furthermore, the mean amplitudes at LFC were more negative than at RFC for third and fourth graders (third graders, $\beta = -0.54$, $SE = 0.17$, $t = -3.26$, $p = .003$; fourth graders, $\beta = -0.72$, $SE = 0.20$, $t = -3.58$, $p = .001$).

The results suggested a significant main effect of consistency ($F_{(2,\ 12)} = 8.84$, $p = .004$). The follow-up analysis revealed that the mean amplitudes for the moderate- and low-consistency conditions were more negative than for the high-consistency condition (low vs. high, $\beta = -1.13$, $SE = 0.32$, $t = -3.49$, $p = .013$; moderate vs. high, $\beta = -1.22$, $SE = 0.32$, $t = -3.78$, $p = .008$). There was also a significant effect of laterality ($F_{(2,\ 108095)} = 139.48$, $p < .001$). Further analysis showed that the mean amplitude in the MFC was more negative than in the LFC and RFC (MFC vs. LFC, $\beta = -1.07$, $SE = 0.09$, $t = -12.53$, $p < .001$; MFC vs. RFC, $\beta = -1.35$, $SE = 0.09$, $t = -15.83$, $p < .001$), and the mean amplitude in the LFC was more negative than in the RFC ($\beta = -0.28$, $SE = 0.09$, $t = -3.30$, $p = .003$). No other significant interaction or effect was found (all ps > .1).

3.3. Brain-behavioral correlation

To examine whether a relationship exists between children's behavioral performance and neural activation among varying consistency levels, we conducted correlation analyses for children in each grade between accuracy differences of every two semantic consistency levels in the recognition phase and their corresponding neural differences in the ERP effects. Tables S8–S10 show the results of the brain-behavioral correlation for each ERP component (see the supplementary document). The significant correlations are displayed in Fig. 4.

For the N170 component, the difference in behavioral performance between high and moderate levels exhibited a positive association with the right-lateralized N170 difference between high- and moderate-consistency conditions in third graders ($r = 0.361$, $p = 0.028$). The behavioral difference was negatively associated with the left-lateralized N170 difference between moderate- and low-consistency conditions in fourth graders ($r = -0.432$, $p = 0.031$). The difference in behavioral performance exhibited a negative association with the right-lateralized N170 difference between high- and low-consistency conditions in fifth graders ($r = -0.377$, $p = 0.048$).

For the P300 component, the accuracy difference was negatively associated with the left-lateralized P300 difference between moderate and low levels in second graders ($r = -0.485$, $p = 0.012$). For third graders, the behavioral difference was negatively correlated with the right-lateralized P300 differences between moderate and high levels ($r = -0.330$, $p = 0.046$), as well as between low and high levels ($r = -0.361$, $p = 0.028$). The difference in behavioral performance between moderate- and low-consistency conditions exhibited a positive association with the right-lateralized P300 difference between moderate- and low-consistency conditions in fourth graders ($r = 0.400$, $p = 0.047$).

For the N400 component, the accuracy difference in high versus low conditions exhibited a negative relationship with the N400 difference at RFC between low- and high-consistency conditions in second graders ($r = -0.477$, $p = 0.014$). The results indicated that for school-age children, their neural activities evoked by different consistency levels during statistical learning could reflect their behavioral learning performance.

4. Discussion

Using a combined ERP and artificial orthography learning paradigm in children from Grade 1 to Grade 5, this study demonstrated a multi-component system underlying children's statistical learning, as reflected by three neural indicators: an early ERP effect, N170, in the occipitotemporal region; and two relatively late ERP effects, P300 and N400, in the parietal-occipital-temporal and frontal-central regions, respectively. Moreover, age-related changes at the neural level were revealed during statistical learning of semantic regularities in children aged 7–11. Specifically, starting with second-grade children aged 8 years, a larger N170 effect occurred in the high-consistency condition, whereas a larger P300 response was elicited in the low- and moderate-consistency conditions. As age increased, no significant difference in P300 response were observed among fifth-grade children aged 11 years.

Consistent with previous studies (He and Tong, 2017; Tong et al., 2020a, 2017), our behavioral results showed that children from 8 years old (i.e., second graders) were able to implicitly acquire semantic radical regularities embedded in a sequence of artificial characters. More importantly, the neurophysiological evidence demonstrated a clear pattern of N170-P300-N400 during children's online statistical learning process of semantic regularities. The enhanced N170 response elicited by the high-consistency condition compared to the moderate- and low-consistency conditions aligned with Tong et al.'s (2020b) study in adults. According to the visual word form familiarity account (Bentin et al., 1999; Maurer et al., 2005), the increased N170 effect observed in the occipitotemporal region is associated with familiar orthographic items (e.g., real words and pseudowords) rather than less familiar orthographic items (e.g., strings). Moreover, the increased N170 indicates visual expertise after short-term character learning among Chinese children, even for preschoolers at 4–5 years old (Zhao et al., 2015). Thus, the N170 in our study reflected orthographic identification at the early stage of children's statistical learning. During the online statistical learning process, pseudocharacters carrying high consistency showed less conflict in orthography-semantics mappings for young learners, which led to greater familiarity with visual form representations.

The feature detection model may offer an alternative explanation for the developmental changes observed in N170. Dehaene and Cohen (2011) suggest that greater neural activation occurs in response to stimuli with higher visual-orthographic features, which is evident in the increased N170 response to words compared to pseudowords (Tong et al., 2016; Zhao et al., 2014). This pattern becomes more pronounced as children's reading skills improve (Zhao et al., 2014). In our study, we found that 7-year-old first graders showed no sensitivity to the association between a pseudocharacter's form and its meaning. However, with more reading experience, 8-11-year-olds began to acquire orthography-semantics regularities embedded in pseudocharacters and became more efficient at encoding information when exposed to orthographic representations displaying higher semantic consistency. This improvement was reflected in the enhanced N170 amplitudes observed in the high-consistency condition compared to both the moderate- and low-consistency conditions for second to fifth graders.

We observed an enhanced P300 effect in second to fourth graders when they encountered the low- or moderate-consistency conditions compared to the high-consistency condition. The larger P300 effects elicited by the less consistent items could be attributed to the violation of expectations during selective attention (Carrión and Bly, 2007). In the current study, both the low-consistency condition (60 % semantic association with food items and 40 % with food containers) and the moderate-consistency condition (80 % semantic association with animals and 20 % with animal body parts) involved semantic violations arising from unexpected and inconsistent orthography-semantics mappings. Consequently, increased attentional resources may have been allocated to processing these inconsistent inputs, as they presented more unexpected and complex regularities during the acquisition of orthographic patterns (Forest et al., 2022).

Moreover, the developmental change of the P300 differences across consistency levels between 8-year-olds and 9-10-year-olds suggests a fine-tuned statistical learning mechanism underlying young children, which is sensitive to a certain level of semantic regularity. Specifically, 8-year-olds allocated greater attentional resources to processing semantically inconsistent patterns embedded in pseudocharacters, as indicated by an increased P300 effect in low and moderate consistency levels relative to the high consistency level. With increasing age, the enhanced P300 effect observed in the moderate-consistency condition likely reflects children's greater cognitive effort devoted to integrating and encoding orthographic-semantic associations that occur with relatively higher probability. This aligns with the hypothesis that enhanced P300 amplitude indicates attentional allocation to form chunks with combined representations during successive presentation, particularly for high-probability predictions (i.e., 90 %, Jost et al., 2015). Thus, although the cognitive mechanisms of children aged 9–10 years are sufficiently developed to allocate attentional resources to items with lower semantic consistency (i.e., 60 %), these children demonstrate increased neural engagement when constructing orthographic-semantic representations at a moderate level of consistency (i.e., 80 %).

We also found that children from Grades 1–5 exhibited a larger N400 response in the moderate- or low-consistency conditions compared to the high-consistency condition. This result partially aligns with a previous study conducted with adults (Tong et al., 2020b), which suggested that the N400 response reflects varying degrees of semantic activation in semantic radicals during online statistical learning of

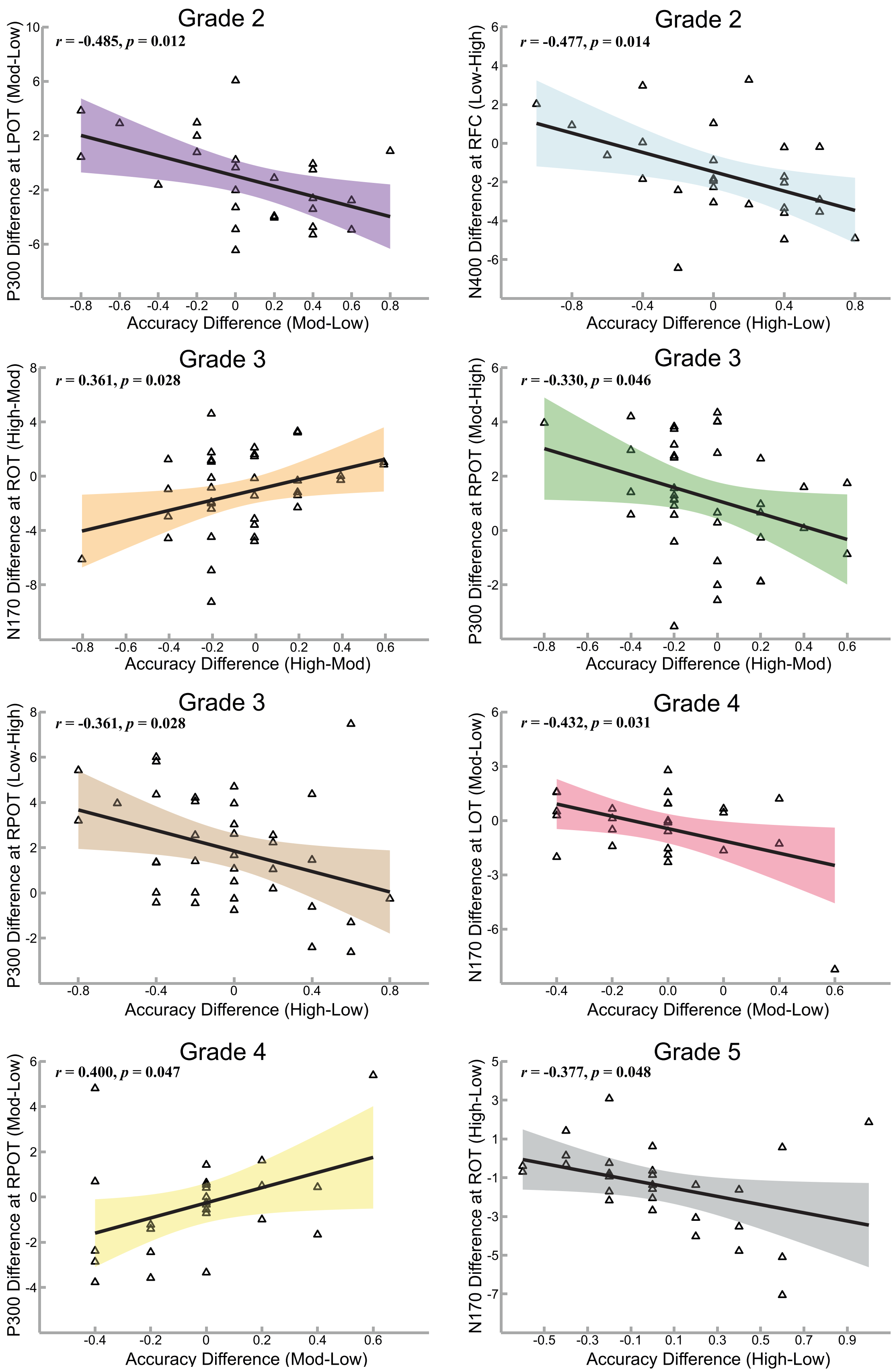


Fig. 4. Significant brain-behavioral correlations in five grades.

orthography-semantics connections. However, there were slight differences in the N400 effect between adults and children. In adults, low-consistency items elicited a greater N400 response than moderate-consistency items, and moderate-consistency items produced higher N400 amplitudes compared to high-consistency items. However, there was no significant difference in the N400 response between the moderate- and low-consistency conditions in children. This qualitative difference between children and adults could be attributed to children struggling to effectively extract and encode semantically inconsistent information, irrespective of the levels of moderate and low consistency (Benau et al., 2011).

This study also reveals a pivotal stage in the development of semantic statistical learning in children aged 8–10. During this period, children progressed in their ability to recognize and allocate attention to the orthographic information present in semantic radicals. They then proceeded to encode semantic information. Specifically, we observed that starting from the second year of primary school, children were able to identify familiar and consistent items through orthographic recognition. This was evidenced by larger N170 responses in the high-consistency condition. Moreover, they displayed increased N400 amplitudes in both the moderate- and low-consistency conditions, indicating their improved ability to encode semantically consistent representations. During the period from age 8–10, 8-year-olds needed to employ more attentional resources to deal with the higher expectancy violation and the uncertainty of orthography-semantics connections embedded in more inconsistent items. This was indicated by increased P300 responses in the low- and moderate-consistency conditions for children in second grade. In the middle period of primary school, children aged 9–10 showed greater attentional modulation when processing items with a relatively higher probability, as evidenced by increased P300 amplitudes in the moderate-consistency condition.

With increasing attentional control, 11-year-olds allocated equal attentional resources to items under all three levels. This was indicated by the nonsignificant P300 effect in fifth graders. These results support the idea that attention plays a critical role in the development of orthographic statistical learning among school-age children (Forest et al., 2023). At the beginning of primary school, children start to modulate their attention to process orthographic information at a sublexical level. As age increases, children allocate more attentional resources to complicated and uncertain orthography-semantics patterns and gradually reduce the engagement of attention as their cognitive abilities improve. These findings elucidate the developmental trajectory of statistical learning of semantic regularities in children.

Moreover, the correlation analyses between behavioral performance and neural difference among varying semantic consistency levels reflected that varying neural indicators elicited during the statistical learning process might predict children's behavioral performance in the recognition phase across 8–10 years. More specifically, for 8-year-olds in the second grade, the increased left-lateralized P300 difference elicited by the moderate versus low levels might indicate worse behavioral performance on the moderate level. Similarly, the enhanced right-lateralized N400 effect elicited by low versus high conditions might indicate worse behavioral performance at the high level. For 9-year-olds in the third grade, the increased right-lateralized P300 difference elicited by moderate and low levels might reveal worse behavioral performance in the high level. For 10-year-olds in the fourth grade, the increased left-lateralized N170 difference elicited by the moderate compared to low levels, as well as the enhanced right-lateralized P300 response elicited by moderate versus low conditions, may indicate better behavioral performance in the low and moderate levels, respectively. These correlations suggest that, during the second and middle years of primary school, increased neural engagement associated with processing semantically inconsistent information may hinder children's acquisition of more regular patterns. However, as children grow older, their heightened neural engagement in extracting orthographic-semantic associations at lower consistency levels likely reflects an improvement in their discrimination abilities.

The findings from this study support the idea of an age-related aspect to statistical learning, as demonstrated by the interactions between consistency and grade in the N170, P300, and N400 effects. This is consistent with previous research (Thomas et al., 2004), which also found age-related differences in statistical learning. However, Thomas et al.'s (2004) findings differ from a separate ERP study conducted by Tong et al. (2023) on 7-9-year-olds' statistical learning of positional regularities, which did not find age-related differences. One possible explanation for this discrepancy is that children's orthographic statistical learning improves gradually over a wider age range, rather than during the first three years of primary school. Additionally, it is important to consider that the developmental trends of statistical learning may vary between functional and positional regularities. As noted by Tong et al. (2017), from kindergarten to grade 5, the contribution of semantic radicals in children's character reading increases, while the contribution of positional radicals decreases. Our study aligns with these previous findings (Ho et al., 2003; Tong et al., 2017), suggesting that an age-related progression occurs in the statistical learning of semantic regularity among school-aged children.

4.1. Implications

The results of this study have both theoretical and educational significance. From a theoretical perspective, our findings illuminate the neural signatures associated with children's statistical learning of semantic regularities in Chinese characters. A key finding is the elicitation of the N400 component, which was not observed in previous studies on positional regularities (e.g., Tong et al., 2023). This suggests that the processing of semantic regularities engages additional or distinct neural resources compared to positional regularity processing. The presence of the N400, typically associated with semantic processing, indicates that even in the context of implicit learning, children are sensitive to process the semantic aspects of character structure. This extends our understanding of statistical learning mechanisms in reading acquisition, suggesting that such learning is not limited to surface-level features but also encompasses deeper, meaning-related patterns in orthography.

The developmental pattern observed in this study lends support to the age-related hypothesis of statistical learning (e.g., Arciuli and Simpson, 2011; Janacsek et al., 2012). Our findings suggest that age plays a significant role in the statistical learning of semantic regularities embedded in pseudocharacters. Specifically, we observed age-related changes in the ERP components associated with semantic regularity processing. These changes indicate that the ability to implicitly detect and learn from semantic patterns in Chinese orthography evolves as children progress through different developmental stages. This developmental trajectory aligns with broader theories of cognitive development that posit increasing efficiency in information processing and pattern recognition with age (Saffran and Kirkham, 2018). Moreover, our results extend the age-related hypothesis to the domain of semantic regularities in Chinese character recognition, an area previously unexplored in this context. This extension provides valuable insights into how children's capacity for statistical learning in reading acquisition may change over time, particularly in logographic writing systems.

Our findings have significant educational implications for Chinese literacy instruction. The observed neural sensitivity to semantic regularities, even in young children, underscores the importance of incorporating semantic aspects of character structure in teaching methods. This could lead to more efficient character learning and reading development. The developmental patterns revealed suggest the need for age-appropriate instruction, with strategies evolving as children's ability to process semantic regularities matures. Future research should explore how this age-related pattern of statistical learning interacts with other cognitive abilities and educational factors, potentially informing the development of targeted assessment tools and intervention strategies for reading difficulties.

4.2. Limitations and future directions

Notably, this study has a few limitations that should be considered. For example, there is a limit between moderate (80 %) and high (100 %) consistency, as well as between moderate (80 %) and low (60 %) consistency. This could potentially make it more challenging for children to identify orthographic-semantic connections under the moderate condition. Moreover, our study primarily focuses on examining the attributes of semantic transparency and semitransparency in characters. It is important to acknowledge that none of the radicals involved in the character-figure pairs have a semantically opaque meaning. Therefore, future studies should aim to explore the comprehensive semantic distributional regularity, including characters with semantically opaque meanings. This broader investigation would provide a more robust foundation for generalizing our findings to real character learning scenarios.

5. Conclusions

Despite the aforementioned limitations, our study provides support for Conway's (2020) multicomponent model of statistical learning. This model suggests that statistical learning involves both implicit and automatic processing of simple patterns as well as explicit and attention-requiring processing of complex regularities and structures. In line with this model, our study reveal a distinct N170-P300-N400 pattern during the learning process. Specifically, the N170 component is associated with orthographic identification while the P300 component reflects attentional allocation. Additionally, the N400 component signifies semantic activation in online statistical learning. These patterns highlight the dynamic nature of attention and the processing mechanisms involved in statistical learning. Furthermore, our findings support the age-related perspective of statistical learning of orthography-semantics connections in Chinese children. Our findings suggest a developmental progression, with a critical period identified between 8 and 10 years old. This age range is crucial for the acquisition and consolidation of orthographic-semantic connections in Chinese children.

Author note

Conceptualization and experimental design: XT and ST; Data curation: RD; Formal data analysis: RD and WZ; Final writing, revision, and editing: RD , ST and XT; Supervision: XT. All authors approved the final version of the manuscript for submission.

Code availability

The analysis scripts used in this study are publicly accessible on OSF at https://osf.io/kapy4/?view_only=09e7690b3e8e4a3697c44f30fc6d10ea.

CRediT authorship contribution statement

Xiuhong Tong: Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Conceptualization. **Rujun Duan:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Wenyuan Zhao:** Formal analysis. **Shelley Xiuli Tong:** Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.dcn.2025.101576.

Data availability

Data will be made available on request.

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