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A study of ERPs acquired during handwritten and printed Chinese character processing in a lexical decision task

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A R T I C L E I N F O

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A B S T R A C T

The aim of this study was to investigate the time course differences in brain processing between handwritten and printed Chinese characters. Behavioural and event-related potential (ERP) data were collected from twenty participants as they performed a lexical decision task in which Chinese handwritten and printed characters served as stimuli. The findings indicated that N1 reflects orthographic regularity during the early processing stage; N400 and the late positive component (LPC) data revealed that reading handwritten words evoke greater ERP amplitudes during the late processing stage. Although handwritten characters evoke greater ERP amplitudes, this did not result in more efficient behavioural outcomes. Therefore, it appears that the greater ERP amplitudes observed in the handwriting task corresponded to deeper meaning comprehension, which is also more challenging for semantic integration.

1. Introduction

Due to scientific and technological advancements, an increasing number of individuals utilize computers in their contribution to modern society. Although we still perform traditional handwriting tasks frequently in our daily lives, we are paying increasingly less attention to it. In reality, handwriting and printing are not the same. Handwriting has its own characteristics, as handwriting is considered a stimulus implying motion (Wamain, 2019). Individuals can glean information about writing movements based on passive observation of static characters (Babcock & Freyd, 1988) due to the order and direction of the different strokes that are deeply ingrained in individuals (and cannot be confused with those of other characters). Furthermore, the sequence of movements required to produce a character has an impact on how we perceive it.

In recent years, with the development of neuroimaging technology, increasing evidence has shown the reactivation of areas engaged during writing movements when characters are observed passively. Comparative studies on handwritten and printed letters have shown that the primary motor cortex is strongly activated when a subject observes handwritten letters instead of printed letters (Longcamp, Anton, Roth, & Velay, 2003, 2006, 2011). Longcamp, Tanskanen, and Hari (2006, 2011) suggested that knowledge related

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to hand movement is more involved in recognizing handwritten characters than in recognizing printed letters, probably because the intrinsic traces of the writing actions are important cues for recognizing unfamiliar shapes of characters (Babcock & Freyd, 1988). In other words, the motion-related activity elicited by visual stimulation, distinguished in the human brain, relies on input from the primary motor cortex (Longcamp et al., 2011a, 2011b). Additionally, Nakamura et al. (2012) conducted a cross-cultural study on Chinese and French handwriting characteristics using fMRI. They found that the visual word form area (VWFA) and Exner's area are involved in both Chinese and French reading, implying that Chinese handwritten characters also contain movement-related information. The primary distinction between handwritten and printed characters lies in the processing differences between them, which indicated that handwritten text requires fewer cognitive resources to interpret than printed text and that the processing of handwritten text has certain advantages (Barnhart & Goldinger, 2010). Differences in the left fusiform gyrus, an essential font-processing region housing the VWFA, have also been observed between handwritten and printed words (Cohen et al., 2000; Dehaene & Cohen, 2011; Polk & Farah, 2002). Barton, Fox, Sekunova, and Iaria (2010) and Longcamp et al. (2011a, 2011b) also reported differences in responses to handwritten and printed text in the left VWFA. Therefore, handwritten words can induce greater ERP amplitudes during processing.

Although previous studies using fMRI technology were effective in revealing the brain areas involved in word processing, event-related potential (ERP) technology is superior to fMRI in revealing the time course of cognitive processing. Moreover, previous fMRI studies did not clearly explain how stronger activation affects processing and psychological meaning. Since each ERP component has its own psychological meaning, ERP studies can complement fMRI studies. Previous studies on visual word recognition focused on the N1 component, sometimes referred to as the N170 component, which is a negative occipito-temporal component that peaks approximately 170 ms after the onset of a stimulus (Aranda, Madrid, Tudela, & Ruz, 2010; Bentin, Allison, Puce, Perez, & McCarthy, 1996). Many previous studies have reported that N1 amplitudes reflect attention allocation (Eimer, Van Velzen, Gherri, & Press, 2006; Luck, Woodman, & Vogel, 2000). The N1 amplitudes evoked by visual word stimuli are significantly larger than those evoked by control stimuli, such as strings of symbols and forms (e.g., Bentin, Mouchetant-Rostaing, Giard, Echallier, & Pernier, 1999; Maurer, Brandeis, & McCandliss, 2005). Therefore, it is generally agreed that the N1 component is sensitive to orthographic regularity (Lin et al., 2011). However, one study reported that nonwords increased the N1 amplitude compared to real words (Nemrodov, Harpaz, Javitt, & Lavidor, 2011), while another study revealed that the N1 amplitude was reduced for nonwords relative to words (Coch & Mitra, 2010). Xue, Jiang, Chen, & Dong (2008) suggested that N1 was modulated by factors (e.g., materials) across previous studies. Wamain, Tallet, Zanone, and Longcamp (2012) suggested that handwritten letters affecting the availability of the motor neural network were only visible at late time windows (300–350 ms and 500–600 ms) after letter presentation. Rey, Dufau, Massol, and Grainger (2009) also deemed that motor experience could not affect letter identification occurring approximately 170 ms after letter presentation. Therefore, whether N1 can reflect differences between activity elicited by handwritten and printed characters is still a topic worth investigating.

The N400 is a crucial ERP component in language-related research and an important aspect of EEG data in the recognition and integration of semantic information, serving as a marker of semantic processing (Kutas & Hillyard, 1984). It is a negative component that peaks approximately 400 ms after the presentation of a stimulus (Kutas & Federmeier, 2011). Generally, the amplitudes of the N400 component are considered to reflect the difficulty of integrating semantic information in context: the more challenging the integration is, the larger the N400 amplitudes are (Kutas & Federmeier, 2011). On the other hand, Barber, Otten, Kousta, and Vigliocco (2013) reported that an increase in N400 amplitudes would indicate greater semantic processing (integration of multimodal information) for words during meaning comprehension. Therefore, the authors revealed that N400 amplitudes can also reflect the level of meaning comprehension when words are presented in isolation: the deeper the level of meaning is activated, the greater the N400 amplitude (Barber et al., 2013; Molinaro, Conrad, Barber, & Carreiras, 2010). There is no conflict between these two viewpoints. Lv and Wang (2012a, 2012b) discovered that regardless of whether the characters were real or false, italicized characters presented in line produced a greater N400 amplitude than characters presented in Song typefaces. This finding indicated that complex characters evoke a greater N400 amplitudes. The semantic activation level when reading handwritten words is deeper than that when reading printed letters, necessitating the allocation of more cognitive resources to integrate semantic information. A deeper level of meaning comprehension requires more cognitive resources to be used to integrate semantic information. This greater demand for cognitive resources implies difficulty in word recognition. In addition to the N1 and N400 components, the present study focused on the late positive component (LPC). The LPC component is widely believed to be involved in attention propensity and stimulus assessment, as well as in responses to task requirements (Polich, 2007). The LPC occurs after the N400 component. Kaan, Harris, Gibson, and Holcomb (2000) considered the LPC to reflect a further integrating process after the N400. A more positive LPC amplitude means that the process is more difficult and requires the utilization of more cognitive resources (Hagen, Gatherwright, Lopez, & Polich, 2006). Some studies have reported increased LPC amplitudes in response to reading metaphorical sentences, suggesting that the semantic processing of metaphors necessitates additional retrieval of information from semantic memory (De Grawe et al., 2010). Furthermore, the LPC is sensitive to orthographic regularity (Kemény, et al., 2018). Research has shown that the LPC can reflect the level of arousal, with highly arousing stimuli often inducing greater LPC amplitudes (Hajcak, Mac Namara, & Olvet, 2010). Previous studies reported that words evoked greater amplitudes than pseudowords (Hasko, Groth, Bruder, Bartling, & Schulte-Körne, 2013) and greater amplitudes than pseudohomophones (Bakos, Landerl, Bartling, Schulte-Körne, & Moll, 2018). Therefore, more positive LPC amplitudes for real words indicate that they require the retrieval of semantic information to be processed, which requires greater cognitive resource consumption.

Based on previous research, it appears that the difference in the time course of processing handwritten and printed words is relatively small. However, fMRI results suggested that handwritten words may evoke greater ERP amplitudes, although it remains unclear whether there are distinct time courses for the two modes of presentation. Additional research is needed in this area. In a study by Mahé, Zesiger, and Laganaro (2015), experimental tasks were found to influence visual word recognition processes. The present study aimed to compare brain activity elicited by processing handwritten and printed Chinese characters, utilizing a lexical decision task, a commonly used paradigm for investigating visual word recognition processes. This task involves a high level of graphic processing, which is particularly significant in Chinese, a logographic language. Therefore, a lexical decision task provides a more direct approach to comparing brain activity elicited by processing printed and handwritten Chinese characters.

During the lexical decision task, participants were presented with characters and were required to determine as quickly and accurately as possible whether they correspond to real characters by pressing two keys. While the lexical decision task mainly involves graphic processing, the semantic aspect is also activated. False characters, in contrast to real characters, do not have actual meanings. Therefore, only real characters elicit greater ERP amplitudes during the semantic stage of processing handwritten text. The lexicogenetic model of visual word recognition posits that lexical units stored in mental dictionaries are counters, which store various attribute information about words, including phonology, orthography, and semantics, among others. While lexical decision tasks involve a high level of graphic processing, Chinese characters, compared to the pinyin characters previously studied, exhibit a unique graphic-semantic correspondence. Therefore, utilizing Chinese characters to explore the differences between brain activity elicited by processing handwritten and printed characters holds clear advantages, particularly in investigating the role of graphene-semantic processing. Currently, there is limited direct research on manipulating the semantic properties of Chinese characters. The current study employed the ERP technique to compare brain activity elicited by processing handwritten and printed characters in a lexical decision task. The focus was on three components: the N1, N400, and LPC. We hypothesized that the greater ERP amplitudes associated with processing handwritten characters would be reflected in faster, more accurate behavioural responses and larger amplitudes of these three ERP components. Specifically, N1 may reveal differences only between real and false characters. This is because the greater ERP amplitudes associated with handwritten characters do not manifest in the early stages (Rey et al., 2009; Wamain et al., 2012). Larger amplitudes of the N400 component and LPC indicate stronger responses related to handwritten words. As LPC is also sensitive to orthographic regularity (Kemény, et al., 2018), greater ERP amplitudes related to handwritten words may only be observed when individuals are reading real characters.

Previous studies have utilized fMRI to elucidate the brain regions involved in word processing, but the findings have not provided a clear understanding of the temporal dynamics of cognitive processing. By recording brain activity, EEG technology can provide highly precise real-time data. Therefore, this study aimed to compare the time courses of cognitive processing for handwritten Chinese characters and printed Chinese characters in the brain using ERPs. Specifically, we focused on three ERP components: the N1, N400, and LPC. We hypothesized that processing handwritten characters would lead to faster response times, more accurate behavioural responses, and larger amplitudes of these three ERP components. In particular, we propose that the N1 component may solely reflect the distinction between genuine and false characters. This is because the heightened brain activation associated with handwriting does not occur in the early stages of word processing (Rey et al., 2009; Wamain et al., 2012). The N400 component may reflect the difference observed when individuals process handwritten and printed words, with larger amplitudes indicating more brain activity when reading handwritten words. Since the LPC is also sensitive to orthographic rules (Kemeny et al., 2018), the greater ERP amplitudes associated with processing handwritten words may only be observed in response to viewing real characters. Therefore, we inferred that genuine characters would elicit differing levels of activation depending on whether they were handwritten or printed, while no distinction would be observed between handwritten and printed false characters. In summary, we hypothesized that the N1 component in the experiment reflects the distinction between true and false characters in the early stages of processing, while N400 and LPC provide support for handwriting, eliciting greater ERP amplitudes during subsequent processing stages.

2. Methods

2.1. Participants

This study was approved by the Institutional Review Board of the School of Psychology at Liaoning Normal University. Twenty-three college students voluntarily participated in the experiment. Before the experiment, the participants were informed of the study objectives and provided written informed consent. In addition, all participants were required to complete an information survey. All participants met the following criteria: (1) Chinese was their native language, (2) right-handed, (3) no history of dyslexia or neurological diseases, and (4) visual acuity was normal or corrected-to-normal. Three subjects were removed from the analysis due to excessive artefacts in the EEG recordings. The remaining 20 participants had a mean age of 20.1 years (ranging from 19 to 22 years) and included 8 females. After the experiment, the participants received cash compensation.

2.2. Materials

First, we selected sixty real characters from the Chinese Character Information Dictionary (Shanghai Jiao Tong University, 1988). Then, sixty false characters were created by exchanging the positions of the real character's radicals. The real and false characters were presented in two fonts: one that resembled handwriting and one in which the letters were printed. Therefore, the experiment had four conditions: real handwriting (RH), real printing (RP), false handwriting (FH), and false printing (FP), amounting to 240 trials in total. The handwritten characters were provided by a volunteer who did not participate in the experiment. The printed characters were presented with the Song typeface, size 72, and the handwriting characters were augmented so that they were the same size, were black in colour, and presented on a grey background using picture processing software.

2.3. Procedure

The experimental program was created using E-Prime (Psychology Software, University of Pittsburgh, http://www.pstnet.com). The experiments were conducted in a quiet room, with participants gazing directly at the centre of the computer screen. The distance from the screen was controlled at approximately 70 cm. Chinese characters were displayed in the centre of the screen. The participants were asked to complete a lexical decision task, which required them to judge whether the words on the screen were real or false. Participants were instructed to press one of two response keys to indicate whether the stimulus was a real Chinese character. The mapping of response keys was counterbalanced across participants. For half of the participants, the right response key was used to signal the 'real' response, and the left response key was used to signal the "false" response; for the other half, the response assignment was reversed. Only when participants completed the practice test with 100% accuracy were they allowed to begin the experiment; otherwise, they had to continue the practice test. The experimental stimuli were presented randomly. There was a 3000 ms rest period after every 3 trials. After completing 60 trials, participants were given a long break and could decide when to initiate the next trial. The specific process of each trial is shown in Fig. 1. In addition to EEG data recordings, response time (RT) and accuracy (ACC) were recorded automatically by E-Prime.

2.4. Electroencephalogram (EEG) recording and processing

EEG data were collected using a 128-channel Hydrocel Geodesic Sensor Net EEG system (EGI, Eugene, USA) with a 100 Hz low-pass filter, a 250 Hz sampling rate, and a 22 bit A/D converter. The data were referenced to the vertex channel (Cz) during acquisition, and all electrode impedances were maintained below 50 kΩ (Ferree, Luu, Russell, & Tucker, 2001). EEGLAB (Delorme & Makeig, 2004) and ERPLAB (Lopez-Calderon & Luck, 2014) were used for offline processing in MATLAB. EEG data were digitally bandpass filtered (0.1–30 Hz) and average referenced. Then, the EEG data were segmented in relation to the onset of the stimuli (200 ms before and 800 ms after) and sorted according to the experimental conditions (handwritten false characters, handwritten characters, printed false characters, and printed characters). Next, only correct-response trials were analysed. The data were then separated into independent components using Infomax independent component analysis (Bell & Sejnowski, 1995). Artefacted independent components were automatically marked for rejection using the ADJUST toolbox (Mognon, Jovicich, Bruzzone, & Buiatti, 2011) in EEGLAB then manually inspected and removed from the data; an average of 11.21 ± 7.82 SD components removed. Segments with remaining artefacts were removed through automatic epoch rejection implemented in EEGLAB (threshold limit: 1000 μV, probability threshold: 5 SD, maximum percentage of trials rejected per iteration: 5%). The mean of the remaining trials after EEG data preprocessing was M = 93.19% (SD = 4.31). Baseline correction was performed using the 200 ms prior to the onset of the stimuli.

After a thorough examination of the topographic maps and grand-averaged ERP waveforms (Luck & Gaspelin, 2017), we selected and analysed the occipito-temporal N1 (130–200 ms), frontal-central N400 (200–400 ms), and central-parietal LPC (400–600 ms) signals. For the occipito-temporal N1 regions of interest (ROIs), 13 electrodes were selected (electrode numbers: 58 (P7), 65 (PO7), 70 (O1), 75 (OZ), 83 (O2), 90 (PO8), 96 (P8), 64 (P9), 95 (P10), 69, 74, 82, and 89). For the frontal-central N400 ROIs, 18 were selected (15, 16 (AFZ), 18, 10, 11 (FZ), 24 (F3), 19 (F1), 4 (F2), 124 (F4), 20, 12, 5, 118, 13 (FC1), 6 (FCz), 112 (FC2), 7, 106). For the central-parietal LPC ROIs, 24 electrodes (42 (CP3), 37 (CP1), 55 (CPz), 87 (CP2), 93 (CP4), 53, 54, 79, 86, 72 (POZ), 67 (PO3), 77 (PO4), 129 (CZ), 31, 80, 47 (CP5), 52 (P3), 60 (P1), 61, 62 (PZ), 78, 85 (P2), 92 (P4), and 98 (CP6)) were selected. See Fig. 2.

2.5. Data analyses

Repeated measures analysis of variance (rmANOVA) was conducted on both behavioural and ERP data using SPSS 22.0. For the behavioural data, rmANOVA was performed on the RT and ACC, with character fonts (printed or handwritten) and lexical category (real or false) as factors. For the ERP data, rmANOVA was carried out on three ERP components, with character fonts (printed or handwritten), lexical category (real or false), and electrodes as factors. p values and degrees of freedom were corrected by the Greenhouse–Geisser correction, if necessary.

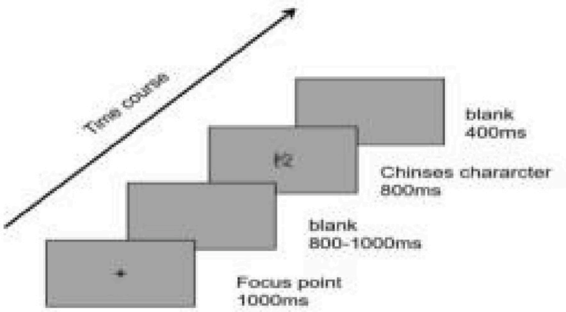


Fig. 1. Procedure of the lexical decision task in each trial.

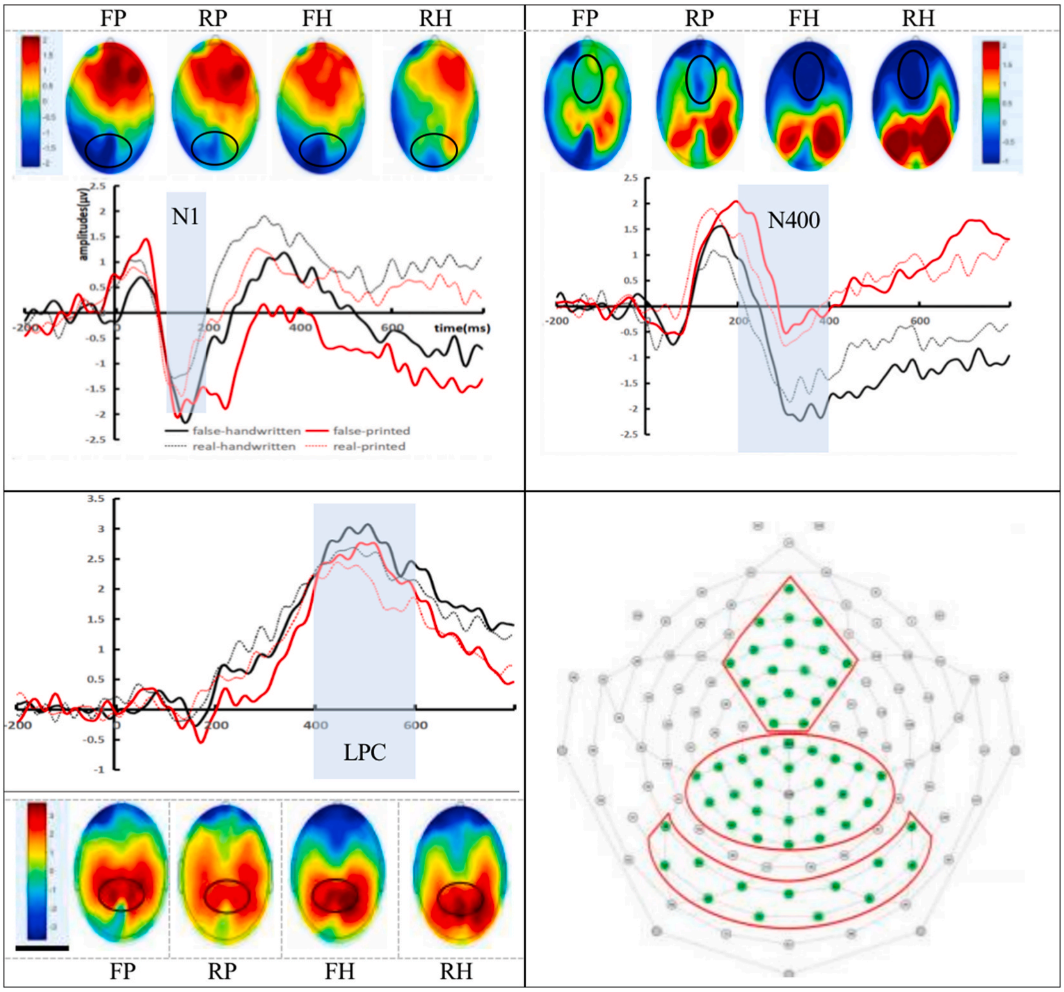


Fig. 2. The grand average of all electrodes in ROIs and the topographic maps of different ERP components. The green dots are the locations of selected electrodes in the 128-channel Hydrocel Geodesic Sensor Net EEG system. Real handwriting (RH), real printing (RP), false handwriting (FH), false printing (FP).

3. Results

3.1. Behavioural results

The RT results indicated that the main effect and the interaction effect were not significant ($p > 0.05$). For the ACC, the main effect of lexical category was significant, $F(1, 19) = 6.318$, $p = 0.021$, $\eta p^2 = 0.250$, and that of real characters (0.984 ± 0.005) was greater than that of false characters (0.970 ± 0.007). The main effect of character font was significant, $F(1, 19) = 6.167$, $p = 0.023$, $\eta p2 = 0.245$, and that of handwritten characters (0.972 ± 0.01) was lower than that of printed characters (0.982 ± 0.01). The interaction

Table 1
Comparison of the RTs and ACC values for real and false characters and for handwritten and printed characters.

Variable	RH	FH	RP	FP
RT	306.211 ± 79.130	301.277 ± 73.320	315.354 ± 76.830	303.344 ± 73.187
ACC	0.981 ± 0.240	0.964 ± 0.402	0.988 ± 0.269	0.977 ± 0.030
N1	−0.771 ± 0.652	−1.642 ± 0.615	−0.897 ± 0.612	−1.718 ± 0.569
N1 latency	161.538 ± 1.865	159.754 ± 1.356	161.185 ± 1.774	162.246 ± 1.889
N400	−1.159 ± 0.405	−1.202 ± 0.422	−0.013 ± 0.500	0.407 ± 0.512
N400 latency	302.278 ± 4.177	304.967 ± 4.845	306.911 ± 3.637	296.567 ± 5.169
LPC	2.517 ± 0.361	2.224 ± 0.376	1.131 ± 0.158	1.928 ± 0.504
LPC latency	472.733 ± 1.947	473.333 ± 3.003	472.200 ± 2.835	477.300 ± 3.289

Note: Real handwriting (RH), false handwriting (FH), real printing (RP), false printing (FP).

effect was not significant, $F(1, 19) = 0.415$, $p = 0.527$, $\eta p^2 = 0.021$. A comparison of the RTs and ACC values for real and false characters and handwritten and printed characters is shown in Table 1.

3.2. ERP results

N1 amplitudes showed that the main effect of lexical category was significant, $F(1,19) = 7.186$, $p = 0.015$, $\eta p^2 = 0.274$. The false characters (-1.686 ± 0.55 μV) evoked more negative amplitudes than did the real characters (-0.834 ± 0.607 μV); see Fig. 3 a. The main effect of character fonts was not significant, $F(1, 19) = 0.084$, $p = 0.775$, $\eta p^2 = 0.004$. The difference between the printed (-1.307 ± 0.573 μV) and handwritten characters (-1.206 ± 0.604 μV) was not significant. The main effect of electrodes and all interaction effects were not significant. There were no significant main effects or interaction effects on the N1 latency.

The N400 amplitude data showed that the impact of lexical category was not significant, $F(1,19) = 0.452$, $p = 0.509$, $\eta p^2 = 0.023$. The difference between false characters (-0.397 ± 0.45 μv) and real characters (-0.586 ± 0.431 μv) was not significant. However, the main effect of character fonts was significant, $F(1,19) = 38.607$, $p < 0.001$, $\eta p^2 = 0.67$. Handwritten characters (-1.18 ± 0.391 μV) evoked more negative amplitudes than did the use of printed characters (0.197 ± 0.470 μV); see Fig. 3b. However, the main effects of electrodes and the interaction effects were not significant. There were no significant main effects or interaction effects on the N400 latency.

LPC amplitude data showed that the main effect of lexical category was not significant. $F(1,19) = 0.647$, $p = 0.431$, $\eta p^2 = 0.033$ indicated that the difference between false characters (2.076 ± 0.357 μv) and real characters (1.824 ± 0.196 μv) was not significant. The main effect of character fonts was marginally significant, with a value of $F(1,19) = 4.222$, $p = 0.054$, $\eta p^2 = 0.182$. The difference between handwritten (2.371 ± 0.344 μv) and printed characters (1.53 ± 0.287 μv) was marginally significant. Please refer to Fig. 2 for details. Furthermore, the main effect of the electrodes was significant, with $F(23,437) = 2.632$, $p < 0.001$, $\eta p^2 = 0.122$. The interaction between lexical category and character fonts was also significant, with a value of $F(1,19) = 5.814$, $p = 0.026$, $\eta p^2 = 0.234$. Simple effect analysis indicated that the effect of character fonts was significant for real characters ($p = 0.002$), as handwritten characters (2.517 ± 0.361 μv) evoked more positive amplitudes than did printed characters (1.131 ± 0.158 μv). However, the effect of character fonts was not significant for false characters ($p = 0.535$), as the difference between handwritten (2.224 ± 0.376 μv) and printed characters (1.928 ± 0.584 μv) was not significant. Please refer to Fig. 4 for details.

4. Discussion

To investigate the difference in the time course of reading Chinese handwritten and printed characters, we collected behavioural and ERP data while participants performed a lexical decision task. However, the reaction time did not have a significant effect on the results. ACC values indicated that handwritten characters had a significantly lower P value ($P = 0.002$) than printed characters. We originally hypothesized that handwriting would be more accurate than printed characters. Therefore, the behavioural results do not support our hypothesis. Greater ERP amplitudes did not lead to more efficient behavioural results.

We analysed the ERP data to illuminate the cognitive processing of handwriting in lexical decision tasks. More specifically, we scrutinized three consecutive ERP components: the N1, N400, and LPC. The findings regarding N1 amplitudes align with those of previous studies (Nemrodov et al., 2011), which indicate that false characters elicit more negative amplitudes than real characters during lexical decision tasks. The N1 component is typically regarded as an indicator of the visual signal associated with the initial stage of word recognition (Lee, Liu, & Tsai, 2012). This finding suggested that orthographic regularity is processed during the early phase of visual word recognition.

On the other hand, the N1 component did not differ between handwritten and printed character conditions, indicating that it cannot reflect the greater ERP amplitudes associated with processing handwritten characters. Previous studies have shown that the N1 amplitude reflects attention allocation (Eimer et al., 2006; Luck et al., 2000). Although numerous studies have suggested that

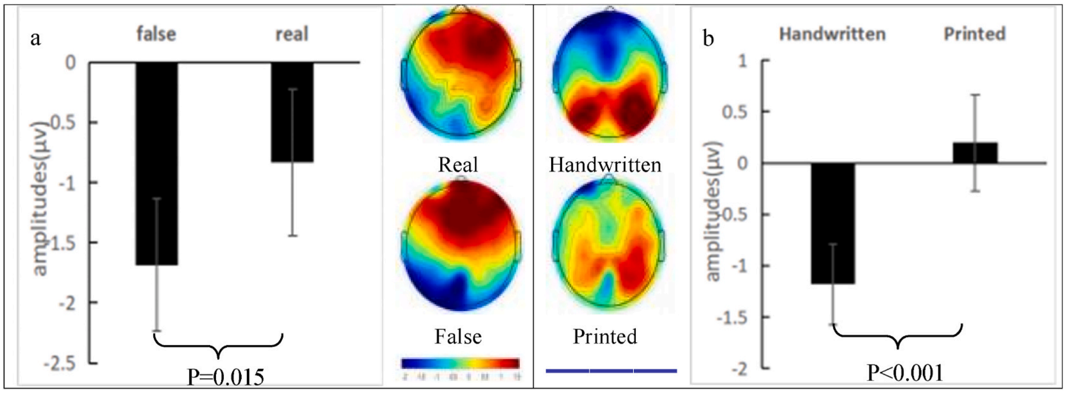


Fig. 3. a shows the N1 amplitudes observed in the false and real conditions; b shows N400 amplitudes elicited by the presentation of handwritten and printed characters.

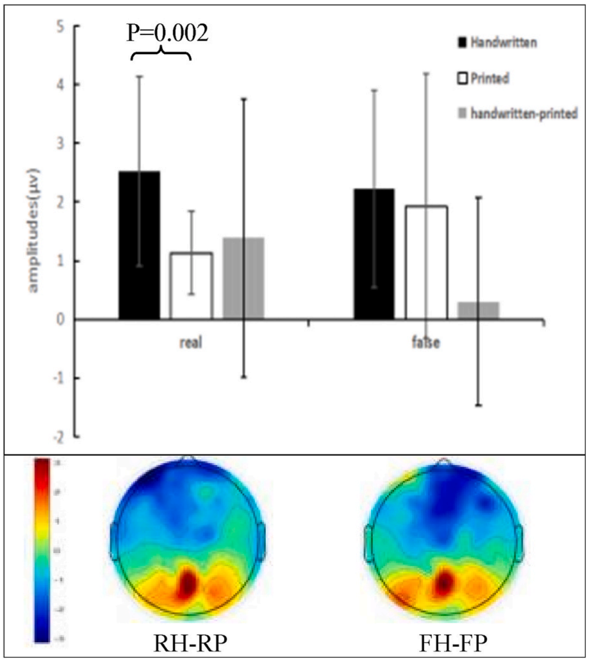


Fig. 4. The impact of different conditions on LPC amplitudes.

handwriting inherently encodes production-related information (underlying dynamic representations) (Longcamp et al., 2003, 2006; 2011; Nakamura, et al., 2012), more attention is not allocated to process handwritten characters in the early stage. This result is consistent with those of previous studies (Rey et al., 2009; Wamain et al., 2012). Therefore, there was no increase in N1 amplitude in response to viewing handwritten characters in the early stage.

The N400 component differed from that in the early stage of word recognition, reflecting the difference between handwritten and printed characters. Specifically, handwritten characters evoke more negative N400 amplitudes than printed characters, indicating that the brain utilizes more resources to process handwritten words, which contain movement information (Longcamp et al., 2003, 2006; 2011; Nakamura et al., 2012). In contrast, the early component N1 did not reflect the difference, suggesting that the movement information in handwritten characters takes longer to process. The findings of previous studies were consistent with the current N400 amplitude results, which showed more activation in response to handwritten characters than in response to printed characters (Longcamp et al., 2003, 2006, 2011). Furthermore, according to Barber et al. (2013), more negative N400 amplitudes in response to handwritten characters reflect a deeper level of meaning comprehension. Therefore, processing handwritten characters appear to use more resources. On the other hand, Kutas and Federmeier (2011) proposed that integrating semantic information is difficult and leads to negative N400 amplitudes. We believe that these two views are not contradictory but rather are different expressions of the same process. Handwritten characters with movement information trigger deeper meaning comprehension, which in turn makes integrating semantic information more challenging to interpret.

Similarly, the LPC results indicate that handwriting evokes a greater response in the brain. Moreover, the actual process of handwriting stimulates more positive amplitudes than actual printed characters. In contrast, there was no difference between the responses elicited by false handwritten and printed characters. Regarding the N400, all real and false handwritten characters are processed. However, on LPC, only the semantic processing of real characters is meaningful; thus, individuals just need to utilize more resources to further integrating process real handwritten and printed characters. Therefore, these LPC results suggested that real characters undergo further processing after the N400. These findings align with previous studies (Kaan et al., 2000), which suggested that LPC represents a further integration process after the N400. Additionally, LPC amplitudes reflect the difficulty and cognitive resources required for processing (Hagen, et al., 2006). Thus, similar to the N400, the LPC results indicated that integrating semantic information in handwriting is more taxing and requires greater cognitive resources than does integrating printed characters. The difference lies in the fact that the LPC reflects only the processing of real characters.

The cognitive process of visual word recognition involves identifying potential lexical features, such as line direction or letter capitalization, among visual stimuli. These basic visual features are then integrated into fundamental writing units, such as alphabetic components or Chinese characters, which are subsequently combined into complete words or Chinese characters. According to the automatic sequence search model, words are stored as visual information, and the process of word recognition can be likened to searching a mental dictionary until a matching word is found. Conversely, lexical generation models posit that lexical units stored in mental dictionaries serve as repositories of information about various word attributes, including phonology, orthography, and semantics. During the word recognition process, words with the most identifiable attribute information are retrieved more rapidly. The EEG results of this study align with the cognitive process of word recognition, indicating that handwriting elicits more activity in the human brain. This supports the notion that words with more identifiable information during word recognition are more readily retrieved. Thus, compared to printed words, handwriting entails more cognitive processes and better aligns with supplementary information, such as stroke movement, facilitating the mobilization and deeper activation of existing attribute information.

5. Limitations and prospects

First, due to the particularity of the university student population, this study chose university students as subjects. Because different age groups have different frequencies of handwriting exposure, caution should be exercised when generalizing the results to other age groups. Further research is needed to determine whether similar findings apply to different age groups.

Second, in the EEG experiment, a delayed response paradigm was used to prevent motor potentials. However, this choice also led to a ceiling effect in behavioural data, limiting the ability to establish a more comprehensive correlation between EEG data and behavioural results. Future research may consider other experimental designs to better integrate EEG and behavioural data.

Finally, EEG technology has limitations in spatial resolution and traceability accuracy. To more accurately understand the processing differences between handwritten and printed Chinese characters in vocabulary decision tasks, future research can combine auxiliary techniques, such as functional magnetic resonance imaging or magnetoencephalography to improve spatial resolution and traceability.

In summary, the present study enhances our understanding of the distinct time course processing between Chinese handwritten and printed characters in lexical decision tasks.

(1) The N1 component primarily reflects the orthographic regularity during the initial processing stage.
(2) The N400 component and LPC had handwriting-induced amplitudes during the later processing stage.
(3) Notably, although handwritten characters evoke higher greater ERP amplitudes, this does not necessarily translate into more efficient behavioural outcomes. Therefore, it appears that the greater ERP amplitudes associated with handwriting reflects a deeper level of meaning comprehension, which is also more challenging in terms of semantic integration.

CRediT authorship contribution statement

Wenhui Li: Funding acquisition, Investigation, Methodology, Conceptualization, Data curation, Formal analysis, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Zhongqing Jiang:** Methodology. **Yihan Xu:** Writing – review & editing. **Tingting Yu:** Methodology. **Xuan Ning:** Conceptualization. **Ying Liu:** Investigation. **Chan Li:** Validation.

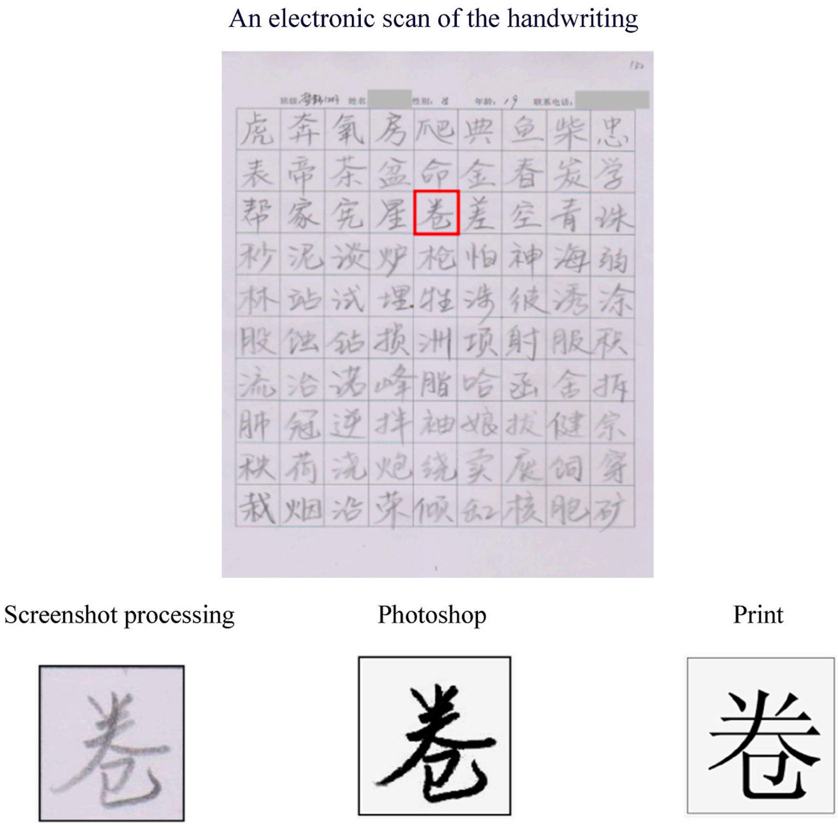
Declaration of competing interest

No conflict of interest exists in the submission of this manuscript, and the manuscript is approved by all authors for publication. We declare that the work is original research that has not been published previously, and not under consideration for publication elsewhere, in whole or in part.

Data availability

Data will be made available on request.

Appendix



References

Aranda, C., Madrid, E., Tudela, P., & Ruz, M. (2010). Category expectations: A differential modulation of the N170 potential for faces and words. *Neuropsychologia, 48*(14), 4038–4045.

Babcock, M. K., & Freyd, J. J. (1988). Perception of dynamic information in static handwritten forms. *American Journal of Psychology*, 111–130.

Bakos, S., Landerl, K., Bartling, J., Schulte-Körne, G., & Moll, K. (2018). Neurophysiological correlates of word processing deficits in isolated reading and isolated spelling disorders. *Clinical Neurophysiology, 129*(3), 526–540.

Barber, H. A., Otten, L. J., Kousta, S. T., & Vigliocco, G. (2013). Concreteness in word processing: ERP and behavioral effects in a lexical decision task. *Brain and Language, 125*(1), 47–53.

Barnhart, A. S., & Goldinger, S. D. (2010). Interpreting chicken-scratch: Lexical access for handwritten words. *Journal of Experimental Psychology: Human Perception and Performance, 36*(4), 906–923.

Barton, J. J., Fox, C. J., Sekunova, A., & Iaria, G. (2010). Encoding in the visual word form area: An fMRI adaptation study of words versus handwriting. *Journal of Cognitive Neuroscience, 22*(8), 1649–1661.

Bell, A. J., & Sejnowski, T. J. (1995). An information-maximization approach to blind separation and blind deconvolution. *Neural Computation, 7*(6), 1129–1159.

Bentin, S., Allison, T., Puce, A., Perez, E., & McCarthy, G. (1996). Electrophysiological studies of face perception in humans. *Journal of Cognitive Neuroscience, 8*(6), 551–565.

Bentin, S., Mouchetant-Rostaing, Y., Giard, M. H., Echallier, J. F., & Pernier, J. (1999). ERP manifestations of processing printed words at different psycholinguistic levels: Time course and scalp distribution. *Journal of Cognitive Neuroscience, 11*(3), 235–260.

Coch, D., & Mitra, P. (2010). Word and pseudoword superiority effects reflected in the ERP waveform. *Brain Research, 1329*, 159–174.

Cohen, L., Dehaene, S., Naccache, L., Lehéricy, S., Dehaene-Lambertz, G., Hénaff, M. A., et al. (2000). The visual word form area Spatial and temporal characterization of an initial stage of reading in normal subjects and posterior split-brain patients. *Brain, 123*(2), 291–307.

De Grauwe, S., Swain, A., Holcomb, P. J., Ditman, T., & Kuperberg, G. R. (2010). Electrophysiological insights into the processing of nominal metaphors. *Neuropsychologia, 48*(7), 1965–1984.

Dehaene, S., & Cohen, L. (2011). The unique role of the visual word form area in reading. *Trends in Cognitive Sciences, 15*(6), 254–262.

Delorme, A., & Makeig, S. (2004). Eeglab: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods, 134*(1), 9–21.

Eimer, M., Van Velzen, J., Gherri, E., & Press, C. (2006). Manual response preparation and saccade programming are linked to attention shifts: ERP evidence for covert attentional orienting and spatially specific modulations of visual processing. *Brain Research, 1105*(1), 7–19.

Ferree, T. C., Luu, P., Russell, G. S., & Tucker, D. M. (2001). Scalp electrode impedance, infection risk, and EEG data quality. *Clinical Neurophysiology, 112*, 536–544.

Hagen, G. F., Gatherwright, J. R., Lopez, B. A., & Polich, J. (2006). P3a from visual stimuli: Task difficulty effects. *International Journal of Psychophysiology, 59*(1), 8–14.

Hajcak, G., Mac Namara, A., & Olvet, D. M. (2010). Event-related potentials, emotion,and emotion regulation: An integrative review. *Developmental Neuropsychology, 35*(2), 129–155.

Hasko, S., Groth, K., Bruder, J., Bartling, J., & Schulte-Körne, G. (2013). The time course of reading processes in children with and without dyslexia: An ERP study. *Frontiers in Human Neuroscience, 7*, 570.

Kaan, E., Harris, A., Gibson, E., & Holcomb, P. J. (2000). The P600 as an index of syntactic integration difficulty. *Language & Cognitive Processes, 15*(2), 159–201.

Kemény, F., Banfi, C., Gangl, M., Perchtold, C. M., Papousek, I., Moll, K., et al. (2018). Print-, sublexical and lexical processing in children with reading and/or spelling deficits: An ERP study. *International Journal of Psychophysiology, 130*, 53–62.

Kutas, M., & Federmeier, K. D. (2011). Thirty years and counting: Finding meaning in the N400 component of the event-related brain potential (ERP). *Annual Review of Psychology, 62*, 621–647.

Kutas, M., & Hillyard, S. A. (1984). Brain potentials during reading reflect word expectancy and semantic association. *Nature, 307*(5947), 161–163.

Lee, C. Y., Liu, Y. N., & Tsai, J. L. (2012). The time course of contextual effects on visual word recognition. *Frontiers in Psychology, 3*, 285.

Lin, S. E., Chen, H. C., Zhao, J., Li, S., He, S., & Weng, X. C. (2011). Left-lateralized N170 response to unpronounceable pseudo but not false Chinese characters—the key role of orthography. *Neuroscience, 190*, 200–206.

Longcamp, M., Anton, J. L., Roth, M., & Velay, J. L. (2003). Visual presentation of single letters activates a premotor area involved in writing. *NeuroImage, 19*(4), 1492–1500.

Longcamp, M., Hlushchuk, Y., & Hari, R. (2011). What differs in visual recognition of handwritten vs. printed letters? An fMRI study. *Human Brain Mapping, 32*(8), 1250–1259.

Longcamp, M., Hlushchuk, Y., & Hari, R. (2011). What differs in visual recognition of handwritten vs. Printed letters? An fMRI study. *Human Brain Mapping, 32*, 1250–1259.

Longcamp, M., Tanskanen, T., & Hari, R. (2006). The imprint of action: Motor cortex involvement in visual perception of handwritten letters. *NeuroImage, 33*(2), 681–688.

Lopez-Calderon, J., & Luck, S. J. (2014). Erplab: An open-source toolbox for the analysis of event-related potentials. *Frontiers in Human Neuroscience, 8*, 213.

Luck, S. J., & Gaspelin, N. (2017). How to get statistically significant effects in any ERP experiment (and why you shouldn`t). *Psychophysiology, 54*(1), 146–157.

Luck, S. J., Woodman, G. F., & Vogel, E. K. (2000). Event-related potential studies of attention. *Trends in Cognitive Sciences, 4*(11), 432–440.

Lv, C., & Wang, Q. (2012). Font effects of Chinese characters and pseudo-characters on the N400: Evidence for an orthographic processing view. *Brain and Cognition, 80*(1), 96–103.

Lv, C., & Wang, Q. (2012). Font effects of Chinese characters and pseudo-characters on the N400: Evidence for an ortho- graphic processing view. *Brain and Cognition, 80*, 96–103.

Mahé, G., Zesiger, P., & Laganaro, M. (2015). Beyond the initial 140 ms, lexical decision and reading aloud are different tasks: An ERP study with topographic analysis. *NeuroImage, 122*, 65–72.

Maurer, U., Brandeis, D., & McCandliss, B. D. (2005). Fast, visual specialization for reading in English revealed by the topography of the N170 ERP response. *Behavioral and Brain Functions, 1*(1), 13.

Mognon, A., Jovicich, J., Bruzzone, L., & Buiatti, M. (2011). Adjust: An automatic EEG artifact detector based on the joint use of spatial and temporal features. *Psychophysiology, 48*(2), 229–240.

Molinaro, N., Conrad, M., Barber, H. A., & Carreiras, M. (2010). On the functional nature of the N400: Contrasting effects related to visual word recognition and contextual semantic integration. *Cognitive Neuroscience, 1*(1), 1–7.

Nakamura, K., Kuo, W. J., Pegado, F., Cohen, L., Tzeng, O. J., & Dehaene, S. (2012). Universal brain systems for recognizing word shapes and handwriting gestures during reading. *Proceedings of the National Academy of Sciences, 109*(50), 20762–20767.

Nemrodov, D., Harpaz, Y., Javitt, D. C., & Lavidor, M. (2011). ERP evidence of hemispheric independence in visual word recognition. *Brain and Language, 118*(3), 72–80.

Polich, J. (2007). Updating P300: An integrative theory of P3a and P3b. *Clinical Neurophysiology, 118*(10), 2128–2148.

Polk, T. A., & Farah, M. J. (2002). Functional MRI evidence for an abstract, not perceptual, word-form area. *Journal of Experimental Psychology: General, 131*(1), 65.

Rey, A., Dufau, S., Massol, S., & Grainger, J. (2009). Testing computational models of letter perception with item-level event-related potentials. *Cognitive Neuropsychology, 26*(1), 7–22.

Shanghai Jiao Tong University. (1988). *Chinese character information dictionary*. Beijing: Science Press.

Wamain, Y. (2019). The role of handwriting in reading: Behavioral and neurophysiological evidence of motor involvement in letter recognition. In *Spelling and writing words* (pp. 93–111). Brill.

Wamain, Y., Tallet, J., Zanone, P. G., & Longcamp, M. (2012). Brain responses to handwritten and printed letters differentially depend on the activation state of the primary motor cortex. *NeuroImage, 63*(3), 1766–1773.

Xue, G., Jiang, T., Chen, C., & Dong, Q. (2008). Language experience shapes early electrophysiological responses to visual stimuli: The effects of writing system, stimulus length, and presentation duration. *NeuroImage, 39*(4), 2025–2037.