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Unconsciously learning task-irrelevant perceptual sequences

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ABSTRACT

We demonstrated unconscious learning of task-irrelevant perceptual regularities in a Serial Reaction Time (SRT) task in both visual and auditory domains. Participants were required to respond to different letters ('F' or 'J', experiment 1) or syllables ('can' or 'you', experiment 2) which occurred in random order. Unbeknownst to participants, the color (red, green, blue or yellow) of the two letters or the tone (1–4) of the syllables varied according to certain rules. Reaction times indicated that people indeed learnt both the color and tonal regularities indicating that task-irrelevant sequence structure can be learned perceptually. In a subsequent prediction test of knowledge of the color or tonal cues using subjective measures, we showed that people could acquire task irrelevant knowledge unconsciously.

1. Introduction

Implicit learning can occur without the intention to learn and without awareness of what has been learned (Reber, 1989). Such learning can lead either to an increase in the number of correct judgments (Reber, 1989) or to faster responding (Nissen & Bullemer, 1987), which may be different cases, judgment-linked and motor-linked implicit learning, respectively, in the terminology of Seger (1998). Although implicit learning goes beyond the limits of intentions to learn and what one is conscious of knowing, implicit learning does have limits. Characterizing what those limits are though is difficult. For example, for motor-linked implicit learning, there has been debate over whether perceptual sequences can be learned as such (rather than motor sequences or perceptual–motor links, e.g., Willingham, Nissen, & Bullemer, 1989), and if they can, whether the perceptual cues have to be task relevant (Jimenez & Mendez, 1999). Here we will explore these suggested limits using the Serial Reaction Time (SRT) task. In a standard SRT experiment, participants are required to respond to sequences of objects, in which at least one of the dimensions of these objects, such as spatial location, color or shape, obeys structural regularities. However, participants are not informed about the sequenced nature of the stimulus dimensions. The fact that people become sensitive to the underlying structure of these sequences has been testified in many experiments, showing that reaction times (RTs) are facilitated by regularities in the sequences (Brown, Aczel, Jiménez, Kaufman, & Grant, 2010; Cleeremans & McClelland, 1991; Cohen, Ivry, & Keele, 1990; Curran & Keele, 1993; Nemeth et al., 2011; Nissen & Bullemer, 1987; Rowland & Shanks, 2006).

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A point of debate in the literature has been whether the SRT task demonstrates only motor learning or also perceptual learning. For example, Howard, Mutter, and Howard (1992) found that people who observed someone else learning a sequence (but did not themselves respond) could respond faster to the sequence later, implying learning of a purely perceptual kind (contrast Kelly & Burton, 2001). Remillard (2003, 2009, 2011) and Deroost and Soetens (2006a) showed perceptual learning using a task in which subjects had to respond to the identity of the one underlined item in a row of items. The identity was randomly determined so the sequence of correct responses was random. Thus, there was no motor sequence to be learned. However, the location of the underlined item followed a sequence, and people showed they learnt this location sequence by their reactions times. Gheysen, Gevers, De Schutter, Van Waelvelde, and Fias (2009) argued that while motor learning had been amply demonstrated, previous studies had not actually unambiguously shown the learning of perceptual information because of possible problems including covert responding (e.g. in the Howard et al., study) or the learning of eye movements (in the Remillard studies; also Mayr, 1996). Gheysen et al. addressed these problems by a color matching task, in which three color squares were followed by a colored target square. There were four response keys, to indicate how many of the three initial squares (0–3) matched the target. The sequence of correct responses was random (so once again there was no motor sequence to be learned), but the sequence of colors for the target was determined. As the target was always central, there were no relevant eye movements to be learned. Thus any learning must have been purely perceptual. Implicit learning occurred on this SRT task, even if it occurred more slowly than motor learning on a similarly structured task with a motor sequence (see Kemény & Lukács, 2011, for a non-significant perceptual learning effect).

If learning perceptual features does not define a hard constraint, are there other constraints on implicit learning? In the Gheysen et al., Remillard and Deroost and Soetens studies, the perceptual information was relevant to predicting the right motor response on each trial. Consistently, Van den Bos and Poletiek (2009) argued that people implicitly learnt only aspects of a structure that were useful to the task they performed. Similarly, Jimenez and Mendez (1999) argued that only stimulus details selected for processing in working memory because of task demands could participate in implicit learning. However, Perlman and Tzelgov (2006) and Rowland and Shanks (2006) provided apparent counter-examples to both these claims. Perlman and Tzelgov found that when people had to name the display colors of a sequence of words, they learnt about the sequence of color words themselves. In this case, people learnt about aspects of the task not useful to them, which they had no need to keep in working memory. However, the Stroop effect showed how likely it was that the words were in working memory, primed to be processed (cf Eitam & Higgins, 2010). Rowland and Shanks (2006) showed people could learn an irrelevant sequence of positions occupied by one shape when learning the sequence of locations of another shape. In this case as well, locations were plausibly primed to be processed, because the primary task was to respond to locations. We will investigate whether perceptual information which is not predicted by the correct motor response nor primed by the main task can nonetheless be learned in both visual and auditory domains.

A key issue to establish is whether the learning is implicit. Neither Perlman and Tzelgov (2006) nor Rowland and Shanks (2006) established whether people were aware of the acquired knowledge. But if this is not established, there is no way of knowing whether these studies tell us anything about specifically implicit learning. In order to assess the conscious status of knowledge, we used the subjective measures recommended by Dienes (2008a).

In sum, our aim was to establish whether on the SRT task *perceptual* learning could occur of genuinely task *irrelevant* information and in such a way that the resulting knowledge was *implicit*. If such learning exists, it would show some postulated limits of implicit learning are not hard and fast: Perceptual information need not be useful, nor even needed in working memory for task requirements, yet still be implicitly learnt. In experiment 1, the participant's task was to discriminate which of two letters were presented. The letters were presented in different colors, which was a purely perceptual feature. The color did not predict which letter would be displayed. Further, colors were not primed by task requirements. In a subsequent prediction task, participants gave trial-by-trial confidence ratings to establish if people were unaware of irrelevant knowledge. We determined whether or not RTs could nonetheless be facilitated by regularities in colors.

2. Experiment 1

2.1. Method

2.1.1. participants

A total of twenty participants (16 women, aged from 19 to 33, $M = 20.25$, $SD = 3.09$) from the university community took part in the main experiment. An additional 10 participants (5 women, aged from 23 to 30, $M = 24.10$, $SD = 2.13$) from the university community took part in a control condition who completed only the prediction task and not the reaction time task. All the participants had normal or corrected-to-normal vision.

2.1.2. Design

On the reaction time task, the within-participant variable was regularity (regular versus random); reaction time (RT) was the dependent variable. On the prediction task, the between participant variable was trained versus untrained; the dependent variable was prediction accuracy.

2.1.3. Materials

The letters ''F'' or ''J'' were the target stimuli, presented on a 15-in. display with 1024×768 pixel resolution, and a viewing distance of approximately 50 cm. The sequence of letters was randomized. Stimuli were presented at the center of the display screen (about 10 cm from the left edge of the display screen). All stimuli were displayed in one of the four colors: red (RGB 255, 0, 0), green (RGB 0, 255, 0), blue (RGB 0, 0, 255) and yellow (RGB 255, 255, 0). The stimulus was displayed for 1.5 s, with no gap between successive stimuli. This created a regular perceptual sequence with a timing independent of motor actions.

For the reaction time task, four letters constituted a trial, six trials composed one block and four blocks made up a phase. The first, second and fourth blocks of each phase were regular blocks and the third one was random. In the regular blocks, the color of the letters followed a fixed order (half of the participants were presented with the sequence ''red, blue, green, yellow'', and the other half were presented with ''blue, red, yellow, green''), while the letters were chosen randomly. The color did not add any information to predicting which letter would be displayed next. In the random blocks, each color could occur randomly with equal probability, with the constraint that no color was immediately repeated. A 10 s break was inserted between every two blocks and a 60 s break between every two phases.

2.1.4. Procedure

All the participants were tested individually. The main experiment included two parts: the serial reaction time task and the prediction task. The control participants only completed the prediction task. The serial reaction time task started with three practice blocks of random sequences, where the colors of the letters were randomized. Subjects were told to press a corresponding key as quickly and accurately as possible according to whether an F or a J was presented. Sixteen experimental blocks were presented after practice (four successive phases of four blocks each), including 12 regular blocks and four randomized blocks inserted at the 3rd, 7th, 11th and 15th positions.

Then, the participants were required to complete a prediction task. In the task, 24 short sequences were presented sequentially. These test sequences were either one or two letters long, starting at each of the four possible starting points, with one-letter sequence repeated two times and two-letter sequence repeated four times. Four options were listed, of which only one answer was correct. The participants were required to predict the color of the next letter. After each prediction, the participants rated their confidence on a 50-point scale (50–100), the lowest point indicating completely guessing, the highest indicating complete certainty and any number in between reflecting gradations of confidence (e.g., Kuhn & Dienes, 2005).

2.2. Results

2.2.1. Error rates

The mean error rates for the four different phases were uniformly low: phase 1: $M = 0.01$, $SD = 0.01$; phase 2: $M = 0.01$, $SD = 0.01$; phase 3: $M = 0.01$, $SD = 0.01$; phase 4: $M = 0.02$, $SD = 0.02$. They were significantly different between the four phases, $F(3, 57) = 2.87$, $p < .05$. However, using pairwise comparison with sequential Bonferroni correction (Hochberg, 1988), no pairwise comparisons were significant while maintaining familywise error at the .05 level.

The error rate for regular blocks was 0.01 ($SD = 0.01$) and for random blocks was 0.02 ($SD = 0.01$). No difference between the regular and the random blocks was detected, $t(19) = 1.22$, $p = .24$.

2.2.2. RTs

For each subject, RTs with incorrect responses or which were more than three standard deviations from the mean RT were excluded from further analysis. The average RT of valid trials across all participants is illustrated in Fig. 1. The learning effect for each phase was calculated as the difference between mean RTs of random blocks and the adjacent two regular blocks. The mean learning effects of the four phases were 4.73 ($SD = 14.26$), 2.99 ($SD = 9.30$), 4.84 ($SD = 9.15$) and 1.28 ($SD = 12.66$); they did not differ significantly, $F(3, 57) = 0.45$, $p > .05$.

The overall mean RT for random blocks was 346 ($SD = 25$) and for the adjacent two regular blocks was 342 ($SD = 22$). The overall learning effect averaged over phases (4 ms) revealed that participants responded faster in the regular blocks than in the random blocks, $t(19) = 2.56$, $p = .02$, $dz = 0.57$, indicating sensitivity to the color regularity.[1]

2.2.3. Prediction test and confidence rating

Participants' knowledge of the regularity was assessed by the prediction test, the accuracy of which for trained participants ($M = 0.48$, $SD = 0.14$) was consistently higher than chance (0.33), $t(19) = 4.78$, $p = .00015$, $d = 1.07$.[2] For the control participants, there was no significant difference between the accuracy of the prediction task ($M = 0.26$, $SD = 0.13$) and chance (0.33), $t(9) = -1.60$, $p = 0.14$. Further, the trained participants performed significantly better than the control participants, $t(28) = 4.07$, $p = .0003$, $d = 1.07$, indicating that learning had taken place due to exposure to the reaction time task (Dienes & Altmann, 2003).

[1] Note dz is a measure of effect size for repeated measures t-tests, given by the formula dz = mean difference/(standard deviation of the difference scores). Thus, $dz * \sqrt{N} = t$.

[2] For a one-sample test, d = (mean difference)/standard deviation. Thus, $d * \sqrt{N} = t$.

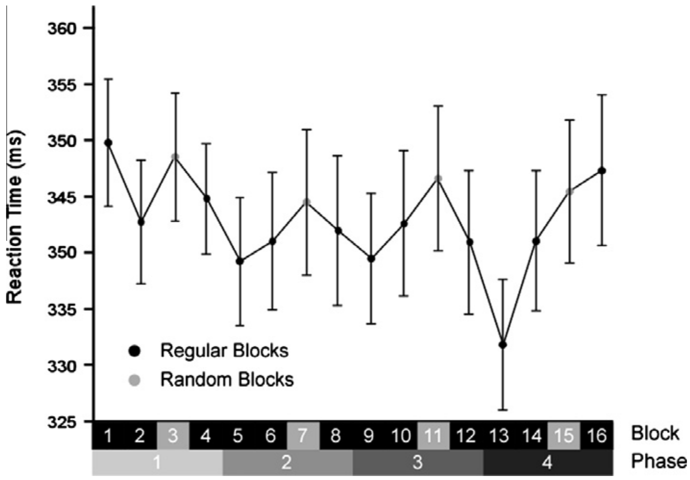

Fig. 1. Mean reaction times in each block in experiment 1. Error bars indicate standard error of the mean.

Table 1
Mean accuracy when participants were guessing (50% confidence rating) or confident (51–100% confidence rating) and the number of participants who were included in the analysis.

	Response proportion (%)	N	Response accuracy
Guess	0.26 (0.18)	18	0.45 (0.13)
Confident to any degree	0.74 (0.18)	18	0.50 (0.18)

Note: Two participants were excluded because either they did not give either a guess or confidence response at all or did so for only one trial. Standard deviations are given in parentheses. "*N*" indicates number of participants included in the analysis.

Prediction can be based on either conscious or unconscious knowledge. We assessed the conscious status of trained people's knowledge by the guessing and zero correlation criteria Dienes (2008a). Table 1 shows the classification accuracy when people gave the lowest confidence possible, defined as completely guessing and when they gave any other rating. In terms of the guessing criterion, we analyzed participants' accuracy when they claimed they were completely guessing, i.e., gave the lowest confidence response. Data from two participants who did not give guess response (50%) at all or did so for only one trial were excluded from this analysis.[3] Although there were four options, a chance baseline of 0.33 was used in case participants consciously noticed that no color was repeated, and because in the random blocks it was also true that no color repeated itself (of course, if performance is significantly better than this baseline, it is significantly better than the more straightforward baseline of 0.25). The findings indicated that participants' accuracy was consistently greater than chance (0.33) even when they believed they were completely guessing, $t(17) = 3.69$, $p = .002$, $d = 0.87$, indicating unconscious knowledge by the guessing criterion.

According to the zero correlation criterion, knowledge is unconscious when people cannot distinguish states of guessing from states of knowing, as shown by no relation between accuracy and "guess" versus "some confidence" responses. In terms of showing unconscious knowledge, it is specifically the distinction between completely guessing and having any confidence that is important (Dienes, 2004), so we divided confidence between 50% (pure guessing) and any other value (51–100%). Table 1 shows the accuracy for such guess and confident responses; the difference in accuracy (the accuracy-confidence "slope") was 5%, which was not significant $t(15) = 0.66$, $p = .52$, $dz = .17$. While the result being non-significant appears to satisfy the zero correlation criterion of unconscious knowledge, a non-significant result in itself cannot be used to assert the null hypothesis. Whenever the zero correlation criterion produces a non-significant result, its sensitivity must be established in order to know whether the result is positive evidence for unconscious knowledge. Thus, we analyzed the result further with a Bayes Factor (Dienes, 2008b, 2011). A Bayes Factor compares two theories, in this case the null hypothesis (that all knowledge is unconscious) and the alternative hypothesis that there exists some conscious knowledge. A Bayes Factor is a number between 0 and infinity, where values greater than three indicate strong evidence for the alternative hypothesis, numbers less than 1/3 indicate strong evidence for the null, and numbers in between 1/3 and 3 indicate data insensitivity (see Dienes, 2011). Assessing the sensitivity of the null result depends on specifying what range of effect sizes could be expected if there were conscious knowledge. It can be shown that the

[3] The learning effect was examined with these two participants excluded. The overall mean RT for random blocks was 341 ($SD = 18$) and for the adjacent two regular blocks was 338 ($SD = 19$). The overall learning effect averaged over phases (3 ms) revealed that participants responded faster in the regular blocks than in the random blocks, $t(17) = 1.97$, $p = .033$, one-tailed, $dz = 0.46$. The result is marginal two-tailed but an independent significant result indicating knowledge of the regularity is shown by the trained group satisfying the guessing criterion.

maximum slope that can be obtained depends on the proportion of confident responses, pc; specifically if the overall accuracy (ignoring confidence) is X% above baseline, then the maximum slope possible is X/pc.[4] Thus, the theory that there exists some conscious knowledge can be represented as a uniform between 0 and X/pc. That is, conscious knowledge, if it exists, was assumed to be plausibly any value from infinitesimally small to the maximum allowed. For the current data, $X = 15\%$, $pc = .74$, thus maximum slope = 20%. With this assumption the Bayes Factor (using the online calculator for the website for Dienes 2008) was 0.85. That is, the data are insensitive, and nothing can be concluded about whether or not there was conscious knowledge, as measured by the zero correlation criterion[5] (note that we have here provided a novel and general method for assessing the sensitivity of the zero correlation criterion; for other applications of Bayes to implicit learning, see Dienes, Baddeley, & Jansari, 2012; Jiang et al., 2012; and Mealor & Dienes, 2012). Nonetheless, we can conclude there was some unconscious knowledge, as indicated by the guessing criterion.

2.3. Discussion

The purpose of experiment 1 was to investigate whether people could unconsciously learn visual perceptual features which were task irrelevant, with no demands for them to be encoded in working memory. Using the trial-by-trial confidence methodology of Dienes (2008a), we showed that simple structure of irrelevant perceptual information can be learnt implicitly.

Experiment 2 aimed to provide converging evidence with different sorts of stimuli structures, i.e. syllables spoken in different Chinese tones, to establish that people can implicitly acquire the structure of irrelevant and unprimed perceptual information. Chinese is a tonal language, meaning that each syllable is spoken with a particular pitch contour or "tone", of which there are four. For example, the first tone is a steady high pitch and the second is a rising pitch. The primary task in experiment two involved distinguishing two syllables. The tones of the syllables were irrelevant to the task but followed a sequence.

Experiment 2 also increased its sensitivity for detecting unconscious knowledge by using the structural knowledge attributions of Dienes and Scott (2005). Dienes and Scott distinguished two different types of knowledge: judgment knowledge and structural knowledge. When a person reliably makes a judgment, e.g. whether the particular test item has the same structure as the training ones, the judgment itself constitutes a particular knowledge content, that is, that the item is legal. The knowledge that enables the judgment is structural knowledge. Structural knowledge might include knowledge of particular items, fragments of items, or other types of rules. Both judgment knowledge and structural knowledge can be conscious or unconscious. When people say they are guessing, both types of knowledge are unconscious. When people have confidence in the judgment, judgment knowledge is conscious but structural knowledge could be unconscious. In this case, people may feel they are using intuition. To assess the conscious status of structural knowledge, Dienes and Scott (2005) asked participant to report the basis of their judgments from four options: guess, intuition, rules, and memory. Unconscious structural knowledge is indicated by guess and intuition attributions and conscious structural knowledge is indicated by rule and memory attributions (see Dienes, 2008a, 2012, for detailed justification of the methodology). By pooling guess and intuition attributions (as in experiment 2), unconscious knowledge can be assessed with greater sensitivity than by just using guess responses (as in experiment 1).

3. Experiment 2

3.1. Method

3.1.1. participants

A total of sixteen (Chinese speaking) participants (11 women, aged from 20 to 30, $M = 23.81$, $SD = 3.56$) from the university community took part in the main experiment. An additional 10 participants (7 women, aged from 18 to 30, $M = 21.6$, $SD = 4.03$) from the university community took part in a control condition with no training phase. All the participants had normal hearing.

3.1.2. Design

The design was identical to that of experiment 1.

[4] X is a weighted average of the performance above baseline when guessing (G) and when confident (C), with the weights being the proportions of each type of response. That is, $X = (1 - pc) * G + pc * C$. By definition, our measure of confidence accuracy relation, the slope, is $C–G$. This will be maximum when all guessing responses are at baseline, i.e. when $G = 0$. In this case, slope = $C–G = C$. Also in this case, $X = pc * C$, with the G term dropping out. Rearranging, $C = X/pc$. Thus, since maximum slope = C in this case, maximum slope = X/pc. QED.

[5] Another criterion is that conscious knowledge exists when the person has knowledge and thinks that they do. This is the complement of the guessing criterion. By this criterion, there was conscious knowledge on those trials when people had confidence, as on those trials they were performing above chance $t(17) = 4.01$, $p < .001$, $d = 0.94$ (see descriptives in Table 1). Notice that the guessing and zero correlation criteria can put the conscious-unconscious divide in different places (Dienes, 2008a): The zero correlation criterion of conscious knowledge requires that the thought that one has knowledge is metacognitively diagnostic of actual knowledge; the criterion of simply being accurate when confident does not (cf Rosenthal, 2005).

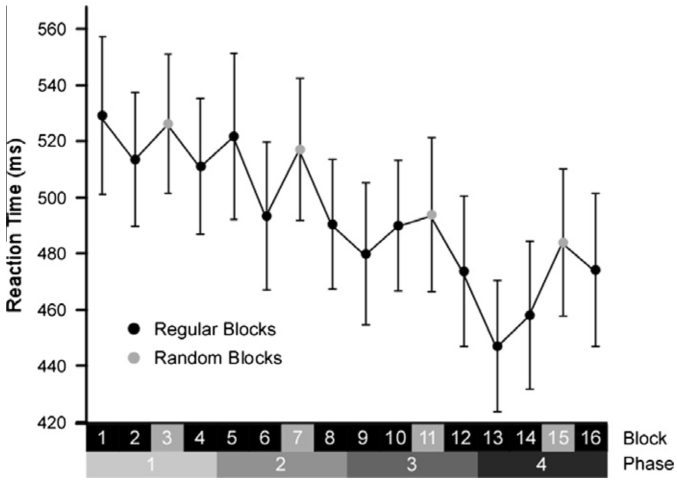

Fig. 2. Mean reaction times in each block in experiment 2. Error bars indicate standard error of the mean.

3.1.3. Materials

The syllables "can" (pronounced 'tsan') or "you" (pronounced 'yo') were the target stimuli. The sequence of syllables was randomized. All stimuli were displayed in one of the four tones: tone1, tone 2, tone 3 and tone 4. In this way, 8 tonal syllables were created by Chinese pronunciation software (*Xunfei interphonic 2.30*), each lasting for 300 ms. There was a fixed 1200 ms gap between stimuli, i.e. SOA was always 1500 ms.

Five syllables constituted a trial, eight trials composed one block and four blocks made up a phase. The first, second and fourth blocks of each phase were regular blocks and the third one was random. In the regular blocks, the tone of the syllables followed a fixed order: 2-1-4-3-1, while the syllables were chosen randomly, with the constraint that no syllable repeated itself more than three times. Note that this sequence is slightly more complex than the one used in experiment 1 (1-2-3-4). In the random blocks, both syllable and tone could occur randomly, with the constraint that no syllable repeated itself more than three times and no tone immediately repeated itself at all. A 10 s break was inserted between every two blocks and a 60 s break between every two phases.

3.1.4. Procedure

The procedure in the training phase was identical to that of experiment 1 except that subjects were told to press a corresponding key as quickly and accurately as possible according to whether an syllable "can" or a "you" was presented orally.

Then, the participants were required to complete a prediction task. In the task, 68 short sequences were presented. These test sequences were either one, two or three syllables long, starting at each of the five possible starting points. The test sequence were presented sequentially from shortest to longest in order to avoid learning structure from the test. Four tones were listed, of which only one answer was correct. The participants were required to predict the tone of the next syllable. After each prediction, the participants gave their structural knowledge attribution: guess, intuition, memory or rule.

3.2. Results and discussion

3.2.1. Error rate

The mean error rates were uniformly low: phase 1: $M = 0.03$, $SD = 0.02$; phase 2: $M = 0.03$, $SD = 0.03$; phase 3: $M = 0.03$, $SD = 0.03$; phase 4: $M = 0.03$, $SD = 0.02$. Error rates did not differ significantly between the four phases, $F(3, 45) = 0.32$, $p > .05$.

The error rate for regular blocks was 0.03 ($SD = 0.02$) and for random blocks was also 0.03 ($SD = 0.02$). The difference was not significant, $t(15) = 1.24$, $p = .23$.

3.2.2. RTs

For each subject, RTs with incorrect responses or which were more than three standard deviations from the mean RT were excluded from further analysis. The average RTs of valid trials across all the participants are illustrated in Fig. 2. The learning effect for each phase was calculated as the difference between mean RTs of random blocks and the adjacent two regular blocks. The mean learning effects for the four phases were 14 ($SD = 50$), 25 ($SD = 36$), 11.94 ($SD = 35$) and 18 ($SD = 39$), respectively. They did not differ significantly, $F(3,45) = 0.43$, $p > .05$

Table 2
The proportions of each attribution and their associated proportion correct ($M \pm SD$).

	Implicit attributions		Explicit attributions	
	Guess	Intuition	Memory	Rule
Proportion correct	0.46 ± 0.17	0.57 ± 0.25	0.71 ± 0.26	0.00 ± 0.00
Response proportions	0.54 ± 0.38	0.45 ± 0.37	0.01 ± 0.03	0.00 ± 0.00

The overall mean RT for random blocks was 505 (SD = 99) and for the adjacent two regular blocks was 489 (SD = 96). The overall learning effect averaged over phases (16 ms) was significant, $t(15) = 2.64$, $p = .019$, $dz = 0.66$.[6]

3.2.3. Prediction test and structural knowledge

Participants' knowledge of the regularity was assessed by the prediction test, in which the accuracy for trained participants ($M = 0.44$, $SD = 0.08$) was consistently higher than chance (0.33), $t(15) = 5.54$, $p < .001$, $d = 1.39$. The accuracy for the untrained control ($M = 0.28$, $SD = 0.06$) was lower than a chance baseline of 0.33, $t(9) = 2.80$, $p < .05$, $d = 0.88$, and was not significantly different from a more straightforward baseline of 0.25, $t(9) = 1.62$, $p > .05$. Furthermore, the accuracy of experimental group was higher than that of control group, $t(24) = 5.55$, $p = .00001$, $d = 2.24$, indicating that the trained group had acquired knowledge from the reaction time task. Was the knowledge unconscious?

For the trained group, guess and intuition attributions were combined as indicators of unconscious structural knowledge (implicit attributions), and memory and rule attributions were combined as indicators of conscious structural knowledge (explicit attributions) (Dienes & Scott, 2005). The proportions of each attribution and their associated proportion correct are shown in Table 2.

For implicit attribution, participants' accuracy was significantly higher than chance (0.33), $t(15) = 5.23$, $p = .0001$, $d = 1.31$, indicating the unconscious structural knowledge of the tonal regularity. Only three participants chose an explicit attribution, so nothing further can be concluded about conscious knowledge.

4. General discussion

The main purpose of the present study was to explore possible limitations on implicit learning in both visual and auditory domains, especially as shown on the SRT task: whether people could learn perceptual features which were task irrelevant, with no demands for them to be encoded in working memory. By showing genuinely implicit learning occurred in this case, it cannot be the case that implicit learning only occurs for features that are part of the task requirement (Jimenez & Mendez, 1999), nor only for features that are most useful for task performance (van den Bos & Poletiek, 2009), nor only for motor regularities or perceptual–motor contingencies (Willingham et al., 1989). Our results show that none of these suggested limitations are hard and fast limitations on implicit learning. Indeed, when all suggested limitations applied together, implicit learning still occurred. In experiment 1, we showed learning of regularities in the colors of stimuli when the only task of participants was to decide on the identity of a letter, and in experiment 2, we showed learning of regularities in the tones of stimuli when the only task of participants was to decide on the identity of a spoken syllables. Indeed, perceptual learning was rapid (contrast Gheysen et al., 2009), if of small effect. These results are consistent with authors who have postulated only soft rather than hard constraints on implicit learning. For example, Eitam, Schul, and Hassin (2009) suggested that implicit learning is a tool for achieving one's goals and hence is sensitive to goal relevance. Similarly, Tanaka, Kiyokawa, Yamada, Dienes, and Shigemasu (2008; see also Kiyokawa, Dienes, Tanaka, Yamada, & Crowe, 2012) argued that implicit learning is sensitive to perceptual attention.

Why does learning of irrelevant dimensions occur? It is already well established that irrelevant dimensions are sometimes processed. For example, in the Garner effect (e.g. Garner, 1988), the reaction time for a different–same response for two objects on a relevant dimension can be influenced by whether the objects are the same or different on an irrelevant dimension. In the Garner case, however, the sameness as such of the two objects is relevant to action control (Eitam & Higgins, 2010), in our case, the predictability of elements is not part of task requirements. In our case, there may, however, be "spill over" of relevance from the relevant to the irrelevant dimensions in that in each case the dimensions applied to the same object and location (cf Eitam & Higgins, 2010) , the color of the letters or the tone of the words. Indeed, in processing

[6] There are various aspects of the sequence people may have learnt. The simplest could be zero order statistical properties, namely, tone 1 was repeated twice as often as others (but all tones had equal frequency in the random sequence). When responses to tone 1 are excluded, the overall mean RT (for tones 2, 3 and 4) for random blocks was 506 (SD = 100) and for the adjacent two regular blocks it was 489 (SD = 95). The overall learning effect averaged over phases (17 ms) revealed that participants responded faster in the regular blocks than in the random blocks, despite these tones being less frequent in regular than random blocks, $t(15) = 2.43$, $p = .028$, $dz = 0.61$. Thus, participants must have learnt more than the fact that tone 1 was frequent. Further, the mean RT for tone 1 was not significantly different from that of the other three tones for regular blocks, $t(15) = 1.53$, $p = .15$, $dz = 0.38$ (tone1: $M = 491$, $SD = 96$; tones 2, 3 and 4: $M = 495$, $SD = 97$). The sensitivity of this null result can be checked by a Bayes Factor, as explained before. The overall learning effect was 15 ms; that sets the order of magnitude that could be expected for learning this particular aspect. Thus, the predictions of the theory that learning of zero order frequencies occurred were modeled as a half-normal with a SD of 15 ms (see Dienes, 2011, Appendix). The Bayes Factor was 1.01, i.e. the data were insensitive. In sum, while the null result does not bear on whether people learnt more than zero order statistics, the significant result does indicate people learnt more than tone frequency.

words, tones may be "chronically relevant" to Chinese participants to some degree. Indeed, prior expectations of relevance have been shown to influence what is implicitly learned (Chen et al., 2011; Leung & Williams, 2011; Ziori & Dienes, 2008). In sum, relevance may be a continuous dimension, consistent with it being a soft constraint on implicit learning.

Another soft constraint may be the presence of structure other than in the perceptual sequence itself. Deroost and Soetens (2006b) found learning of a complex perceptual sequence only when combined with a structured motor sequence. Similarly, Deroost, Zeischka, and Soetens (2008) obtained learning of an irrelevant sequence when the primary sequence was also structured. Consistently, Dienes et al. (2012) postulated that the presence of structure itself increases the rate of implicit learning (as the less the noise and the more the structure, the more optimal it is to have a larger learning rate). While additional structure may modulate implicit perceptual learning, it is a soft constraint: Here we show learning even when the primary task has a random structure, a state of affairs which should reduce learning rate.

Another constraint on learning is the nature of the structure to be learnt, a constraint not yet well specified for implicit learning generally (cf e.g. Dienes & Longuet-Higgins, 2004; Jiang et al., 2012). The fact we used a simple first order sequence may well be important for detecting learning in conditions where it is expected to be weak. Deroost and Soetens (2006b) detected implicit perceptual learning only for simple and not complex sequences (cf Kelly & Burton, 2001; Remillard, 2003). Perceptual learning is itself not limited to first order constraints, however; Remillard (2011) found implicit perceptual learning of up to fourth order probabilities. Whether unattended information can be processed and learnt to higher than first order could be usefully explored in the future. In our case, the structure of the sequence was 1-2-3-4 in experiment 1 and slightly more complex in experiment 2: 2-1-4-3-1. Learning remained in experiment 2, but whether people could learn second order conditionals under the conditions of experiments 1 or 2 is not known.

The fact people can learn artificial grammars demonstrates implicit perceptual learning (e.g. Dienes, 2008a; Reber, 1989). However, Seger (1998) argued that different mechanisms may underlie learning in the SRT task, which ultimately involves the speeding of motor responses, rather than learning artificial grammars, which involves making judgments (cf Gebauer & Mackintosh, 2007). Indeed, the speeding of processing, or fluency, appears to play almost no role in artificial grammar learning (Scott & Dienes, 2010). Nonetheless, we showed that people could become sensitive to regularities in variations in a perceptual feature, color and tone, in ways that affected their reaction times. As found by Gheysen et al. (2009), we show perceptual learning on the SRT task in both visual and auditory domains. Further, we go beyond demonstrations of perceptual learning in the artificial grammar learning literature by showing learning of irrelevant information. Lavie (2005) argued that irrelevant stimuli are processed to the extent that the perceptual load is low (cf Rowland & Shanks, 2006). In the current task, perceptual load was low compared to artificial grammar learning, where there can be a strong if not complete reduction in processing of irrelevant stimuli (Eitam et al., 2009; Kiyokawa et al., 2012; Tanaka et al., 2008).

To conclude, a simple structure of irrelevant perceptual information can be implicitly learnt. However, specifying the actual limits on implicit learning remains a difficult but important goal.

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