



Learning without consciously knowing: Evidence from event-related potentials in sequence learning

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ABSTRACT

This paper investigated how implicit and explicit knowledge is reflected in event-related potentials (ERPs) in sequence learning. ERPs were recorded during a serial reaction time task. The results showed that there were greater RT benefits for standard compared with deviant stimuli later than early on, indicating sequence learning. After training, more standard triplets were generated under inclusion than exclusion tests and more standard triplets under exclusion than chance level, indicating that participants acquired both explicit and implicit knowledge. However, deviant targets elicited enhanced N2 and P3 components for targets with explicit knowledge but a larger N2 effect for targets with implicit knowledge, revealing that implicit knowledge expresses itself in relatively early components (N2) and explicit knowledge in additional P3 components. The results help resolve current debate about the neural substrates supporting implicit and explicit learning.

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1. Introduction

The issue of whether people can learn without conscious knowledge has been widely investigated in sequence learning (e.g., Destrebecqz et al., 2005; Fu, Fu, & Dienes, 2008; Hoffmann, Sebal, & Stöcker, 2001; Jiménez, 2003; Wilkinson & Shanks, 2004; Willingham, Wells, & Farrell, 2000). Typically, participants are presented a serial reaction time (SRT) task in sequence learning, in which the sequence of buttons to be pressed is structured and the participant is told which button to press by a corresponding location on a screen being indicated (Cleeremans, Destrebecqz, & Boyer, 1998; Nissen & Bullermer, 1987). Thus, the participant can in principle follow instructions without being aware that the sequence is structured. People come to respond faster when the sequence is maintained rather than switched, however, indicating that they have acquired sequential knowledge. Subjects can often recognize or generate the sequence after being trained on it, therefore, it has been argued, people must have been conscious of the sequence (e.g., Cleeremans & McClelland, 1991; Perruchet & Amorim, 1992; Shanks, Wilkinson, & Channon, 2003). However, being discriminatively sensitive to the sequence in recognition and generation tests does not mean a person is conscious of their knowledge of the sequence (Dienes, 2008a; Rosenthal, 2002, 2005). Indeed, other SRT studies have argued that people are often not conscious of their knowledge of the sequence because subjects often deny that there was a sequence, they cannot freely report it, or if they can generate the sequence, they cannot control its generation, or else they claim to be using only intuition in generating the sequence (e.g., Destrebecqz &

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Cleeremans, 2001, 2003; Fu, Dienes, & Fu, 2010; Fu et al., 2008; Goschke & Bolte, 2007; Willingham, Nissen, & Bullemer, 1989; Willingham et al., 2000; Ziessler, 1998). In general, such objective measures as recognition and generation tests do not in themselves indicate conscious knowledge, but may be passed by using the same knowledge that allows performance in the SRT task (Berry & Dienes, 1993).

Destrebecqz and Cleeremans (2001, 2003) adopted the process dissociation procedure (PDP), to measure the conscious status of knowledge acquired in the serial reaction time (SRT) task. The PDP takes the ability to control as the measure of whether knowledge is conscious or not (cf. Higham, Vokey, & Pritchard, 2000). Destrebecqz and Cleeremans found that participants came to respond faster when the sequence was consistently structured rather than switched in the training phase. However, when participants were asked to freely generate a sequence same as or different from the one they were trained on (i.e., using an inclusion or exclusion test, respectively), there was no difference in the number of chunks from the trained sequence under inclusion and exclusion when the response stimulus interval (RSI) was zero, suggesting that participants lacked control over the use of their knowledge. Fu et al. (2010) showed that whether subjects were conscious of knowing the sequence as shown by confidence ratings was strongly related to Jacoby's PDP estimates of ability to control the use of the knowledge in the SRT task. This paper will further explore the relation between conscious knowledge (as measured by the PDP method) and event-related brain potentials (ERPs).

The measures of awareness in the above studies were all applied after learning. Eimer, Coschke, Schlaghecken, and Stürmer (1996) first investigated whether ERPs could be used as an online-measure for knowledge acquisition during SRT learning itself. They combined the standard SRT task with a variation of the oddball paradigm, in which the locations were replaced by four capital letters. Whether subjects were conscious of the sequence was measured by a set of explicit tasks including recognition after learning. They found that participants showed a larger enhanced frontocentral N2 component (negative components peaking 250–300 ms after stimulus onset, see Folstein and Van Petten (2008) for a review) for deviant targets for subjects who passed the explicit tasks rather than those who did not. Thus, they suggested that the N2 enhancement might be regarded as an indicator of the amount of explicit knowledge, though this point remains moot given recognition tasks can be passed based on implicit knowledge. That is, implicit and explicit knowledge may have been confounded in the recognition measure, so subjects counted as having explicit knowledge may also have had implicit knowledge. Unlike other studies, they found no P3 effect, which usually follows an N2 effect, in Experiment 1, and only a small P3 effect in Experiment 2.

Rüsseler, Hennighausen, Münte, and Rösler (2003) compared differences on ERPs in sequential learning between subjects who were informed (intentional group) or were not informed (incidental group) of the presence of a repeating sequence. This manipulation enhanced people's ability to generate the sequence. They found that intentional learners showed enhanced frontocentral N2b- and P3b-components for deviant targets, but there were no such effects for incidental learners. They suggested that both N2b and P3b reflected conscious processing. However, using a similar manipulation, Ferdinand, Mecklinger, and Kray (2010) found a larger N2b for deviant stimuli in both intentional and incidental groups. They argued that the N2b might be related to a gradual development of knowledge about the sequence structure producing expectancies of the next stimulus. Therefore, although Eimer et al. (1996) and Rüsseler et al. (2003) established relations between recognition and generation performance and N2 and P3 components, this does not entail a relation between these components and distinctively conscious knowledge. The next two studies resolve this problem more satisfactorily by using PDP but have another problem we will come to.

Schlaghecken, Stürmer, and Eimer (2000), using PDP, divided what each participant learned into chunk-internal (i.e., explicitly learned) and chunk-external (i.e., implicitly learned) targets based on the inclusion and exclusion performance. They found that the amplitudes of N2b- and P3b-components were enhanced only for deviants of chunk-internal rather than chunk-external targets. Thus, they also suggested that the enhancement of N2b and P3b components could be used as an online measure of explicit knowledge. Moreover, the effect of deviants on reaction times (i.e., RT benefits for standard) did not differ between chunk-internal and chunk-external targets, revealing that people implicitly acquired some knowledge. Miyawaki, Sato, Yasuda, Kumano, and Kuboki (2005), using PDP, replicated the behavioral results but found only an enhanced N2 effect for chunk-internal targets.

The use of PDP is useful for measuring conscious knowledge. But there is still a caveat in interpreting their results: their studies may have lacked power to determine the ERP correlates of distinctively implicit knowledge because they did not make a distinction between the parts of the sequence that people had implicitly learned and those of the sequence that people did not learn at all. It is known that subjects do not uniformly learn all parts of a sequence (e.g., Wilkinson & Shanks, 2004). Whereas “chunk-internal” refers to parts of the sequence we know the subject has explicitly learned, “chunk-external” refers to a mixture of implicitly learned and unlearned parts of the sequence (cf. Schlaghecken et al., 2000). Thus, it is not surprising that it was difficult to detect ERP components for chunk-external positions. Therefore, it is still unclear to what extent the N2 and P3 components reflected explicit knowledge rather than implicit knowledge.

The purpose of the present study is to explore how implicit and explicit knowledge is reflected in ERPs in sequence learning, where explicit knowledge is measured by PDP. We will explore whether N2 and P3 components have different roles in the acquisition of explicit and implicit knowledge. Compared to previous studies we will both (a) isolate consciously known chunks by using PDP rather than by using just generation or recognition; and (b) increase power for detecting the ERP concomitants of implicit knowledge by identifying those parts of the sequence actually implicitly learned by subjects. Thus, we will eliminate confounds in previous studies.

2. Method

2.1. Participants

Twenty-one right-handed students (10 male, 11 female), aged 20–26 ($M = 22.29$, $SD = 1.88$) years, voluntarily took part in this experiment. All of them gave informed consent and were paid for their attendance. And they all had normal or corrected-to-normal vision. Data of two participants had to be discarded due to excessive eye-movements or movement-related artifacts.

2.2. Stimuli and apparatus

Participants were seated in an electrically shielded, dimly lit and sound attenuated room. Stimuli were uppercase letters Z, V, X, and P which were sequentially presented in a black square in the centre of the computer's screen against a gray background. The visual angle was approximately 1° from a constant viewing distance of 60 cm. Most previous studies used a repeating sequence, in which the deviant stimulus randomly replaced one element of the sequence. Thus, the deviant stimulus might have disrupted either the first- or second- or third-order structure of the sequence. To be clear, the present study used two second-order conditional sequences (SOC1 = X–P–V–X–Z–V–Z–P–X–V–P–Z; SOC2 = X–P–Z–V–P–X–Z–P–V–Z–X–V). The sequences were balanced for frequency (each letter occurred three times), transition frequency (each possible transition from one letter to another occurred once), reversal (e.g., Z–V–Z) frequency (one in each sequence), repetitions (no repetitions in either sequence) and rate of full coverage (see Reed & Johnson, 1994). Each of the SOC sequences included 12 triplets. The difference between the sequences was in their second-order conditional structure. For example, X–P was followed only by a V in SOC1 but only by a Z in SOC2. SOC1 could be divided into triplets such as X–P–V, P–V–X and V–X–Z; SOC2 could be divided into triplets such as X–P–Z, P–V–Z and V–X–P, non-overlapping with the SOC1 triplets. Each triplet defined by its first two elements (e.g., X–P) in SOC1 (e.g., X–P–V) had a corresponding triplet in SOC2 (e.g., X–P–Z). The stimulus sequence in training was probabilistic. To generate the probabilistic sequence, each stimulus followed the training SOC1 triplets with a probability of .875 and the transfer SOC2 triplets with a probability of .125. *Standard* stimuli followed the training (SOC1) triplets and *deviant* stimuli followed the transfer (SOC2) triplets. For example, in the sequence X–P–V–Z–P–V–X–... , the third stimulus V completed the SOC1 triplet X–P–V and thus was a standard stimulus, the fourth stimulus completed the SOC2 triplet P–V–Z and thus was a deviant stimulus, and so on. Each specific standard triplet (e.g., X–P–V) occurred seven times in a block and each specific deviant triplet (e.g., X–P–Z) occurred once in each block, for a total of 105 and 15 times, respectively, in the training phase.

2.3. Procedure

Participants were exposed to a serial four-choice RT task, which included 15 training blocks of 98 trials, for a total of 1470 trials. Each block of 98 stimuli consisted of 96 triplets, including 84 standard triplets and 12 deviant triplets. On each trial, a letter appeared on the screen and participants were instructed to respond as quickly and as accurately as possible by pressing one of the four keys D, F, J, and K on the keyboard by the left and right middle and index fingers. Each stimulus remained on the screen until a response was given. The response stimulus interval was 500 ms. Response latencies were measured from the onset of the target to the completion of a correct response and errors were recorded. Rests of at least 30 s occurred between every two blocks.

To measure the conscious status of the knowledge of each triplet, two trial-by-trial generation tests were used after the SRT task. The two tests were identical except that the instructions were opposite to each other. The aim was to explore whether people acquired explicit knowledge about the difference between standard and deviant triplets, as reflected by RT benefits to standard compared with deviant stimuli in training. At the beginning of the test phase, participants were informed that the stimuli had followed a regular sequence, in which most of stimuli were determined by the previous two. On each test trial of the inclusion test, they first responded to a short sequence of two movements as in the training and then were required to generate the next target that appeared most frequently after the previous two in training.² On each test trial of the exclusion test, they first responded to a short sequence of two movements as in the training phase and then were required to generate the next target that appeared rarely after the previous two in training. In each test, 12 different test trials (corresponding to the 12 different triplets in the training) were presented in a random order, which repeated eight times to make 96 test trials altogether. That is, there were eight test trials for each of the 12 triplets in either inclusion or exclusion test. Before each test, there were two practice test trials.

2.4. Data acquisition

During the training and test phases, the EEG was recorded from 64 scalp sites using Ag–AgCl electrodes in an elastic cap according to the International 10–20 system, with an on-line reference to the left mastoid and off-line algebraic re-reference

² Subjects were informed that could not repeat the second letter in predicting the next target (i.e., the third letter of the triplet) in each test. A subject had to predict one of the remaining three letters in order for the test to progress.

to the average of left and right mastoids. The vertical and horizontal electrooculogram (EOG) were recorded with two pairs of electrodes placed above and below one eye and at the left and right orbital rim. EEG and EOG signals were amplified with 0.16–100 Hz bandpass filter and digitized at 256 Hz by BioSemi ActiveTwo amplifier (BioSemi, Amsterdam, NL). The baseline for the ERPs was 100 ms before the presentation of each stimulus. Trials with various artifacts were rejected, with a criterion of $\pm 80 \mu\text{V}$. The ERPs were then averaged separately for each experimental condition.

2.5. Data analysis

Although the instructions in inclusion and exclusion tests were opposite, the dependent variable for inclusion and exclusion performance was the proportion of standard triplets generated. Thus, the awareness of each triplet was measured by more standard triplets being generated under inclusion than exclusion tests. For each type of triplet, the chance level of standard triplets under exclusion (or inclusion) is 2.64 (i.e., $.33 * 8$), i.e., 3 to the nearest whole number. Given an exclusion performance at chance (i.e., 3) for a given triplet type, the probability of inclusion being 5 or more is .088, i.e., an inclusion advantage over exclusion of 2 or more is just significant at the 10% level. Thus, an “explicit triplet” was defined by at least four standard triplets under inclusion and at least two more occurrences of standard triplets under inclusion than exclusion tests; or else the triplet was a non-explicit triplet. This criterion is liberal in order to minimize the risks of missing conscious knowledge. In addition, procedural learning was measured by greater RT benefits for standard compared with deviant triplets in the second (blocks 8–15) than the first (blocks 1–7) half of the training phase. Specifically, a “procedural learning triplet” was defined by more than 40 ms of RT benefit for standard triplet compared with the corresponding deviant triplet in the second half than in the first half of training; otherwise, the triplet was an unlearned triplet. Forty ms is twice the average learning effect (20 ms); this is arbitrary, based simply on a prior expectation that roughly 50% of the triplets would be learned (cf. Fu et al., 2010). Nonetheless, the criterion will at least separate better learned from less well learned triplets, which is all that is needed. If procedural learning triplets were non-explicit they were called implicit triplets. Although the overall RT difference for standard vs. deviant triplets reflects learning, that difference also reflects response biases. That is, people might respond to a standard stimulus faster than the corresponding deviant stimulus even without learning. Our measure of a change in that difference over blocks subtracts out response biases to leave just the learning effect.

As in previous studies (Eimer et al., 1996; Rüsseler et al., 2003), the EEG data in the training phase were analyzed. The EEG data were digitally filtered with a bandpass of 0.5–40 Hz, and were averaged off line for epochs of 800 ms, starting 100 ms prior to stimulus onset and ending 700 ms afterwards. Only the ERPs to deviant and standard targets that were not preceded by a deviant target were further analyzed, as per previous work (Eimer et al., 1996; Miyawaki et al., 2005; Schlaghecken et al., 2000). Trials with eye blinks or RTs of more than 1200 ms or less than 300 ms were excluded from analysis (3.85% of trials, 1200 ms or 300 ms is beyond two standard deviations from mean RTs). For the sake of averaging ERPs over enough trials, the factors explicit knowledge and procedural knowledge were analyzed separately. The mean N2 and P3 amplitudes were measured in time windows of 230–310 ms and 340–530 ms, respectively, after stimulus onset at the following 5 sites at midline: AFz, Fz, FCz, Cz, Pz, based on previous research that analyzed the effects of electrodes mainly at the midline (e.g., Eimer et al., 1996; Schlaghecken et al., 2000). The time window was chosen because it best captured the difference between standard and deviant targets and was relatively free from overlap with adjacent ERPs.

3. Results

3.1. Behavioral data

Participants were trained over 15 blocks and RT analyses were conducted for all correct responses. Fig. 1 shows the mean RTs for all standard and deviant stimuli in training for all participants. An ANOVA on RTs with stimulus type (standard vs. deviant) and block (15 levels) as within-subject variables revealed a significant effect of stimulus type, $F(1, 18) = 25.62$, $MSE = 3194.45$, $p < .001$, indicating that participants responded to standard stimuli more quickly than to deviant ones. The main effect of block was significant, $F(14, 252) = 12.24$, $MSE = 2239.02$, $p < .001$, and so was the stimulus type by block

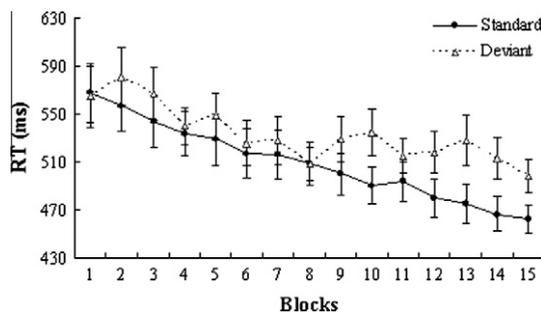


Fig. 1. Mean RTs for standard and deviant targets in training for all participants. Error bars depict standard errors.

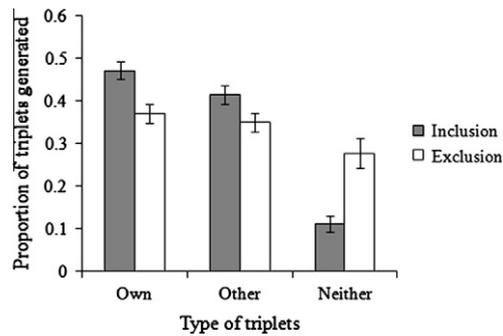


Fig. 2. Mean proportion of triplets generated by all participants under inclusion and exclusion instructions. Own, number of SOC triplets generated from the training sequence; other, number of SOC triplets from the transfer sequence; neither, number of triplets from neither the training nor the transfer sequence. Error bars depict standard errors.

interaction, $F(14,252) = 2.59$, $MSE = 1085.09$, $p < .01$, suggesting greater RT benefits for standard later in practice than earlier on, i.e., procedural learning occurred.

Participants were asked to complete 96 generation test trials in each of the inclusion and exclusion tests. We computed the proportion of generated triplets that were part of the training or transfer sequence in both inclusion and exclusion. An “own” triplet is a triplet that was part of the training sequence; an “other” triplet is a triplet that was part of the transfer sequence; a “neither” triplet is a triplet that was neither “own” nor “other” (Fu et al., 2008). Fig. 2 shows the mean proportion of triplets generated in the inclusion and exclusion test for all participants. The generation performance of own triplets under inclusion was greater than that under exclusion, $t(18) = 3.69$, $p < .01$, indicating that participants had some control over the sequential knowledge, i.e., the learning resulted in some conscious or explicit knowledge. Nonetheless, the exclusion performance of own triplets was marginally significantly above chance (i.e., .33), $t(18) = 1.92$, $p = .071$, indicating participants could not fully withhold their response of the standard in the exclusion task, i.e., participants also acquired some unconscious or implicit knowledge. The inclusion performance of other triplets was significantly above chance, $t(18) = 4.09$, $p = .001$, and marginally significant above exclusion performance, $t(18) = 1.81$, $p = .088$. That is, the performance pattern of other triplets was similar to the performance pattern of own triplets, indicating a partial failure to distinguish other from own triplets. In sum, the results suggested that participants acquired both explicit and implicit knowledge of the differences between standard and deviant stimuli.³

To investigate the dependence of procedural learning on explicit knowledge, the amount of procedural learning (difference between standard and deviant targets in the second half vs. the first half of training) and the amount of explicit knowledge (inclusion minus exclusion performance of own triplets) for each of the 12 triplets were calculated for each participant. We regressed procedural learning on explicit knowledge for each participant. The regression coefficients were then tested against zero using one sample t -test over subjects (i.e., this is the method recommended by Lorch and Myers (1990) and used previously in implicit learning research by e.g., Dienes and Longuet-Higgins (2004)). Fig. 3 shows the plot of procedural learning against explicit knowledge for each of the 12 triplets for each participant. The mean intercept was significantly above zero (17 ms, $SE = 5.6$), $t(18) = 3.11$, $p < .01$, indicating there was procedural learning when there was no explicit knowledge. The mean slope was not detectably different from zero (21 ms, $SE = 18$), $t(18) = 1.16$, $p = .26$, that is no relation between procedural learning and explicit knowledge was detected. All regression methods assume that there is no error in measuring the independent variables, because such measurement error flattens the regression line. However, as can be seen in Fig. 3, the intercept falls squarely in the body of the data, so this problem will have minimal impact on the intercept.

From Fig. 3 we can see some procedural triplets with explicit knowledge. To further investigate the explicitness of procedural triplets, we calculated the generation performance for procedural triplets for each participant. As can be seen in Table 1, there were large individual differences in the inclusion–exclusion difference for procedural triplets, ranging from -0.08 to 0.75 . That is, there was large variability in the measured amount of explicit knowledge for procedural triplets. Previous studies have divided participants into implicit and explicit learners on the basis of a measure of explicit knowledge. For example, Eimer et al. (1996) divided participants into explicit and implicit learners in implicit sequence learning on the basis of verbal reports and recognition tests. To obtain a sufficient number of epochs for each average waveform, we did not further divide triplets into explicit, implicit and unlearned triplets but discarded participants whose procedural learning might be accompanied by explicit knowledge. To obtain relatively pure implicit knowledge, we excluded participants whose average generation difference for procedural learning triplets was greater than 0.20. Here, a tougher criterion is adopted for the average than for defining a single triplet as non-explicit because we need to exclude explicit knowledge for ANY triplet over a set of triplets. Nine participants were excluded.

Fig. 4 shows the mean RTs for all standard and deviant stimuli obtained over the training for the remaining ten participants. As can be seen from Fig. 4, the RT pattern was same as for all participants in Fig. 1. An ANOVA on RTs with stimulus

³ Participants tended to generate more “neither” triplets under exclusion than inclusion, $t(18) = 4.25$, $p < .01$, indicating some appropriate control, i.e., conscious or explicit knowledge.

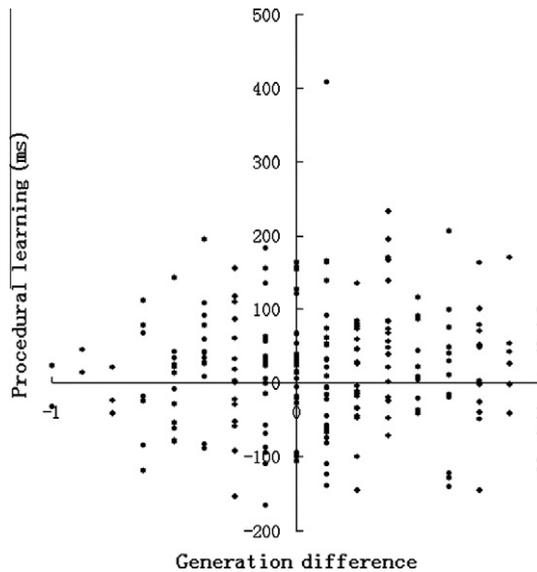


Fig. 3. The plot of procedural learning against explicit knowledge for each triplet over participants.

Table 1

Inclusion and exclusion performance for triplets with procedural knowledge for each participant.

Subject	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Inclusion	.48	.67	.59	.55	.28	.78	.59	.50	.57	.29	.68	.42	.35	.79	.70	.33	.40	.63	.51
Exclusion	.31	.25	.37	.52	.34	.34	.43	.18	.52	.37	.18	.21	.38	.04	.32	.33	.40	.63	.30
Difference	.17	.42	.22	.03	-.06	.44	.16	.32	.05	-.08	.50	.21	-.03	.75	.38	0	0	0	.21

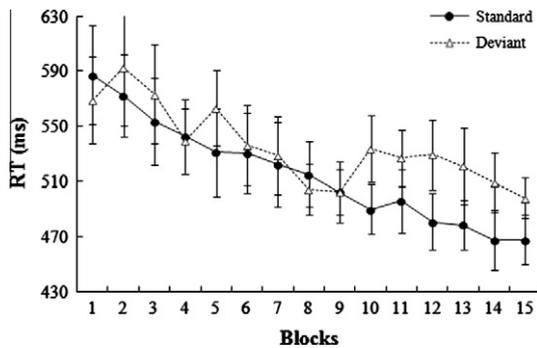


Fig. 4. Mean RTs for standard and deviant targets in training for the ten participants whose procedural learning might be not accompanied or contaminated by explicit knowledge. Error bars depict standard errors.

type (standard vs. deviant) and block (15 levels) as within-subject variables revealed a significant effect of stimulus type, $F(1,9) = 18.67$, $MSE = 1508.47$, $p < .01$, indicating RT benefits for standard compared with deviant stimuli. The main effect of block was significant, $F(14, 126) = 7.74$, $MSE = 2526.14$, $p < .001$, which was modulated by a significant interaction of block by stimulus type, $F(14, 126) = 1.93$, $MSE = 1203.90$, $p < .05$, indicating greater RT benefits for standard later in practice than earlier on, i.e., procedural learning. Importantly, for these remaining ten participants we did not detect a difference between inclusion and exclusion performance of own triplets ($M = .45$, $SE = .05$ vs. $M = .43$, $SE = .03$) for procedural learning triplets, $t(9) = .90$, $p = .39$, 95% CI of the difference $[-.04, .08]$. Both inclusion and exclusion performance of own triplets with procedural learning were significantly above chance, $t(9) = 2.82$, $p < .05$, $t(9) = 2.95$, $p < .05$, respectively. These results revealed that their procedural learning was implicit and provide converging evidence with the regression analysis for the existence of implicit knowledge.

The number of explicit triplets ranged from 1 to 5, with a mean of 3.16. The number of procedural triplets ranged from 2 to 7 with a mean of 4.79. No correlation was detected between the number of explicit triplets and the number of procedural learning triplets, $r = .27$, $p = .26$. Next, trials with RTs greater than 1200 ms or less than 300 ms were dropped; these amounted to 3.85% of trials. We will consider correlates of explicit knowledge and implicit knowledge sequentially.

3.2. ERP data: Correlates of explicit knowledge

First, we consider the difference between triplets with and without explicit knowledge. Fig. 5 shows the grand average ERP waveforms for standard and deviant targets with explicit and non-explicit knowledge for all participants. An ANOVA on N2 amplitude with electrode sites (AFz, Fz, FCz, Cz, Pz), experimental half (first half vs. second half), stimulus type (standard vs. deviant), and explicit knowledge (explicit vs. non-explicit) as within-subjects variables revealed a significant stimulus type effect, $F(1, 18) = 5.17$, $MSE = 9.08$, $p < .05$, and a marginally significant interaction of stimulus type by explicit knowledge, $F(1, 18) = 3.32$, $MSE = 11.96$, $p = .085$. Further analysis revealed that there was a significant stimulus type effect for targets with explicit knowledge, $F(1, 18) = 7.04$, $p < .05$, but not for targets with non-explicit knowledge, $F(1, 18) = .04$, $p = .86$, indicating that only deviant targets of explicit triplets led to enhanced N2 effects. No other effects were significant (all $ps > .19$).

A similar ANOVA on P3 amplitude revealed a significant stimulus type by explicit knowledge interaction, $F(1, 18) = 4.46$, $MSE = 8.16$, $p < .05$. The deviant targets of explicit triplets elicited an enlarged P3 effect ($M = .76$, $SE = .35$), $F(1, 18) = 4.77$, $MSE = 11.37$, $p < .05$, but no P3 effect for deviant targets of non-explicit knowledge ($M = -.12$, $SE = .21$), $F(1, 18) = .35$, $MSE = 3.99$, $p = .56$, 95% CI of the difference $[-.55, .31]$. There was also a significant interaction of stimulus type by electrode, $F(4, 72) = 3.32$, $MSE = .46$, $p < .05$, $\epsilon = .54$, indicating larger P3 effects at frontal and central than parietal sites. No other effects

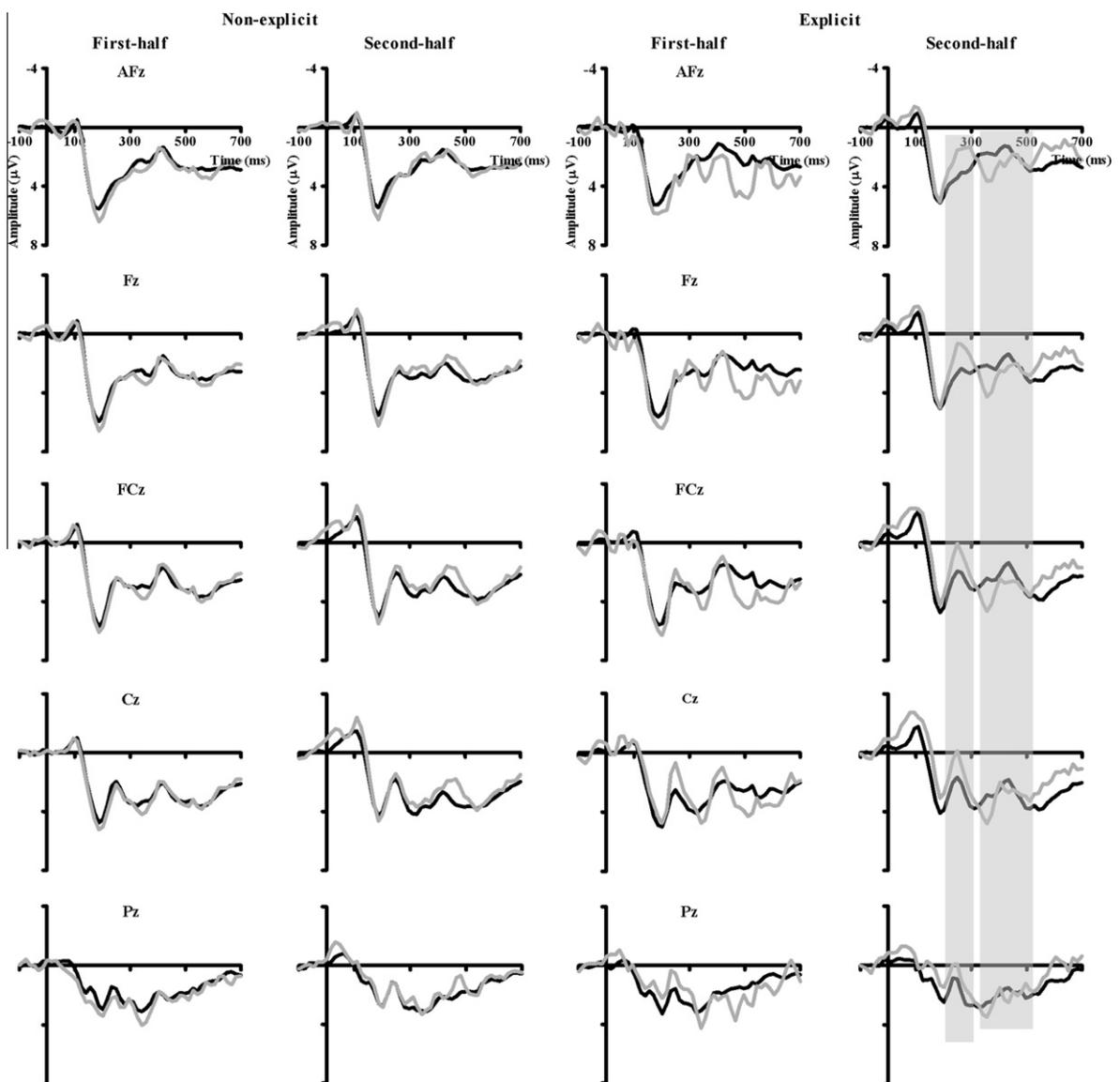


Fig. 5. The grand average ERP waveforms of all participants at electrode sites (AFz, Fz, FCz, Cz, and Pz) for standard (black line) and deviant targets (grey line), plotted separately for each experimental half and for targets with explicit and non-explicit knowledge.

were significant (all $ps > .12$). Thus, there is clear evidence for a role of P3 in distinguishing explicit from non-explicit triplets, though the first ANOVA provided marginal and partial evidence for some relation between explicit triplets and N2.

In order to separate the contribution of explicit and procedural knowledge to these effects, the N2 or P3 effect for explicit triplets (i.e., deviant minus standard amplitude averaged over the five sites) was simultaneously regressed on explicit knowledge (measured by the difference between inclusion and exclusion performance), procedural learning (measured by the difference in RT benefits for standard vs. deviant between the first half and second half), and their interaction. This revealed a significant relation between the P3 effect and explicit knowledge, $B = 6.06$, $t(15) = 2.47$, $p < .05$, but no relation between the P3 effect and procedural learning, $B = .002$, $t(15) = .26$, $p = .80$, and no interaction between explicit and procedural knowledge, $B = -.15$, $t(15) = -1.55$, $p = .14$. A similar regression with N2 effect for explicit triplets as dependent variable revealed no relation between the N2 effect and explicit knowledge, $B = -1.53$, $t(15) = -.55$, $p = .59$, but a significant relation between the N2 effect and procedural learning, $B = -.02$, $t(15) = -2.14$, $p < .05$, and no interaction, $B = -.11$, $t(15) = -1.05$, $p = .31$. Thus, P3 appears to be an indicator of explicit knowledge and N2 of procedural learning for explicit triplets.

3.3. ERP data: Correlates of implicit knowledge

Next, we consider the ERP difference between triplets with and without implicit knowledge. For this implicit knowledge, we excluded the nine participants whose procedural learning might be accompanied or contaminated by explicit

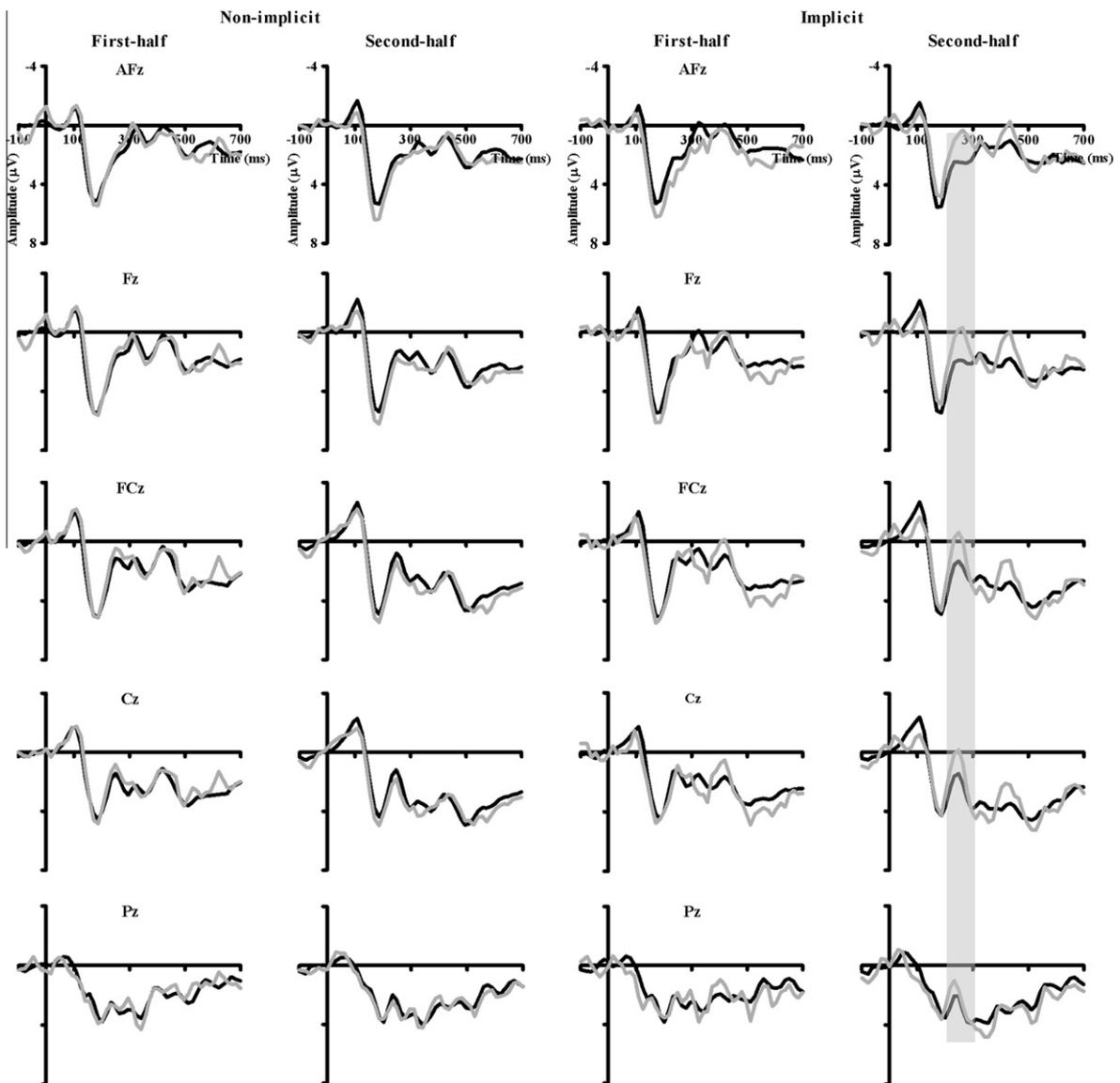


Fig. 6. The grand average ERP waveforms of the remaining ten participants at electrode sites (AFz, Fz, FCz, Cz, and Pz) for standard (black line) and deviant targets (grey line), plotted separately for each experimental half and for targets with implicit and non-implicit knowledge.

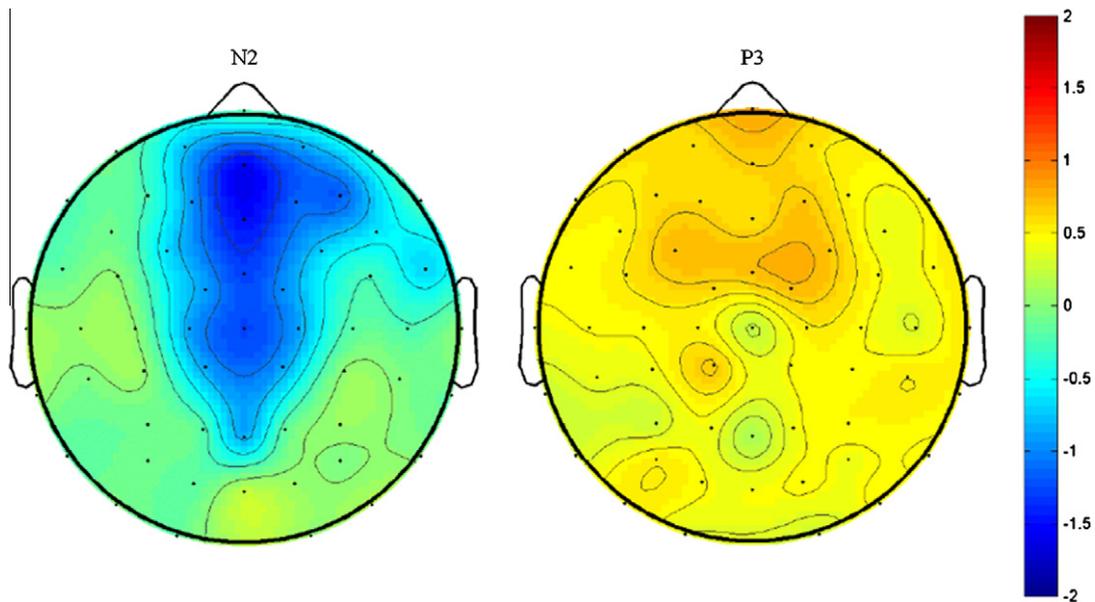


Fig. 7. Scalp distribution of the N2 and P3 effects in the second half of the experiment for explicit triplets computed as the difference potential between the standard and deviant triplets for all participants.

knowledge. Fig. 6 shows the grand average ERP waveforms for standard and deviant targets with implicit and non-implicit knowledge for the remaining ten participants. An ANOVA on N2 amplitude with electrode sites (AFz, Fz, FCz, Cz, Pz), experimental half (first half vs. second half), stimulus type (standard vs. deviant), and implicit knowledge (implicit vs. non-implicit) as within-subjects variables revealed a significant stimulus type by implicit knowledge by experimental half interaction $F(1,9) = 8.42$, $MSE = 3.08$, $p < .05$, a stimulus type by experimental half by electrode interaction $F(4,36) = 3.64$, $MSE = .32$, $p < .05$, $\epsilon = .35$, and an implicit knowledge by experimental half by electrode interaction, $F(4,36) = 4.17$, $MSE = .43$, $p < .01$, $\epsilon = .42$, and all of them were moderated by the four-way interaction, $F(4,36) = 2.92$, $MSE = .48$, $p < .05$, $\epsilon = .41$. Further analysis revealed that deviant items elicited N2 effects only for targets with implicit knowledge in the second half at electrode sites AFz, Fz, and FCz, the mean effects $1.64 \mu\text{V}$ ($SE = .51$), $1.53 \mu\text{V}$ ($SE = .50$), $1.12 \mu\text{V}$ ($SE = .45$), respectively, $F(1,9) = 10.44$, $MSE = 1.29$, $p = .01$, $F(1,9) = 9.36$, $MSE = 1.25$, $p < .05$, $F(1,9) = 6.19$, $MSE = 1.02$, $p < .05$, respectively, confirming that N2 reflects the acquisition of implicit knowledge. No other effects were significant (all $ps > .10$).

Similarly, an ANOVA on P3 revealed no significant effects involving stimulus type (all $ps > .17$). There was no evidence that P3 was relevant for implicit knowledge, the mean P3 effect was $-.03 \mu\text{V}$ ($SE = .27$), the 95% CI for the standard deviant difference for targets with implicit knowledge was $[-.65, .59]$. The upper limit of this confidence interval excludes the size of N2 effects found in the second half for deviants with implicit knowledge (all $1.12 \mu\text{V}$ or greater), and also excludes the size of P3 effect found for explicit triplets reported above (i.e., $.73 \mu\text{V}$).⁴ Bayes Factors can be used to establish the strength of evidence for a theory predicting an effect over the null hypothesis, or vice versa (Dienes, 2008b, 2011). The Bayes Factor varies from 0 to infinity. Any value less than a 1/3 is strong evidence for the null over the theory, over 3 is strong evidence for the theory over the null, and a value between 1/3 and 3 indicates data insensitivity. Thus a Bayes Factor can provide what p values cannot in distinguishing between evidence for the null ($BF < 1/3$) from no evidence either way because data are insensitive ($1/3 > BF < 3$). To know the evidence for a theory one needs to know what the theory predicts. Where we have obtained effects, the effects have been on the order of magnitude of one microvolt. Following Dienes (2011, Appendix) we modeled the predictions of a difference as a half-normal with a standard deviation equal to 1 microvolt. For a mean P3 effect of $-.03$ and standard error of $.27$ (corrected up to $.27 * (1 + 20/10^2) = .32$, to account for low degrees of freedom), the Bayes Factor (using the free online calculator for the website for Dienes (2008b)) was $.28$, i.e., strong evidence for the null hypothesis over the theory that there was a P3 effect for implicit knowledge. Similarly, for the P3 effect in just the second half, the Bayes Factor was $.29$. There is positive evidence for the null hypothesis, not just insensitive data. That is, we can exclude P3 as a marker of implicit knowledge with some sensitivity.

Finally, Figs. 7 and 8 show the scalp distribution of N2 and P3 effects which were mainly at frontal regions in the present study.

⁴ As the N2 effect only occurred in the second half for implicit knowledge, we also looked at the P3 effect in just the second half for implicit knowledge: The P3 effect was $-.14 \mu\text{V}$, $SE = .33$, with a 95% confidence interval $[-.90, .62]$, whose upper limit is still lower than any of the obtained effects for P3 or N2.

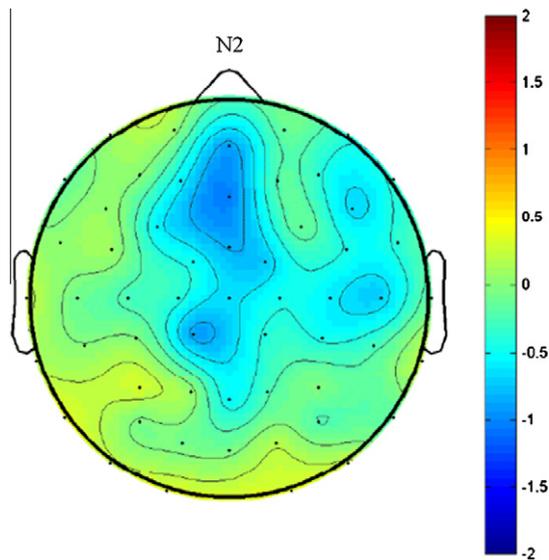


Fig. 8. Scalp distribution of the N2 effect in the second half of the experiment for implicit triplets computed as the difference potential between the standard and deviant triplets for the remaining ten participants.

4. Discussion

The behavioral results showed that there were greater RT benefits for standard compared with deviant later than early on, indicating that participants acquired some sequential knowledge of the SOC sequence in the training. After training, participants generated overall more standard and deviant triplets under inclusion than exclusion and more standard triplets under exclusion than chance, suggesting that they acquired both explicit and implicit knowledge. Interestingly, we found that greater RT benefits for standard triplets in the second than in the first half did not necessarily lead to explicit knowledge, providing further evidence that people can implicitly acquire sequential knowledge. That is, people can learn without conscious awareness.

More importantly, the ERP results showed that the acquisition of implicit knowledge elicited N2 enhancement for deviant targets, suggesting that the emergence of N2 effect was linked with the acquisition of implicit knowledge. While this contradicts previous claims, our study deals with two possible problems that all previous studies were susceptible to: namely, we use a measure of awareness less likely to treat unconscious knowledge as conscious, and we measure what parts of the sequence were procedurally learned. Consistent with our findings, Eimer et al. (1996) found that the N2 effects were not limited to participants with explicit knowledge but also were found in participants with implicit knowledge, although the N2 effects were larger for explicit participants than for implicit participants. Ferdinand et al. (2010) also found a larger N2b for deviant stimuli for implicit learners. Nevertheless, both Schlaghecken et al. (2000) and Miyawaki et al. (2005) found no N2 effects for chunks without explicit knowledge. In fact, when dividing the sequence into triplets with explicit and non-explicit knowledge on the basis of inclusion and exclusion performance, we also did not find significant N2 effects for chunks with non-explicit knowledge.

However, such chunks without explicit knowledge included chunks which were not procedurally learned. Thus, it is not surprising that the N2 effect was reduced or eliminated in the previous studies. In our experiment, the number of triplets with overall RT benefits for standard compared with deviant (i.e., $RT_{\text{deviant}} - RT_{\text{standard}} > 0$ ms) ranged from 5 to 9, with an average of 7.16. That is, there were 4.84 (i.e., 40% of the total) triplets with no RT benefits for standard over deviant.⁵ Schlaghecken et al. (2000) and Miyawaki et al. (2005) did not analyze chunks into those procedurally learned vs. unlearned. We divided the sequence into triplets with procedural learning and no learning on the basis of RT benefits for standard vs.

⁵ To explore the characteristic of the triplets with no RT benefits for standard over deviant triplets, we calculated and compared the average RTs for standard and deviant triplets of each type of the 12 triplets for all 19 participants. There were significant RT benefits for standards over deviants for seven triplets ($RT_{\text{benefits}} > 52$ ms, $ps < .01$), marginally significant RT benefits for standards for one triplet ($RT_{\text{benefits}} = 45$ ms, $p = .073$), but significant RT benefits for deviants over standards for four triplets ($RT_{\text{benefits}} > 61$, $ps < .01$). The later four standard triplets were V–X–Z, X–Z–V, Z–V–Z, and V–Z–P, while the corresponding deviant triplets were V–X–P, X–Z–P, Z–V–P, and V–Z–X. The letters Z, V, X, and P were responded by pressing keys D, F, J, and K on the keyboard by the left and right middle and index fingers. Thus, the keys corresponding to the four standard triplets were F–J–D, J–D–F, D–F–D, and F–D–K, and the keys corresponding to the four deviant triplets were F–J–K, J–D–K, D–F–K, and F–D–J. For the first triplet, beginning with F–J, the deviant was continuous which may be especially easy to remember; for the third one, beginning with D–F, the standard triplet was a reversal which should be easy to remember but people may have a bias against reversals (Pronk & Visser, 2010). However, it is not easy to understand why people showed response bias for the second and fourth deviant triplets. For the second one, beginning with J–D, after pressing J and D from right to left, pressing a key by the other hand might be easier than pressing a key by the same hand. For the fourth one, beginning with F–D, after pressing F and D from right to left, pressing a key near the second key by the other hand might be easier than pressing a key far from the second one by the other hand.

deviant triplets between the first and second half of training. We did not use the overall RT benefits for standard in training as the criterion for procedural learning because we wanted to distinguish learning effects from response biases; thus we were interested in the change in RT over training. To obtain relatively pure implicit knowledge, we deleted participants whose procedural learning might be contaminated by explicit knowledge. We found enhanced N2 effects for targets with implicit knowledge, providing new evidence that the enhanced N2 effect is related to the acquisition of procedural knowledge independently of explicit knowledge. Even for triplets with explicit knowledge, we found a relation between procedural learning and the N2 amplitude rather than the P3 component. Conversely there was a relation between explicit knowledge and the P3 amplitude rather than the N2 component, confirming that N2 and P3 components reflect different processes in sequence learning. The N2 effect may reflect a mismatch with the procedural anticipation for the next stimulus which occurs even when a person is not aware of having knowledge.

We adopted trial-by-trial tests rather than free-generation tests used by Eimer et al. (1996) and Schlaghecken et al. (2000) as the measure of conscious knowledge because the tests could allow us look more specifically at the conscious status of each training triplet. When triplets were divided into those with and without explicit knowledge, we found that deviant items for triplets with explicit knowledge had enhanced N2 and P3 components, in principle consistent with Rüsseler et al. (2003) and Schlaghecken et al. (2000). Thus, the disagreement arises only from the meaning of N2 effects.

Although Schlaghecken et al. (2000) and Rüsseler et al. (2003) suggested N2 and P3 components might be associated with the acquisition of explicit knowledge, recently, it has been showed that the N2 and P3 reflect functionally distinct processes (e.g., Folstein & Van Petten, 2008; Smith, Johnstone, & Barry, 2007, 2008). Dimoska, Johnstone, and Barry (2006) found that in the stop-signal task, stop-signal trials elicited a larger N2 on failed-stop trials but a larger P3 on successful-stop trials, relative to ignore-signal trials, suggesting that N2 might reflect the detection of response-conflict while P3 might reflect the outcome of inhibition or control. Smith et al. (2008) found that the N2 NoGo effect was not different between overt and covert inhibition tasks but the P3 NoGo effect was increased for motor compared with non-motor inhibition, indicating that the N2 effect might reflect cognitive process such as the participants' recognition of the need for inhibition while the P3 effect might reflect a motor inhibition process.

In line with these findings, we found N2 effect for targets with implicit knowledge but large P3 effects for targets with explicit knowledge, revealing that the N2 effect may reflect a mismatch with the anticipation for the next stimulus while the P3 effect may reflect cognitive control and motor inhibition of the prepared response. In the SRT task, cognitive control is associated with conscious knowledge of whether an element can come next (i.e., it reflects conscious "judgment knowledge": Fu et al., 2010; for dissociations between control and consciousness in other paradigms see Dienes & Perner, 2007; Wan, Dienes, & Fu, 2008). Indeed, the conscious status of judgment knowledge was measured by whether people could flexibly control the generation of the next target according to instructions (e.g., Destrebecqz & Cleeremans, 2001, 2003; Norman, Price, & Duff, 2006; Schlaghecken et al., 2000; Wilkinson & Shanks, 2004). Thus, the dissociation between implicit and explicit knowledge we find is consistent either with models in which the conscious status of knowledge is regarded as key for separating different systems or with models for which flexibility vs. rigidity is a key distinctive feature rather than consciousness per se (see Henke (2010) for a review).

The relation of N2 and P3 to conscious awareness has also been investigated in other domains about which similar methodological and theoretical conclusions can be drawn. Koivisto, Revonsuo, and Lehtonen (2006), using a subliminal perception paradigm, found relations between both N1–N2 and P3 and reports of seeing the stimulus, even though P3 was also strongly modulated by other factors such as whether attention was global or local. Of course, if seen stimuli are stronger perceptually than unseen, indicators of perception per se, regardless of whether it is conscious, can covary with seen vs. unseen. Unconfounding strength of perception with awareness of seeing was achieved by Lau and Passingham (2006), who thus provide a useful paradigm for looking at the role of N2 and P3 in conscious perception. Kovisto et al. suggested that P3 may in part reflect reflective consciousness. However, in a similar paradigm, Bernat, Shevrin, and Snodgrass (2001) found that visual stimuli subjects were not conscious of could elicit P3, indicating P3 is not in itself a *unique* sign of conscious processing. Nonetheless, Del Cul, Baillet, and Dehaene (2007), again using a perception paradigm, argued conscious awareness requires a build-up of activity in frontal areas taking about 300 ms to achieve, and marked by a particularly strong P3. On these grounds, N2 would be too early to mark whether a person is aware of knowing, and a strong P3 would indicate awareness of knowing – in the SRT task amongst others – even though P3 by itself is only a probabilistic indicator.

The N2 and P3 effects were mainly at frontal regions in the present study (Figs. 7 and 8). Previous research using functional MRI or PET found that the striatum played an important role in implicit sequence learning (e.g., Doyon, Owen, Petrides, Sziklas, & Evans, 1996; Peigneux et al., 2000; Wilkinson & Jahanshahi, 2007), while the anterior cingulate/medial prefrontal cortex (ACC/MPFC) specifically correlated with the acquisition of explicit knowledge in sequence learning (e.g., Destrebecqz et al., 2003; Hazeltine, Grafton, & Ivry, 1997). Nonetheless, some research also found that the ACC reacted to sequence violations in the absence of awareness (e.g., Ursu, Clark, Aizenstein, Stenger, & Carter, 2009), and the striatum and dorsolateral PFC was activated in both implicit and explicit sequence learning in somewhat distinct subregions (e.g., Schendan, Searl, Melrose, & Stern, 2003; Willingham, Salidis, & Gabrieli, 2002). Thus, our findings that only the frontal region contributed to the acquisition of implicit knowledge may be because the EEG reflects mostly activity in cortical areas such as the prefrontal cortex rather than activity in subcortical areas such as the striatum. Nonetheless, the different latencies and waveforms in the acquisition of implicit and explicit knowledge suggested that implicit and explicit learning depend on different neural substrates.

A problem with any correlational attempt to identify brain regions associated with cognitive processes is that the identified region may be downstream of where the key processing occurs. For example, if the implicit learning was in part

perceptual, the N2 effect might reflect faster consequent motor planning, rather than the original site of associative learning. Perceptual, motor and perceptual-motor learning can all occur on implicit SRT tasks (e.g., Gheysen, Gevers, De Schutter, Van Waelvelde, & Fias, 2009), and may have all occurred in the current task. Could the N2 universally reflect implicit learning or is it just for one of these components, or indeed for a process that the learning site feeds into? Future research could begin to tackle this question by using tasks that separate motor and perceptual learning (e.g., Deroost & Soetens, 2006; Gheysen et al., 2009; Remillard, 2009).

5. Conclusion

This study provided evidence that implicit knowledge expresses itself in relatively early components (N2) and differs from later emerging explicit knowledge in P3 components. These findings suggest that people can learn without consciously knowing and that there might be different neural substrates supporting the acquisition of explicit knowledge and implicit knowledge.

Acknowledgments

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