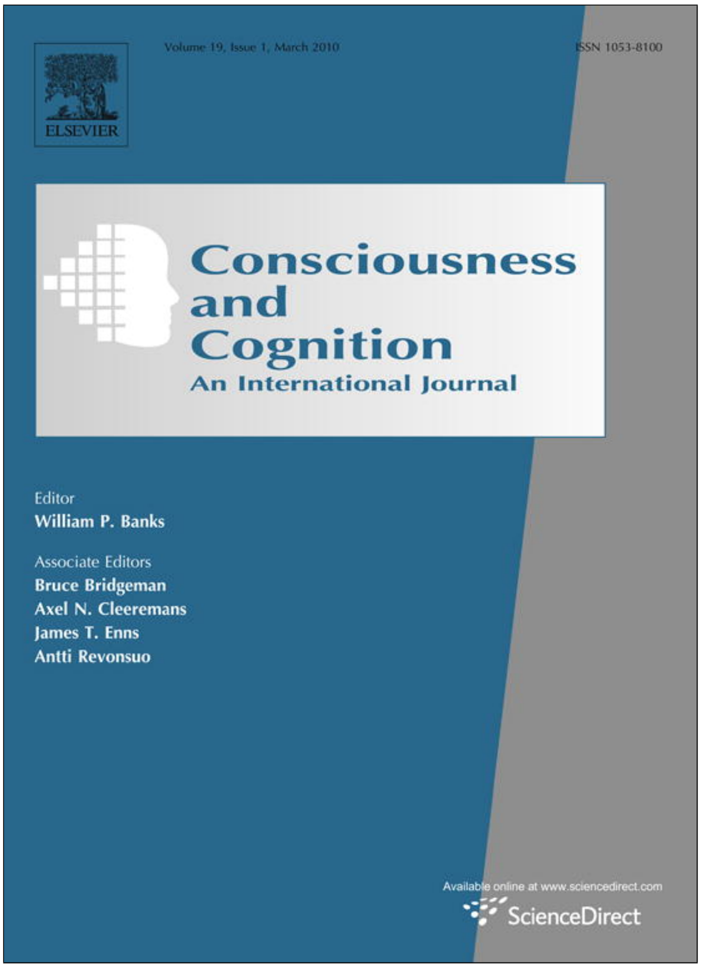
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Can unconscious knowledge allow control in sequence learning?

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A B S T R A C T

This paper investigates the conscious status of both the knowledge that an item is legal (judgment knowledge) and the knowledge of why it is legal (structural knowledge) in sequence learning. We compared ability to control use of knowledge (Process Dissociation Procedure) with stated awareness of the knowledge (subjective measures) as measures of the conscious status of knowledge. Experiment 1 showed that when people could control use of judgment knowledge they were indeed conscious of having that knowledge according to their own statements. Yet Experiment 2 showed that people could exert such control over the use of judgment knowledge when claiming they had no structural knowledge: i.e. conscious judgment knowledge could be based on unconscious structural knowledge. Further implicit learning research should be clear over whether judgment or structural knowledge is claimed to be unconscious as the two dissociate in sequence learning.

1. Introduction

Since Jacoby (1991) developed the Process Dissociation Procedure (PDP) to dissociate the contributions of conscious and unconscious knowledge to task performance, PDP has been used widely (e.g. Destrebecqz & Cleeremans, 2001, 2003; Dienes, Altmann, Kwan, & Goode, 1995; Goschke, 1998; Jiménez, Vaquero, & Lupiáñez, 2006; Kane, Picton, Moscovitch, & Winocur, 2000; McBride & Dosher, 1999; Reingold, 1995). In the method, a person is asked to perform opposing tasks with the same information: for example, in a subliminal perception experiment, to complete a stem or refrain from completing a stem with a word just briefly displayed (e.g. Debner & Jacoby, 1994). If the knowledge is conscious, the presumption is one can use it according to the task requested; conversely it is presumed that if the knowledge is unconscious it will have the same consequence whatever one's intentions. Indeed, Jacoby (1991) redefined conscious and unconscious influences in terms of their volitional rather than their phenomenological characteristics (contrast Tunney & Shanks, 2003).

Whereas Jacoby takes control to be definitional of whether knowledge is conscious or not (cf. Higham, Vokey, & Pritchard, 2000), Rosenthal (2002, 2005) suggests that a conscious mental state is a mental state of which one is conscious, the central assumption of higher order thought theory. On either approach, the sort of control that can be acquired by habit can be performed unconsciously. For example, Schmidt, Crump, Cheesman, and Besner (2007) found that people could gradually learn contingency information and exert control over responding with the information without any awareness of the contingency present. But as even executive control can logically be exerted by knowledge or intentions of which one is not conscious, the measured conscious status of knowledge based on PDP and higher order thought theory need not agree (see Seth, Dienes, Cleeremans, Overgaard, & Pessoa, 2008 for a discussion of the relation between different theories and measures of consciousness). For example, Dienes et al. (1995) and Wan, Dienes, and Fu (2008), using the artificial grammar learning task, found

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that people could choose which one of two grammars to use while believing they were literally guessing. Dienes and Perner (2007) also argued that a key feature of hypnosis is unconscious performance of executive function tasks, e.g. people can exclude habitual responses while remaining unaware of the relevant mental states or of what had been excluded. Following higher order thought theory, control is relevant to consciousness only when it is based on awareness of knowing rather than guessing. For example, the ability to refrain from completing a stem in a subliminal perception experiment reflects conscious knowledge only to the extent that the person refrains from completing the stem because *they thought they saw the word* (cf. Fu, Fu, & Dienes, 2008). In fact, it would seem strange to count the ability to control as an indication of conscious seeing if the person sincerely denied seeing the word at all.

Destrebecqz and Cleeremans (2001, 2003) adopted PDP to measure the conscious status of knowledge acquired in the serial reaction time (SRT) task. In the SRT task, the participant is told which of several buttons to press by a corresponding location on a screen being indicated. Unbeknownst to subjects, the order of the buttons follows a structured sequence. 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 (*own chunks*) under inclusion (I) and exclusion (E) when the response stimulus interval (RSI) was zero, i.e. they found $I = E$. Further, E was greater than the number of chunks from a transfer sequence (*other chunks*; constituting the baseline, B), i.e. they found $E > B$, confirming that participants lacked control over the use of their knowledge (a low score on the exclusion task indicates high control). Their results provided new and intriguing evidence of unconscious knowledge in sequence learning, given that awareness of knowledge would allow control.

However, Wilkinson and Shanks (2004) and Norman, Price, and Duff (2006) did not replicate the crucial findings but found $I > E$ and $E = B$, suggesting that participants had ability to control the use of their knowledge. Fu et al. (2008) replicated both Wilkinson and Shanks (2004) and Destrebecqz and Cleeremans (2001, 2003) by manipulating variables distinguishing the experiments such as reward, task difficulty, and amount of training. They found that reward moved exclusion performance towards baseline and adding noise to the sequences or shortening training led to above-baseline exclusion performance, suggesting that generation can be based on knowledge one cannot control. Interestingly, some subjects who could control their knowledge in our previous study often denied that they knew what the structure was at the end of the experiment. Anecdotally, it seems that sometimes people may not be conscious of knowledge that allows control in sequence learning.

Dienes and Scott (2005) pointed out that the PDP just measures the conscious status of judgment knowledge rather than structural knowledge (for a related theoretical framework, see Norman, Price, Duff, & Mentzoni, 2007; Norman et al., 2006). Judgment knowledge refers to the knowledge directly expressed by a judgment, for example, knowing that a person is angry or that this position comes next in the sequence. Structural knowledge refers to the knowledge of the structure of a domain that enabled the judgment, i.e. the basis of (reason for) their judgment (e.g. knowing that angry people in general have specified characteristics). In terms of the Serial Reaction Time (SRT) task, structural knowledge is knowledge about the structure of the sequences in the training phase, and in principle may consist of knowledge of conditional probabilities, fragments of the sequence, the whole sequence, of abstract patterns (including symmetries, runs or alternations as such) and so on. Judgment knowledge is knowledge of whether a particular location is legal given the context.

In PDP, subjects only need to know which location is legal, not why it is, so it measures the conscious status only of judgment knowledge. Similarly, confidence ratings about whether a predicted next item is legal also measure the conscious status of judgment knowledge. To distinguish judgment knowledge from structural knowledge, Dienes and Scott (2005) used an attribution test, in which they asked participants to attribute the basis of their classification decisions to either guess, intuition, rules or memory in an artificial grammar learning task. When a person says the knowledge was a pure guess or based only on intuition, the person is claiming they are not aware of what the basis of their judgment is; i.e. any structural knowledge is prima facie unconscious. By contrast, if a person says the judgment is based on memory or a rule they could state they are claiming to be aware of relevant structural knowledge. Similarly, the difference between intuition and guess responses is whether judgment knowledge is conscious or unconscious. Dienes and Scott (2005) and Scott and Dienes (2008) found that it was the distinction between conscious and unconscious structural knowledge that separated qualitatively different types of knowledge in an artificial grammar learning task, e.g. sensitivity to a secondary task. Dienes and Scott (2005), Scott and Dienes (2008) and Wan et al. (2008) present other evidence for meaningful qualitative differences between each of the attribution types, suggesting subjects typically do use the labels to describe corresponding experiences. For example, instructions to search for rules increases the number of conscious structural knowledge attributions, including rules.

One might also expect the distinction between conscious and unconscious structural knowledge rather than between conscious and unconscious judgment knowledge to be most relevant to different types of sequence learning as well. Computational models of implicit sequence learning typically involve neural networks where structural knowledge is embedded in weights of devices like Simple Recurrent Networks (SRN; e.g. Cleeremans, 1993). By contrast, conscious structural knowledge resulting from hypothesis testing is plausibly regarded as coded in activation patterns that have propositional structure (cf. Cleeremans, 1997; O'Brien & Opie, 1999). In principle, the unconscious structural knowledge embedded in weights could lead to either conscious or unconscious judgment knowledge; for example, Destrebecqz and Cleeremans (2003) simulated unconscious structural knowledge in an SRN that sometimes in the model yielded $E > B$ and sometimes not. That is, conscious judgment knowledge could be derived from the qualitatively different structural knowledge in weights (unconscious) and hypotheses (conscious).

In summary, control can be exerted on the basis of knowledge one is not conscious of as well as knowledge one is conscious of (Dienes et al., 1995; Dienes & Perner, 2007; Schmidt et al., 2007; Wan et al., 2008), even judgment knowledge one is not conscious of. Yet PDP has become a common method for measuring the conscious status of knowledge in sequence learning (e.g. Higham et al., 2000; Jiménez et al., 2006; Miyawaki, Sato, Yasuda, Kumano, & Kuboki, 2005; Norman et al., 2006; Schlaghecken, Stürmer, & Eimer, 2000; Vokey & Higham, 2004). We will investigate whether, as a matter of fact, control is exerted only when people believe they have relevant knowledge in sequence learning. A convergence of the two measures – control of knowledge and stated awareness of judgment knowledge that a sequence is legal – would be heuristically useful for researchers.

Logically, one can fail to be conscious of either structural or judgment knowledge. Given PDP is shown to be useful in indicating the conscious status of judgment knowledge in sequence learning under standard conditions, we will investigate whether PDP can indicate judgment knowledge is conscious while structural knowledge is unconscious. A demonstration of the latter would question the continued use of PDP as the single method of choice in measuring the conscious status of knowledge in sequence learning, given the possibility that the theoretically and empirically most interesting divide might be between conscious and unconscious structural knowledge rather than or in addition to between conscious and unconscious judgment knowledge (Dienes, 2008).

Below we show how to combine the PDP method and subjective measures to measure the conscious state of judgment and structural knowledge. Experiment 1 uses a test phase in which people attempt to control the use of their knowledge (PDP) and also indicate confidence in their decisions to measure the conscious status of judgment knowledge. Experiment 2 introduces a test of the conscious status of structural knowledge, by applying the attribution measures of Dienes and Scott (2005) to sequence learning.

2. Experiment 1

In implementing PDP, Destrebecqz and Cleeremans (2001, 2003) asked people to freely generate 100 successive positions such that they did or did not follow the sequence. In contrast to this free generation, Wilkinson and Shanks (2004, Experiment 3) argued that a sensitive measure of exclusion performance could be obtained by presenting participants with a series of locations and then have the person generate a successor. By constraining the initial sequence, participants are unable to use generation strategies like constantly cycling through a particular sequence of locations which they could do in free generation; because of counterbalancing, such strategies force exclusion performance to be the same as baseline if such a recycled short sequence is correctly known to be irrelevant. Further the trial-by-trial generation tests allow us to combine PDP with subjective measures: on each test trial, we asked subjects to report their confidence after the generation.

Wilkinson and Shanks (2004, Experiment 3) asked people to provide a continuation after each of a set of five movement sequences taken from the training phase. However, in a pilot experiment we found that such test sequences taken only from the training phase allowed people to consciously learn the sequence during the test phase. In order to avoid the risk of providing information about the target sequence during these trials, Jiménez and Vázquez (2005) presented not only the 12 contexts that can be generated from the training sequence but also the 12 contexts that can be built out of the control sequence. Instead we simply reduced the test sequences from 5 to 2 movements: thus each test trial was completely uninformative about the sequence the person was trained on, because trained and untrained sequences differed only in the third elements of any triplet.

Furthermore, Fu et al. (2008, Experiment 3), using free-generation tests, found that the amount of training influenced participants' ability to control their knowledge. Thus, we also used short and long training conditions, similar to Fu et al.

2.1. Method

2.1.1. Participants

Fifty-four undergraduate students (28 male, 26 female) took part in this experiment. None of them had previously taken part in any implicit learning experiment. They were randomly assigned to two groups (7-block, $n = 27$; 15-block, $n = 27$). They were told before the generation tests that in addition to an attendance fee of ¥20, they would receive an additional ¥50 for good generation performance. One of the 54 participants received the reward; she belonged to the 15-block group.

2.2. Apparatus and materials

The experiment was programmed in Virtual C++ 6.0 and run on Pentium-compatible PCs. The display consisted of a square in the center of the computer's screen against a gray background. The stimuli were letters Z, V, X, and P, which corresponded to numerals 1, 2, 3, and 4 from two second-order conditional sequences (SOC1 = 3-4-2-3-1-2-1-4-3-2-4-1; SOC2 = 3-4-1-2-4-3-1-4-2-1-3-2). In the SOC sequences, each letter, which always appeared in the central square, was completely determined by the previous two letters. 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. 1-2-1) frequency (one in each sequence), repetitions (no repetitions in either sequence), and rate of full coverage (see Reed & Johnson, 1994). The difference between the sequences is in their second-order conditional structure. For example, 3-4 was followed only by a 2 in SOC1 but only by a 1 in SOC2.

A deterministic SOC sequence can be broken down into 12 sequential chunks of three locations, or triplets (e.g. SOC1 can be broken down into the triplets 3-4-2, 4-2-3, 2-3-1, and so on; and SOC2 can be broken down into 3-4-1, 4-1-2, 1-2-4, and so on). In each triplet, the third one was completely determined by the previous two. To generate the probabilistic sequences, we arranged for the corresponding probability to be less than 1.0. That is, every two were followed by the corresponding one from the training SOC sequence with a probability of .875, and they were followed by the corresponding one from the other SOC sequence with a probability of .125.

2.3. Procedure

2.3.1. Training phase

Participants were exposed to a serial four-choice RT task, which included 7 or 15 training blocks in the training phase depending on the condition. Each block consisted of 98 trials, for a total of 686 or 1470 trials. On each trial, a letter appeared in the square, which was in the center of the screen and covered visual angle of approximately 1°. Participants were instructed to respond as quickly and as accurately as possible by pressing the corresponding key. Keys D, F, J, and K corresponded to letters Z, V, X, and P. Participants were required to respond to Keys D and F with the middle and index finger, respectively, of their left hand and to Keys J and K with the index and middle finger, respectively, of their right hand. Each block began at a random point in one of the two sequences. The target was removed as soon as a correct key had been pressed, and the next stimulus appeared after 500 ms (i.e., RSI = 500 ms). Response latencies were measured from the onset of the target to the completion of a correct response. Thirty-second rest breaks occurred between any two experimental blocks. For counter balancing purposes, about half of the participants in each condition were trained on SOC1 and half on SOC2.

2.3.2. Test phase

The test phase involved two blocks of trial-by-trial generation tests (inclusion and exclusion). At the beginning of the test, participants in each group were informed that the targets had followed a regular repeating sequence, in which most letters were determined by the previous two. Participants were instructed that on each test trial they would first respond to a short sequence of two movements as in the training, and then they would be required to generate the next target by pressing a key. In the inclusion test, they were required to generate the next target that appeared most frequently in the training (i.e. the high-probability target); and in the exclusion test, they were required to generate the next target that rarely appeared in the training (i.e. the low-probability target). In each test, 12 different test trials were presented in a random order; each test trial was presented eight times to make 96 test trials altogether. After each generation response, participants were required to report the confidence level of their judgment by choosing one of: 50%, 60%, 70%, 80%, 90%, and 100%. Participants were told that 50% meant complete guessing and that 100% meant certainty that their response was correct.

2.4. Results

2.4.1. Training data

Trials with RTs greater than 1000 ms were dropped; these amounted to 2.47% and 1.36% of the trials in the 7-block and 15-block groups, respectively.

Fig. 1a shows the mean RTs obtained over the training phase in Experiment 1. For the 7-block group, an ANOVA on RTs with probability (probable vs. improbable) and blocks (7 levels) as within-subject variables revealed a significant effect of

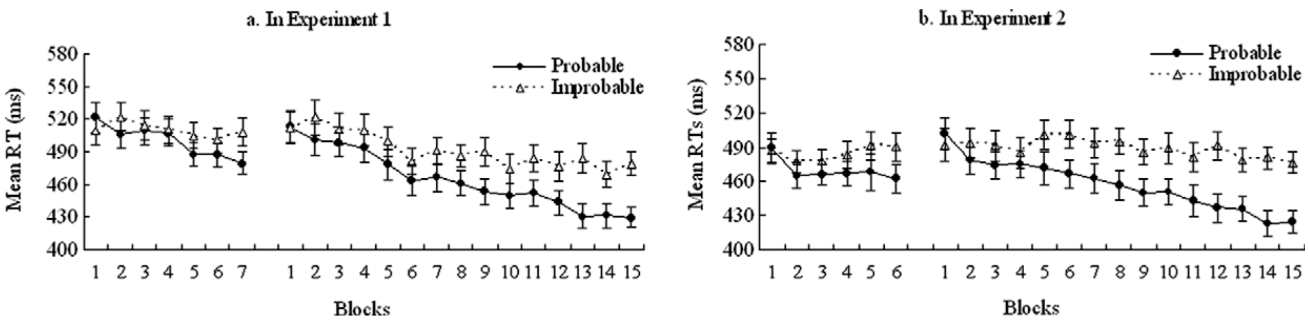

Fig. 1. Mean reaction times (RTs) across training blocks for different training groups in Experiments 1 and 2. The probabilistic data were broken down into probable targets, which were consistent with the training sequence and improbable targets, which were not. Ms = milliseconds. Error bars depict standard errors.

probability, $F(1, 26) = 11.77$, $MSE = 824.15$, $p < .01$, indicating that participants responded to probable locations more quickly than to improbable ones. The main effect of block was significant, $F(6, 156) = 4.87$, $MSE = 1024.84$, $p < .001$, and so was the probability by block interaction, $F(6, 156) = 3.04$, $MSE = 750.95$, $p < .01$, indicating learning, i.e. a greater probability effect later in practice than earlier on. For the 15-block group, an ANOVA on RTs with probability (probable vs. improbable) and blocks (15 levels) as within-subject variables revealed a significant effect of probability, $F(1, 26) = 56.12$, $MSE = 2607.83$, $p < .001$, indicating that participants responded to probable locations more quickly than to improbable ones. The main effect of block was significant, $F(14, 364) = 24.35$, $MSE = 988.23$, $p < .001$, and so was the probability by block interaction, $F(14, 364) = 4.38$, $MSE = 607.90$, $p < .001$, indicating learning i.e. a greater probability effect later in practice than earlier on.

In order to compare the probability effects of the two training conditions, an ANOVA on the last three blocks of each training condition with training as a between-subjects variable, probability (probable vs. improbable) and blocks (3 levels) as within-subject variables was used. This revealed a significant probability effect, $F(1, 52) = 67.00$, $MSE = 1341.01$, $p < .001$, and a probability by training interaction, $F(1, 52) = 10.96$, $MSE = 1341.01$, $p < .01$, indicating a greater probability effect in the 15-block group than in the 7-block group. The main effect of training also reached significance, $F(1, 52) = 7.50$, $MSE = 18060.98$, $p < .01$, revealing that RTs were faster in the 15-block group than in the 7-block group.

The mean error proportions for probable and improbable were .05 and .07 in the 7-block group and .04 and .08 in the 15-block group, indicating that the RT effects were not compromised by speed-error trade-offs.

2.4.2. *Test data*

We computed proportions of generated triplets that were or were not part of the training in both inclusion and exclusion tasks. 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 part of neither training nor transfer sequence. The maximum number of each type of triplet was 96. Fig. 2a shows the mean proportion of triplets generated for each group in Experiment 1. If participants learned the training sequence explicitly, then they should be able to control the expression of their knowledge. We would expect that they would produce more own than other triplets in the inclusion task, but not in the exclusion task. Thus, evidence of implicit knowledge would come from either the finding $I = E$ or $E > B$, where I and E refer to the proportion of own triplets generated in the inclusion and exclusion tasks, and B refers to an appropriate baseline level of generation. We take the proportion of other triplets as the baseline because own and other triplets are counterbalanced across participants (cf. Wilkinson & Shanks, 2004).

We first compared the proportion of own triplets generated under inclusion and exclusion instructions in the two conditions. An ANOVA with training condition as a between-subjects variable and instructions (inclusion vs. exclusion) as a within-subject variable revealed a significant instruction effect, $F(1, 52) = 38.21$, $MSE = .01$, $p < .001$, and an instruction by training interaction, $F(1, 52) = 14.47$, $MSE = .01$, $p < .001$. The interaction revealed that there was an instruction effect for the 15-block group, $F(1, 52) = 49.85$, $p < .001$, but not for the 7-block group, $F(1, 52) = 2.83$, $p = .10$. That is, participants in the 15-block group generated more own in inclusion than exclusion (i.e. $I > E$), but participants of the 7-block group could not (i.e. $I = E$).

Now we consider the relation between E (own triplets) and B (other triplets) in exclusion. For the exclusion tests, an ANOVA with training condition as a between-subjects variable and type of triplet (own vs. other) as a within-subject variable revealed only a significant training effect, $F(1, 52) = 14.18$, $MSE = .01$, $p < .001$, suggesting that participants generated more own and other triplets under exclusion in the 7-block group than in the 15-block group. That is, participants in the 7-block rather than 15-block group expressed more knowledge of the structure shared by both SOC sequences under exclusion. Crucially, the interaction was non-significant, $F(1, 52) = .45$, $MSE = .01$, $p = .51$. That is there was no evidence for length of training modulating the difference between E and B.

In our previous study (Fu et al., 2008), we used free generation, i.e. participants were asked to freely produce 96 key presses making sure they either followed (inclusion) or failed to follow (exclusion) the training regularities. With free

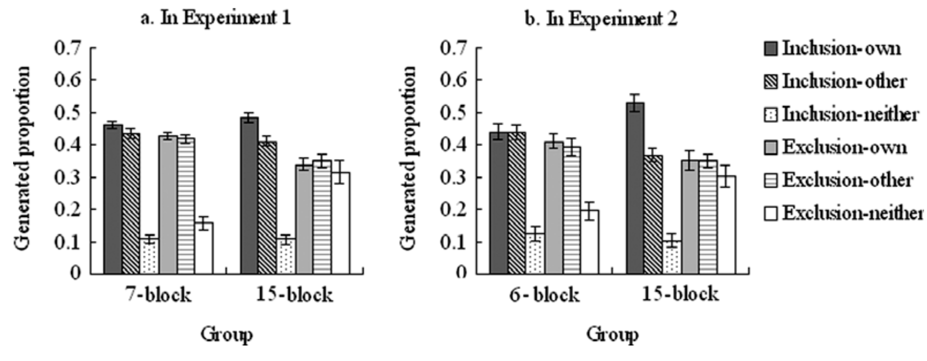

Fig. 2. Mean proportion of triplets generated by different training groups in Experiments 1 and 2. Own = proportion of triplets generated from the training sequence; other = proportion of triplets from the transfer sequence; neither = proportion of triplets from neither training nor transfer sequence. Error bars depict standard errors.

generation, we found $E > B$ after 6 blocks of training and $E = B$ after 15 blocks (Fu et al., 2008, Experiment 3). A crucial difference between the free generation of Fu et al. and the constrained generation in this experiment is that under free generation participants can continuously produce those perhaps few triplets that they know; in the current experiment participants are tested on all triplets equally making it harder to demonstrate knowledge if only a few triplets are known. Schlaghecken et al. (2000) emphasized the importance of distinguishing *well-learned* from *less-learned* chunks. To distinguish *well-learned* triplets from *less-learned* triplets, we assumed that RT differences between training and transfer triplets would be greater for well-learned than less-learned triplets. We calculated the average RT differences between training and transfer triplets for all the 7 blocks of the 7-block group and the last 7 blocks of the 15-block group. They were 15.82 ms and 36.56 ms for the 7-block and the 15-block groups, respectively. Therefore, we took 35 ms as a criterion for well-learned triplets. If the RT difference between a training triplet (e.g. 3-4-2) and the corresponding transfer triplet (3-4-1) was more than 35 ms then the triplet was classified as a *well-learned* triplet; or else as a *less-learned* triplet. That is, the overall group mean was used for classifying triplets for each subject. There were 5.11 and 6.22 well-learned triplets in the 7- and 15-block groups, respectively. Fig. 3a shows proportions of triplets generated for well- and less-learned triplets in Experiment 1.

We first compared the proportion of own triplets generated under inclusion and exclusion instructions in the 7- and 15-block groups. An ANOVA on proportions with training condition as a between-subjects variable and instruction (inclusion vs. exclusion) and learning level (well- vs. less-learned) as within-subject variables revealed a significant instruction effect, $F(1, 52) = 25.55$, $MSE = .01$, $p < .001$, and a significant instruction by training effect, $F(1, 52) = 11.69$, $MSE = .01$, $p < .001$. The interaction revealed that there were more own triplets in inclusion than exclusion for the 15-block group (i.e. $I > E$), $F(1, 52) = 35.90$, $p < .001$, but not for the 7-block group (i.e. $I = E$), $F(1, 52) = 1.34$, $p = .25$. The main effect of learning level was significant, $F(1, 52) = 40.96$, $MSE = .01$, $p < .001$, so was the learning level by instructions interaction, $F(1, 52) = 8.59$, $MSE = .02$, $p < .01$. The interaction revealed that there was an instruction effect for the well-learned triplets, $F(1, 52) = 25.52$, $p < .001$, but there was not for the less-learned triplets, $F(1, 52) = .56$, $p = .46$. There was a significant training effect, $F(1, 52) = 5.68$, $MSE = .01$, $p < .05$, and a marginally significant training by learning level interaction, $F(1, 52) = 3.26$, $MSE = .01$, $p = .077$. The interaction revealed that there was a training effect for the well-learned triplets, $F(1, 52) = 7.42$, $p < .01$, but not for the less-learned triplets, $F(1, 52) = .31$, $p = .58$. That is, the training effect was expressed only by *well-learned* rather than less-learned triplets.

For the exclusion test, an ANOVA with training condition as a between-subjects variable and learning level (well- vs. less-learned) and type of triplet (own vs. other) as within-subject variables revealed a training effect, $F(1, 52) = 4.14$, $MSE = .03$, $p < .05$, indicating that participants generated more own and other triplets in the 7-block group than in the 15-block group. There was also a significant learning level by type of triplet by training interaction, $F(1, 36) = 4.43$, $MSE = .04$, $p < .05$. The three-way interaction revealed that there were more own than other for the well-leaned triplets in the 7-block group (i.e. $E > B$), $F(1, 52) = 7.85$, $p < .01$, but not for the well-learned triplets in the 15-block group (i.e. $E = B$), $F(1, 52) = 2.04$, $p = .16$. There were no differences between own and other for the less-learned triplets in either group (i.e. $E = B$, both ps > .55).

After each test trial, participants gave a confidence rating on a 50–100% scale. We calculated the regression of performance difference between inclusion and exclusion against confidence ratings separately for each participant (cf. Dienes & Longuet-Higgins, 2004). Fig. 4 shows mean generation differences between inclusion and exclusion against confidence of the 7- and 15-block groups in Experiment 1. For the 7-block group, the average I–E difference was not above chance level (i.e. zero) when people gave 50% confidence (given on 17% of test trials), $t(23) = .12$, $p = .90$, and the average slope was also not significantly different from chance (i.e. zero), $t(23) = .72$, $p = .48$, suggesting that participants could not demonstrate control over knowledge whatever their confidence. For the 15-block group, there was no difference between I and E for the 50% confidence rating (given on 20% of test trials), $t(22) = -.46$, $p = .65$, indicating that when people thought they had no knowledge, they also had no ability to control. But the average slope was significant, $t(22) = 5.27$, $p < .001$, indicating that the conscious status of judgment knowledge was associated with ability to control use of that knowledge.

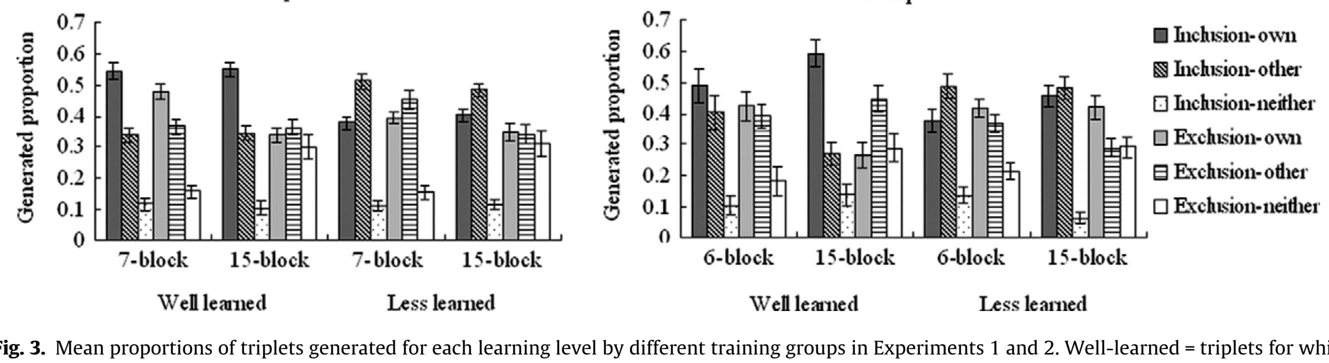

Fig. 3. Mean proportions of triplets generated for each learning level by different training groups in Experiments 1 and 2. Well-learned = triplets for which the RT difference between the training and transfer was more than 35 ms; less-learned = triplets for which the RT difference between the training and transfer was less than 35 ms. Error bars depict standard errors.

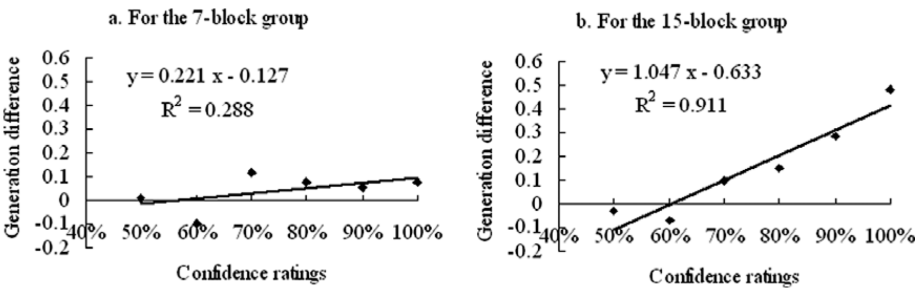

Fig. 4. Mean differences between inclusion and exclusion for each confidence rating by the 7- and 15-block groups in Experiment 1. Error bars depict standard errors.

2.5. Discussion

For both the 7- and 15-block groups, RTs were faster for probable than improbable target locations, confirming that participants acquired sequential knowledge. After the training, participants in the 15-block group generated more own triplets under inclusion than exclusion instructions (i.e. $I > E$), but participants in the 7-block group generated no more own in inclusion than exclusion (i.e. $I = E$). Importantly, in the 15-block group, ability to control, as indicated by the difference between I and E, was closely related to awareness of having knowledge, as indicated by confidence ratings. When people were not aware of having any relevant knowledge, they also could not control whether own or other triplets were produced. The two methods of measuring the conscious status of judgment knowledge – control and confidence ratings – converged in this experiment, where the knowledge was that a triplet was or was not legal.

Although the 7-block group showed by their RTs that they had acquired knowledge, they could not use this knowledge to control: we found $I = E$ and $E = B$. It would be nice to show that the lack of evidence for control is not due to a lack of sensitivity. Interestingly, if we distinguish knowledge discriminating the two SOC sequences from knowledge that both sequences have in common, there was evidence that the 7-block group unconsciously used knowledge of the second sort; participants in the 7-block group generated both own and other triplets significantly above chance level 0.33 ($t(26) = 9.65$, $p < .001$, $t(26) = 7.34$, $p < .001$, respectively) during exclusion. In our former study (Experiment 3, Fu et al., 2008), we found positive evidence for a lack of control, namely above-baseline exclusion performance with free-generation tests. Free generation may well be a more sensitive test because it allows participants to focus on those triplets that they actually know; indeed, their structural knowledge will be continually pressing to produce those very triplets. By contrast, in the current test phase, participants were forced to respond to all possible triplets equally often.

To further explore this, we distinguished *well-learned* triplets from *less-learned* triplets, as defined by RTs in the training phase. There was above-baseline exclusion performance (i.e. $E > B$) for well-learned triplets in the 7-block group but the exclusion performance for well-learned triplets in the 15-block group was at baseline (i.e. $E = B$). This pattern fits the claims of Cleeremans and Jiménez (2002): With small amounts of learning, low quality representations have little effect, then they begin to influence performance causing unintended effects ($E > B$ for 7-block), but eventually people acquire meta-knowledge about their knowledge (i.e. conscious judgment knowledge) and can control it ($I > E$ and $E = B$ for 15-block). These data further show that with sensitive measures, *uncontrollable* judgment knowledge can arise even when the RSI is 500 ms; Destrebecqz and Cleeremans (2001) found uncontrollable judgment knowledge only for RSI's less than 250 ms (cf. also Norman et al., 2006).

So far we have considered only the conscious status of judgment knowledge. To explore the relation between control and the conscious status of structural knowledge, in Experiment 2 we combined the trial-by-trial test methodology of Wilkinson and Shanks (2004, Experiment 3) with the attribution tests used by Dienes and Scott (2005).

3. Experiment 2

Dienes and Scott (2005) suggested that unconscious structural knowledge can be inferred from unconscious judgment knowledge but conscious judgment knowledge leaves the conscious status of structural knowledge completely open. For example, in natural language a person may not have conscious knowledge of the structure of the language but may consciously know that a particular sentence or word in a sentence is grammatical or not. To distinguish structural knowledge from judgment knowledge, Dienes and Scott (2005), using an artificial grammar learning paradigm, asked people to report the basis of their judgments using one of a set of fixed options: Guess, intuition, rules, and memory. They found that unconscious structural knowledge could lead to both conscious and unconscious judgment knowledge.

When both structural and judgment knowledge are unconscious, the phenomenology is that of arbitrary guessing; when structural knowledge is unconscious and judgment knowledge is conscious, the phenomenology is that of intuition; when structural knowledge is conscious, people may be aware of either using memory or using rules. As Dienes and Scott, we asked subjects to report the basis for their judgment from the options of guess, intuition, rules and memory in each test trial. The guess category indicated that it seemed to the participant that the judgment had no basis whatsoever and they could just as well have flipped a coin to arrive at the judgment. The intuition category indicated that the participant had some confidence in their judgment, and they knew to some degree the judgment was right, but they had absolutely no idea why it was right. The rules category indicated the participant felt they based their answer on some rule or rules acquired from the training phase and which they could state if asked. The memory category indicated that the person felt the judgment was based on memory for particular items or parts of items from the training phase. To guarantee all subjects remembered the meanings of guess, intuition, rules and memory, the definitions were presented on each trial.

It may be that the letters we used in Experiment 1 allows easier hypothesis testing strategies than the locations more typically used in the SRT tasks (Tubau & Lopez-Moliner, 2004). Thus, we used spatial locations as stimuli in Experiment 2.

3.1. Method

3.1.1. Participants

Sixty-four undergraduate students (32 male, 32 female) took part in the experiment. None of them had previously taken part in any implicit learning experiment. They were randomly assigned to two groups (6-block, $n = 32$; 15-block, $n = 32$). They were told that in addition to an attendance fee of ¥20, they would also be rewarded according to their trial-by-trial generation performance as detailed later.

3.2. Apparatus and materials

Apparatus and materials were identical to Experiment 1 except that the display consisted of a yellow background and four blue target-location bars, which corresponded to the keys D, F, J, and K on the computer's keyboard from left to right. The bars were arranged in a horizontal line on the computer's screen and separated by intervals of 3 cm. The stimulus was a blue circle 1 cm in diameter that appeared above one of the four positions on each trial.

3.3. Procedure

3.3.1. Training phase

The procedure in training was similar to Experiment 1. Participants in the 6- and 15-block groups were exposed to a serial four-choice RT task, which included 6 or 15 training blocks in the training phase. Each block consisted of 98 trials, for a total of 588 and 1470 trials depending on the condition. Each block of target location trials began at a random point in one of the two sequences. RSI was zero (corresponding to Fu et al.'s Experiment 3).

3.3.2. Test phase

The test phase involved two blocks of trial-by-trial generation tests (inclusion and exclusion). In each test, two practice trials were first presented and then the 12 test trials presented in a random order. The exclusion instructions were slightly different from Experiment 1: In Experiment 2 subjects were asked to predict the location of a subsequent stimulus that *could not* appear in training after the given context (rather than to predict the rare stimulus). To encourage participants to do their best, for each correct generation, participants were rewarded an additional ¥1 (corresponding to the extra 0.25 dollar for each correct test sequence in Wilkinson and Shanks' Experiment 3). After generation, participants were required to report the basis of their judgment by ticking one of: guess, intuition, rules, or memory. Participants were provided with definitions taken from Dienes and Scott (2005). Half of the participants first performed the inclusion test, and then the exclusion test; and half first performed the exclusion test, then the inclusion test.

3.4. Results

3.4.1. Training data

Trials with RTs greater than 1000 ms were dropped; these amounted to 0.45% and 0.74% of the trials in the 6- and 15-block groups. Fig. 1b shows the mean RTs obtained over the training phase in Experiment 2. For the 6-block group, an ANOVA on RTs with probability (probable vs. improbable) and blocks (6 levels) as within-subject variables revealed a significant effect of probability, $F(1, 31) = 47.86$, $MSE = 545.70$, $p < .001$, indicating that participants responded to probable locations more quickly than to improbable ones. The main effect of block was also significant, $F(5, 155) = 8.12$, $MSE = 924.12$, $p < .001$, and so was the probability by block interaction, $F(5, 155) = 5.60$, $MSE = 313.97$, $p < .001$, indicating learning i.e. a greater probability effect later in practice than earlier on. For the 15-block group, an ANOVA on RTs with probability (probable vs. improbable) and blocks (15 levels) as within-subject variables revealed a significant effect of probability, $F(1, 31) = 119.14$, $MSE = 1375.36$, $p < .001$, indicating that participants responded to probable locations more quickly than to improbable ones. The main effect of block was significant, $F(14, 434) = 7.02$, $MSE = 1347.57$, $p < .001$, and so was the probability by block interaction, $F(14, 434) = 3.64$, $MSE = 499.75$, $p < .001$, indicating learning, i.e. a greater probability effect later in practice than earlier on.

In order to compare probability effects of the two training conditions, an ANOVA on the last three blocks of each training condition with training as a between-subjects variable, probability (probable vs. improbable) and blocks (3 levels) as within-subject variables was conducted. This revealed a significant probability effect, $F(1, 62) = 141.30$, $MSE = 614.17$, $p < .001$, and a probability by training interaction, $F(1, 62) = 7.06$, $MSE = 614.17$, $p = .01$, suggesting that a greater probability effect in the

15-block group than in the 6-block group. The block by training interaction also reached significance, $F(1, 62) = 7.12$, $MSE = 717.59$, $p = .001$, indicating that a greater block effect in the 6-block group than in the 15-block group.

The mean error proportions for probable and improbable were .03 and .05 for the 6-block group and .02 and .06 for the 15-block group, which indicated that the RT effects were not compromised by speed-error trade-offs.

3.4.2. Test data

Fig. 2b shows the mean proportion of triplets generated for each group in Experiment 2. We first compared the proportion of own triplets generated under inclusion and exclusion instructions in the two conditions. An ANOVA with training condition (6-block vs. 15-block) as a between-subjects variable and instructions (inclusion vs. exclusion) as a within-subject variable revealed a significant instruction effect, $F(1, 62) = 12.67$, $MSE = .03$, $p = .001$, and an instruction by training interaction, $F(1, 62) = 6.66$, $MSE = .03$, $p < .05$. The interaction revealed that there was an effect of instruction for the 15-block group, $F(1, 62) = 18.85$, $p < .001$, but there was not for the 6-block group, $F(1, 62) = .48$, $p = .49$. The results indicated that participants in the 15-block group generated more own triplets in inclusion than exclusion (i.e. $I > E$), but those in the 6-block group could not (i.e. $I = E$).

For the exclusion tests, an ANOVA with training condition as a between-subjects variable and type of triplet (own vs. other) as a within-subject variable revealed only a significant main effect of training, $F(1, 62) = 6.06$, $MSE = .02$, $p < .05$, suggesting that participants generated more own and other triplets in the 6-block group than the 15-block group. That is, participants in the 6-block rather than 15-block group expressed more knowledge of the structure shared by both SOC sequences under exclusion.

As in Experiment 1, we computed proportions of triplets for well- and less-learned triplets in each training condition. There were 4.78 and 5.47 well-learned triplets in the 6- and 15-block groups, respectively. Fig. 3b shows proportions of triplets generated for well- and less-learned triplets in Experiment 2.

We first compared proportions of own triplets for well- and less-learned triplets generated in the 6- and 15-block groups. An ANOVA on proportions with training condition as a between-subjects variable and instruction (inclusion vs. exclusion) and learning level (well- vs. less-learned) as within-subject variables revealed that there was a significant instruction effect, $F(1, 62) = 8.90$, $MSE = .07$, $p < .01$, and a significant instruction by training interaction, $F(1, 62) = 6.73$, $MSE = .07$, $p < .05$. The interaction revealed that there were more own triplets in inclusion than exclusion for the 15-block group, $F(1, 62) = 15.56$, $p < .001$, but not for the 6-block group, $F(1, 62) = .08$, $p = .78$. The instruction by learning level interaction also reached significance, $F(1, 62) = 7.38$, $MSE = .09$, $p < .01$, suggesting that there were greater own triplets in inclusion than exclusion for the well-learned triplets (i.e. $I > E$), $F(1, 62) = 12.07$, $p = .001$, but not for the less-learned triplets (i.e. $I = E$), $F(1, 62) = .00$, $p = .95$. That is, control over knowledge was only for the well-learned triplets.

For the exclusion test, an ANOVA with training condition as a between-subjects variable and learning level (well- vs. less-learned) and type of triplet (own vs. other) as within-subject variables revealed a significant training effect, $F(1, 62) = 4.30$, $MSE = .03$, $p < .05$, indicating that there were more own and other generated in the 6-block group than the 15-block group. The learning level by triplet type interaction reached significance, $F(1, 62) = 5.46$, $MSE = .08$, $p < .05$, revealing that there were more own than other for the less-learned triplets (i.e. $E > B$), $F(1, 62) = 4.94$, $p < .05$, but not for the well-learned triplets (i.e. $E = B$), $F(1, 62) = 2.00$, $p = .16$. There was also a significant learning level by triplet type by training interaction, $F(1, 62) = 4.51$, $MSE = .08$, $p < .05$. The three-way interaction revealed that subjects in the 15-block group generated more own than other for the less-leaned triplets (i.e. $E > B$), $F(1, 62) = 5.98$, $p < .05$, but generated more other than own for the well-learned triplets (i.e. $E < B$), $F(1, 62) = 5.27$, $p < .05$, while subjects in the 6-block group generated equally own and other triplets for both less- and well-learned triplets (i.e. $E = B$, both $ps > .40$).

After each test trial, participants had to report the basis of their judgment by ticking one of four options: guess, intuition, rules, or memory. We analyzed the total $I–E$ difference for each attribution (future studies could explore each attribution separately for well-learned and less-learned triplets; unfortunately there were insufficient data in this study). Fig. 5 shows proportions of each attribution for each training condition in Experiment 2. An ANOVA with attributions (guess vs. intuition vs. rules vs. memory) and instructions (inclusion vs. exclusion) as within-subject variables and training condition (6-block vs. 15-block) as a between-subjects variable was conducted. It revealed a significant attribution effect, $F(3, 186) = 10.10$,

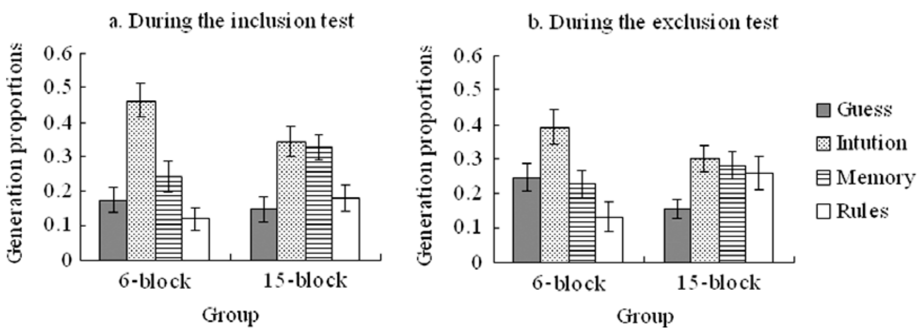

Fig. 5. Mean proportion of each attribution under inclusion and exclusion in the 6- and 15-block groups in Experiment 2. Error bars depict standard errors.

MSE = .11, $p < .001$, which was qualified by a significant attribution by training interaction, $F(3, 186) = 2.67$, *MSE* = .11, $p < .05$. The interaction indicated that there were more intuition attributions in the 6- than 15-block group, $F(1, 62) = 3.64$, *MSE* = .10, $p = .06$, but more rules attributions in the 15- than 6-block group, $F(1, 62) = 2.93$, *MSE* = .10, $p = .09$. The attribution by instruction interaction was also significant, $F(3, 186) = 2.99$, *MSE* = .03, $p < .05$, indicating that there were more guess ($F(1, 62) = 2.96$, *MSE* = .02, $p = .09$) and intuition attributions ($F(1, 62) = 3.48$, *MSE* = .03, $p = .07$) but less rules attributions during inclusion than exclusion ($F(1, 62) = 4.53$, *MSE* = .02, $p < .05$).

Guess attributions indicate the participant is unaware of both judgment and structural knowledge; intuition attributions that the participant is aware of judgment knowledge but not structural knowledge; and rules and memory indicate the participants were aware of both judgment and structural knowledge, so the categories of rules and memory were collapsed. Fig. 6 shows mean proportions of own triplets generated for guess, intuition, and rules and memory attributions in Experiment 2. To explore the relation between control and the conscious status of structural knowledge, we compared the *I*–*E* difference for each attribution type. For the 6-block group, there were no differences for own triplets between inclusion and exclusion for any attribution type (all *ps* > .47). For the 15-block group, there were no differences for own triplets between inclusion and exclusion for guess attribution, $t(16) = .59$, $p = .55$, but the proportion of own triplets was greater in inclusion than exclusion for the intuition attribution, $t(25) = 2.46$, $p < .05$, and also for rules and memory attributions, $t(29) = 3.66$, $p = .001$. The findings of $I > E$ for both intuition and rules and memory indicated that the ability to control could be based on both conscious and unconscious structural knowledge.

3.5. Discussion

For both the 6- and 15-block groups, RTs were faster for probable than improbable target locations, indicating that participants learned the sequence. After training, participants in the 15-block group generated more own triplets under inclusion than exclusion (i.e. $I > E$), but participants in the 6-block group did not generate more own triplets in inclusion than exclusion (i.e. $I = E$), providing no evidence for conscious judgment knowledge in the 6-block group. Moreover, further analysis revealed that for the 15-block group, there were $I = E$ and $E > B$ for the less-learned triplets while there were $I > E$ and $E < B$ for the well-learned triplets, indicating that participants in the 15-block group acquired some knowledge they could control and some they could not. While the pattern produced by distinguishing well-learned and less-learned triplets differed from Experiment 1 in detail, it fits the general schema of Cleeremans and Jiménez (2002), that as training progresses knowledge comes first to have unintended consequences ($E > B$ for less-learned triplets) and then comes under control as meta-knowledge emerges ($E = B$ or $E < B$ for well-learned triplets).

Interestingly, like participants in the 7-block group in Experiment 1, participants in the 6-block group generated both own and other triplets significantly above chance levels during exclusion ($t(31) = 3.58$, $p = .001$, $t(31) = 2.49$, $p < .05$, respectively), providing further evidence that the short training phase led participants to unconsciously use knowledge of that which both SOC sequences have in common. This conclusion is tentative without knowing what biases an untrained control group would have for these stimuli. We ran 32 additional control participants on one block of training on a random sequence (except immediate repetitions were prohibited) and then the test phase. The 6-block group produced significantly more own and other triplets in exclusion than the control group did (9.66 cf. 8.41), $t(62) = 2.23$, $p < .05$. In sum, the 6-block group could not refrain from generating a sequence with the general properties of the SOC sequences, despite the fact, in Experiment 2, subjects were asked to exclude any continuation of the sequence that occurred in training.

We used spatial locations as in Fu et al. (2008, Experiment 3) but unlike Fu et al., we did not find above-baseline exclusion in the 6-block group. Free-generation tests, as used by Fu et al., should in general be more sensitive to unconscious knowledge than trial-by-trial generation tests, as we used here, because they measure precisely what each participant has learned while trial-by-trial generation tests measure all possible knowledge about the SOC sequence. In support of the argument that it is just a sensitivity issue, the difference in proportion of own rather than other triplets given in exclusion after 6 blocks of training was not significantly different in Experiment 2 than Experiment 3 of Fu et al., $F(1, 53) = .60$, *MSE* = .01, $p = .44$. More

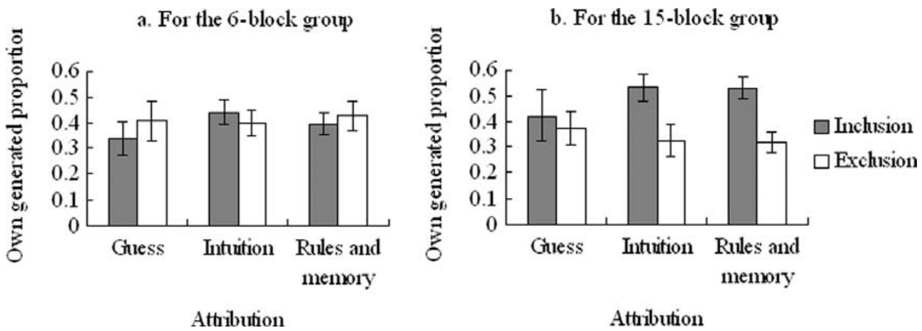

Fig. 6. Mean proportions of triplets generated for guess, intuition, and rules and memory attribution by the 6- and 15-block groups in Experiment 2. Error bars depict standard errors.

importantly, we found $E > B$ for the less-learned triplets but $E < B$ for the well-learned triplets in the 15-block group, revealing that conscious knowledge and unconscious knowledge coexisted on this task.

In terms of what people claimed their decisions were based on, we found that with training (6 blocks vs. 15 blocks) people gave less attributions indicating unconscious structural knowledge. That is, training allowed structural knowledge to become more conscious. When people were not conscious of judgment knowledge, as indicated by using the guess attribution, they also lacked control, as indicated by a zero difference between inclusion and exclusion. That is, conceptually replicating Experiment 1, awareness of judgment knowledge went together with the ability to use it in controlled ways. However, when participants gave either unconscious or conscious structural knowledge attributions (intuition or rules and memory), the 15-block group generated more own triplets under inclusion than exclusion (i.e. $I > E$). That is, the conscious judgment knowledge expressed in an inclusion–exclusion difference could apparently be based on unconscious as well as conscious structural knowledge. When PDP indicates that all the knowledge it measures is conscious, it is nonetheless possible for all structural knowledge to be unconscious – because the knowledge tested by PDP is only judgment knowledge.

4. General discussion

The aim of the experiments was to determine the relation between awareness of knowing, as revealed by subjective measures, on the one hand, and ability to control the use of knowledge as revealed by the PDP, on the other. Both awareness of knowing (e.g. Merikle, 2007; Weiskrantz, 1986, 1997) and control (Jacoby, 1991) have been presented as key methods for determining the conscious status of knowledge, so it is important to know how and when the methods agree and disagree (cf. Seth et al., 2008). Experiment 1 found that the ability to control knowledge was closely related to confidence ratings, indicating that when PDP indicated people could control use of knowledge that an item was legal, they were indeed conscious of having that knowledge according to their own statements of confidence ratings. This suggests that the conscious state of judgment knowledge can be measured by both PDP and subjective measures. Experiment 2 showed that people could exert such control over the use of judgment knowledge when claiming they had no idea why a sequence was legal: i.e. conscious or controllable judgment knowledge could be based on unconscious structural knowledge. This suggests that the conscious state of structural knowledge can not be measured by the PDP.

4.1. Control and conscious awareness

The two experiments found convergence when the knowledge was judgment knowledge, i.e. when the knowledge was whether a triplet was legal or not. When people believed they were guessing, they also lacked control, as shown by the equivalent level of inclusion and exclusion performance. As their reported confidence increased, so did their ability to control. This agreement between subjective measures and PDP in sequence learning is certainly heuristically useful for researchers as to a first approximation it means they do not need to worry about which measure they use when considering the conscious status of judgment knowledge. Note however that agreement is not guaranteed. Dienes et al. (1995) and Wan et al. (2008) document cases of disagreement in artificial grammar learning and Dienes and Perner (2007) document cases of disagreement in hypnosis. The Stroop effect also shows a case where conscious judgment knowledge goes with a lack of control. Future research could work towards ensuring agreement by making sure exclusion is based on whether one was aware of knowing or not. For example, people could be asked to generate the first completion that comes spontaneously to mind (to ensure use of relevant unconscious structural knowledge) and then to choose another item only if they had any confidence that the generated item was legal. Such instructions appropriately ask participants to base exclusion only on whether they have relevant higher order thoughts of knowing.

Confidence ratings and PDP only assess the conscious status of judgment knowledge. Experiment 2 showed that when people have conscious structural knowledge, because participants in the 15-block group indicated that they based their answers on stateable rules and memories, they could control the use of their knowledge, as shown by inclusion and exclusion differences. In this case, control went with conscious structural knowledge, as one would typically expect. Conscious rules and memories did not guarantee the ability to control, of course: there was no $I–E$ difference for conscious attributions when participants were in the 6-block group. Jacoby's method relies strictly on veridical knowledge. Moreover, when people said they used only intuition, i.e. when they had no idea why their answer was correct, they could still control the use of their knowledge. In this case, control is provided by unconscious structural knowledge. This is an important conceptual point for researchers to bear in mind. For example, Jiménez et al. (2006; Experiment 4) wondered why PDP measures did not discriminate the amount of conscious knowledge in two conditions in a sequence learning task: the two conditions may well have differed substantially in the amount of conscious structural knowledge but there is no reason why this should show in PDP measures, which measure the conscious status of only judgment knowledge. Our emphasis on the distinction between the conscious status of judgment and structural knowledge also finds support in Norman et al. (2007). In their experiments, elements in the sequence varied in position, color and shape, though color and shape were in fact irrelevant to determining the next item in the sequence: only position was important. People were asked at the end of the experiment to indicate the nature of any regularity in the sequence; some people referred only to shape or color or to nothing at all. Nonetheless, such people were able to control their judgments of the next likely location: evidence of conscious judgment knowledge combined with unconscious structural knowledge.

4.2. Conscious and unconscious judgment knowledge measured by the PDP method

We found an $E = B$ after a short training phase whether the stimuli were spatial or non-spatial in the two experiments, which was different from our previous finding of $E > B$ when using free-generation tests (Experiment 3, Fu et al., 2008). In order to explore whether this is because free-generation tests are more sensitive to unconscious knowledge than trial-by-trial generation tests, we distinguished well-learned and less-learned triplets based on the difference between RT to the probable and to the improbable targets. It may be that in free generation, once very well (and consciously) learned triplets are excluded, triplets learned well enough to control behaviors, but not well enough to become conscious (cf. Cleeremans & Jiménez, 2002), are the ones constantly pushing to be expressed: Free generation becomes a sensitive test of the few triplets with just the right properties to create $E > B$. Indeed, selecting triplets according to their learning in the training phase confirmed this prediction.

Interestingly, we found that short training made people generate more own and other triplets than chance (and greater than the control group in Experiment 2) under exclusion whether the stimuli were spatial locations or symbolic letters. This replicated our previous findings (Experiment 3, Fu et al., 2008), and suggested there were two kinds of knowledge: (a) concrete knowledge which is relevant to distinguishing own and other triplets such as 3-4 being followed only by a 2 in SOC1 and so on, and (b) abstract knowledge which concerns properties both SOC sequences have in common such as the rarity of trills (e.g. 3-4-3) and runs (1-2-3) and so on. Participants after a shorter training generated own and other triplets significantly above chance level under exclusion, suggesting that they acquired some unconscious judgment knowledge.

In sum, our results provide new insight in the dissociation of conscious and unconscious knowledge in sequence learning. We found that the conscious status of (judgment) knowledge that an item is legal can be measured by both PDP and subjective measures but the (structural) knowledge of why it is legal can be measured only by subjective measures. Since conscious judgment knowledge can be based on both conscious and unconscious structural knowledge, further implicit learning research should be clear over whether judgment or structural knowledge is claimed to be unconscious as the two dissociate in sequence learning.

Acknowledgments

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