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ORIGINAL ARTICLE

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Measuring unconscious knowledge: distinguishing structural knowledge and judgment knowledge

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Abstract This paper investigates the dissociation between conscious and unconscious knowledge in an implicit learning paradigm. Two experiments employing the artificial grammar learning task explored the acquisition of unconscious and conscious knowledge of structure (structural knowledge). Structural knowledge was contrasted to knowledge of whether an item has that structure (judgment knowledge). For both structural and judgment knowledge, conscious awareness was assessed using subjective measures. It was found that unconscious structural knowledge could lead to both conscious and unconscious judgment knowledge. When structural knowledge was unconscious, there was no tendency for judgment knowledge to become more conscious over time. Furthermore, conscious rather than unconscious structural knowledge produced more consistent errors in judgments, was facilitated by instructions to search for rules, and after such instructions was harmed by a secondary task. The dissociations validate the use of these subjective measures of conscious awareness.

Introduction

This paper will explore the development of conscious and unconscious knowledge. We consider the artificial grammar learning task in particular, but the concepts introduced apply to any task that involves subjects making judgments. This paper extends the use of subjective measures of conscious knowledge by distinguishing between two different knowledge contents, namely structural knowledge and judgment knowledge, and applying subjective measures of conscious knowledge to each.

We take unconscious knowledge to be knowledge one has without being conscious of having it. In this, we are following a version of higher order thought theory (cf. Rosenthal 1986, 2005). Rosenthal developed an account of when a mental state is a conscious mental state. He appeals to a common (though not universal, e.g., Block, 2001) intuition that for a mental state to be a conscious mental state, we should be conscious of being in the mental state. According to the theory, the relevant way of being conscious of being in the mental state is to have a thought to the effect that we are in the mental state. Because this is a thought about a mental state, e.g., a thought about a thought, it is called a higher order thought. For example, if a blindsight patient looks at an object moving up, and his visual system forms a representation "An object is moving up," then the person sees that an object is moving up. But that first order representation does not make the seeing conscious seeing. For there to be conscious seeing there must be a representation like "I see that an object is moving up." It is precisely this higher order thought that a blindsight patient lacks, and that is why their seeing is not conscious seeing.

It follows from the higher order thought theory that any method of assessing the conscious or unconscious status of knowledge is credible only to the extent that it plausibly measures the existence of relevant higher order thoughts. The most direct way of assessing relevant higher order thoughts, of determining whether people are aware of their mental states, is to require them to report or discriminate their mental state in each trial on which a judgment is made. One can, for example, require that people report a confidence rating for each judgment, where the confidence rating asks people to discriminate between literally guessing and knowing to some degree. Dienes, Altmann, Kwan, & Goode (1995)

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recommended two measures of conscious and unconscious knowledge based on such confidence ratings. First, for the guessing criterion, take all the cases where the person claims to be literally guessing, to have no knowledge at all, and determine if performance is above baseline. If so, there is knowledge (performance above baseline), but the person is not aware of having knowledge (they believe they are guessing), so the knowledge is prima facie unconscious. Second, for the zero correlation criterion, determine if there is a within-subject relationship between confidence and accuracy. If the person is aware of being in occurrent states of knowing when they occurrently know and guessing when they guess, they should give higher confidence ratings when they are more accurate. Conversely, no relationship between confidence and accuracy is an indication that people are not aware of when they know and when they guess. (For the assumptions of these measures, see Dienes, 2004; Dienes & Perner, 2004.)

The learning paradigm in which these subjective measures of conscious and unconscious knowledge have been most extensively explored is artificial grammar learning (Chan, 1992; Dienes et al., 1995; Redington, Friend, & Chater, 1996; Dienes & Altmann, 1997; Allwood, Granhag, & Johansson, 2000; Tunney & Altmann, 2001; Channon et al., 2002; Dienes & Perner, 2003; Tunney & Shanks, 2003; Dienes & Longuet-Higgins, 2004; Tunney, in press). In the artificial grammar learning paradigm, introduced by Reber (1967), participants are first exposed to strings of, e.g., letters and asked to simply look at them or memorize them. This is called the training phase. The strings are generated by a complex set of rules, typically a finite state grammar. Participants are informed of the existence of the rules only at the end of the training phase, and are then asked to classify new strings according to whether they obey the rules or not. Depending on the grammar, participants can classify test strings about 65% correctly after just a few minutes of training. Consistent with the claim that the knowledge typically acquired in this way includes unconscious knowledge, participants can classify correctly above baseline when they believe they are literally guessing (e.g., Dienes et al., 1995; Tunney & Shanks, 2003) and sometimes there is no relationship between confidence and accuracy either (e.g., Dienes & Perner, 2003; Dienes & Longuet-Higgins, 2004). Typically, the subjective measures indicate the existence of some unconscious knowledge according to the guessing criterion and some conscious knowledge according to the zero correlation criterion. Typically, participants acquire both conscious and unconscious knowledge.

But what exactly is the knowledge that this methodology shows is conscious or unconscious? In the training phase of an artificial grammar learning experiment, participants acquire knowledge of the structure of the training items. Call this structural knowledge. Structural knowledge may consist of knowledge of particular items, knowledge of fragments of items, knowledge of other types of rules, or knowledge embedded in connectionist weights. We will leave the exact nature of the structural knowledge open in this paper. In the test phase, participants use their structural knowledge to form a new piece of knowledge: Whether a particular test item has the same structure as the training items. Call this judgment knowledge.

Both structural knowledge and judgment knowledge can be conscious or unconscious, depending on the existence of relevant higher order thoughts. If the participant's structural knowledge includes the rule "An M can start a string," that knowledge is conscious if there is a higher order thought like "I know that an M can start a string" and unconscious otherwise. The judgment knowledge that "MVXVV has the same structure as the training strings" is conscious if the participant has a higher order thought like "I know that MVXVV has the structure of the training strings" and not otherwise. The guessing criterion and zero correlation criterion measure the conscious or unconscious status of judgment knowledge, not structural knowledge (Fig. 1).

Presumably, conscious structural knowledge leads to conscious judgment knowledge. But if structural knowledge is unconscious, judgment knowledge could be conscious or unconscious. Consider natural language. If shown a sentence we can know it is grammatical and consciously know that it is grammatical, but not know at all why it is grammatical. When structural knowledge is unconscious, but judgment knowledge is conscious, the phenomenology is of intuition. Intuition is knowing that a judgment is correct, but not knowing why. When both structural knowledge and judgment knowledge are unconscious, the phenomenology is of guessing. In both cases we have unconscious structural knowledge. But in the first case, that of intuition, the zero correlation and guessing criteria may show all knowledge is conscious, because those criteria only assess judgment knowledge.

It would be nice to assess not only the conscious or unconscious status of judgment knowledge, but also that of structural knowledge. Knowing the conscious or

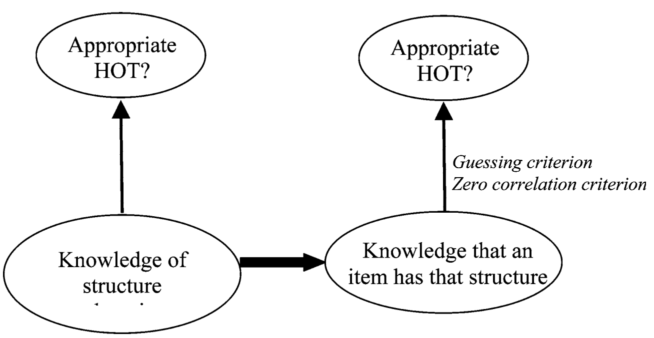

Fig. 1 Structural knowledge and judgment knowledge. When structural knowledge is unconscious, judgment knowledge can be conscious or unconscious. In knowledge of natural language, for example, we can have knowledge of structure with no relevant higher order thought making that knowledge conscious, but we may know whether a sentence has that structure, and also have the higher order thought that we know this

unconscious status of judgment knowledge allows some handle on the conscious or unconscious status of structural knowledge, because unconscious structural knowledge can be inferred from unconscious judgment knowledge. But the problem is that conscious judgment knowledge leaves the conscious status of structural knowledge completely open. For example, Mathews (1997) argued that the lack of confidence picked up by the guessing criterion may be characteristic of implicit learning only in the early stages of implicit knowledge acquisition. Similarly, Perruchet, Vinter, and Gallego (1997) pointed to our native language as a case where implicit knowledge plausibly gives rise to a relationship between confidence and grammaticality judgment accuracy. Furthermore, Allwood et al. (2000; Experiment 2) found a close relationship between confidence and judgment accuracy in an artificial grammar learning task, but felt implicit learning was still in operation. In discussing the use of confidence scales in implicit learning research, Reber (personal communication, 1994) urged us to distinguish between "knowing that we know" and "knowing what we know." We address these issues by distinguishing structural and judgment knowledge (cf. Dienes & Berry, 1997; Dienes & Perner, 1999), and by introducing a measure of the conscious or unconscious status of structural knowledge to complement the existing measures for judgment knowledge (cf. Lau, 2002). In this paper, we will ask participants to report any awareness they have of their structural knowledge.

In two experiments using the artificial grammar learning paradigm, we asked people to report the basis of their judgments using one of a set of fixed options: Guess, intuition, pre-existing knowledge, rules, and memory. The guess category indicated that it seemed to the participant that the judgment had no basis whatsoever, 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 (anything from a small amount to complete certainty); they knew to some degree the judgment was right, but they had absolutely no idea why it was right. The pre-existing knowledge category indicated that the judgment did not seem to be based on any knowledge gained from the training phase, but instead from knowledge they had anyway concerning letter patterns. The rules category indicated that the participant felt they based their answer on some rule or rules acquired from the training phase that 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.

The "guess" and "intuition" responses were taken to indicate those cases where structural knowledge was probably unconscious. The "rules" and "memory" responses were taken to indicate those cases where structural knowledge was probably at least partially conscious. The "pre-existing knowledge" response was added for completeness.

The first aim of Experiment 1 was to assess the proportions of these different types of responses and the associated accuracy in classifying strings in a typical artificial grammar learning situation. A second aim was to assess how the proportions of these responses changed over time. Participants were tested twice in the test phase in immediate succession. Redington et al. (1996) speculated that with practice with a domain, for example an artificial grammar, participants might learn to calibrate confidence with accuracy. Plausibly, the acquisition of unconscious structural knowledge initially leads to unconscious judgment knowledge. With further domain experience, people may come to know that they have relevant knowledge, learn to detect its use, and thus have conscious judgment knowledge even while structural knowledge remains unconscious (as in natural language; cf. Mathews, 1997). If this were the case, there would be a reduction in "guess" responses over time and a corresponding increase in "intuition" responses. Finally, an aim of both Experiments 1 and 2 was to investigate theoretically motivated dissociations between performance based on conscious and unconscious structural knowledge in order to validate our means of measuring whether structural knowledge was conscious or unconscious. Reber (1989) argued that conscious knowledge of the structure of a domain would lead to more consistent errors in classifying the same item twice compared with unconscious knowledge. Thus, Experiment 1 investigated the consistency with which participants classified the same item twice according to whether structural knowledge was measured as being conscious or unconscious.

Experiment 1

Methods

Design and participants

The two-grammar design of Dienes and Altmann (1997) was used. Specifically, participants were trained in one of two grammars, grammar A or B, and all participants were tested on the same test items, consisting of an equal mixture of grammar A and B items. For participants trained in grammar A, the grammar A test items were the grammatical items and the grammar B test items were the nongrammatical items; and vice versa for participants trained in grammar B. Twenty-five volunteers from the University of Sussex were used, such that 12 participants were trained in grammar A and 13 in grammar B.

Materials

The two grammars and the exact training and test stimuli were taken from Dienes and Altmann (1997), following Dienes et al. (1995) and Reber (1969). The two grammars are shown in Fig. 2.

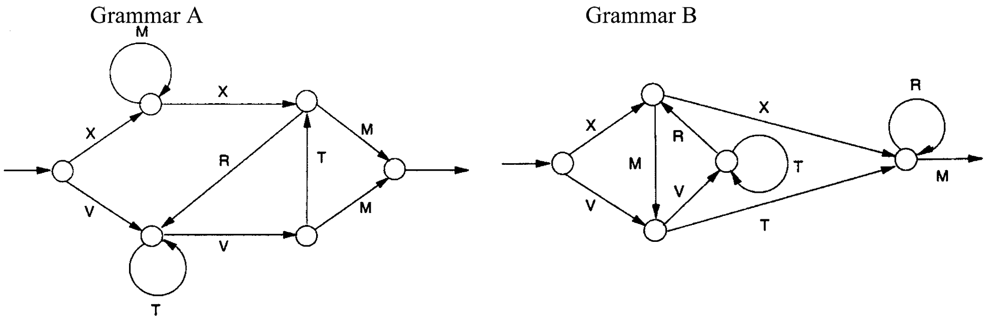

Fig. 2 The two grammars used in Experiments 1 and 2

Each grammar used the letters M, T, V, R, and X as terminal elements. Starting bigrams and end-letters were the same for both grammars. Each grammar could potentially generate a set of 52 grammatical strings of 5–9 letters in length. For each grammar, 18 of these were selected to form the training set (listed in Dienes & Altmann, 1997). A set of 29 strings (some having appeared in the training set) was selected from each grammar to form a test set comprising 58 items (listed in Dienes & Altmann, 1997).

Procedure

In the training phase, participants were shown one training item at a time on a card for 5 s and were asked to copy each item down as they saw it. Participants were then informed of the existence of a set of rules determining letter order in the strings and were asked to classify the test items. After each classification decision they reported the basis of the their judgment by ticking one of the following options: Guess, intuition, pre-existing knowledge, rules, or memory. Participants were provided with the same definitions as given in the Introduction. The 58 test items were repeated once. All participants received the same test items in the same order.

Results

As there were no main effects or interactions involving which grammar the person was trained in (grammar A versus B), this factor is not reported further.

Overall performance

Overall, 64% (SD = 13%) of the test items were classified correctly, which is significantly better than 50%, $t(24) = 5.60$, $p < .0005$. That is, the training phase did result in learning. The effect of time was significant, with participants classifying a greater percentage of test items correctly the first time (67%, SD = 11%) than the second time (61%, SD = 15%) through the test items, $t(24) = 3.80$, $p = .001$. The effect of time was not anticipated (contrast Reber, 1989; Dienes, Kurz, Bernhaupt, & Perner, 1997).

Proportion of different structural knowledge attributions

None of the participants used the pre-existing knowledge category, and so this category was dropped from subsequent analyses. Figure 3 shows the proportion of the four remaining attributions (regardless of whether the classification response was correct or incorrect) for each of the two times. A 4 × 2 (attribution [guess versus intuition versus rules versus memory] by time [first half of testing versus second half]) repeated measures ANOVA on proportion of responses indicated only a main effect of attribution, $F(2.4, 57.6) = 16.32$, $p < .0005$ (with Huyn-Feldt correction). It can be seen that for the materials and procedure used, attributions indicating unconscious structural knowledge were more common than attributions indicating conscious structural knowledge. There was no significant difference between the proportion of guess and intuition responses or between the proportion of rule and memory responses, $ps > .10$. Guess and intuition attributions were therefore added together to make the total proportion of responses based on unconscious structural knowledge (implicit responses); and rule and memory proportions were added together to make the total proportion of responses based on at least some conscious structural

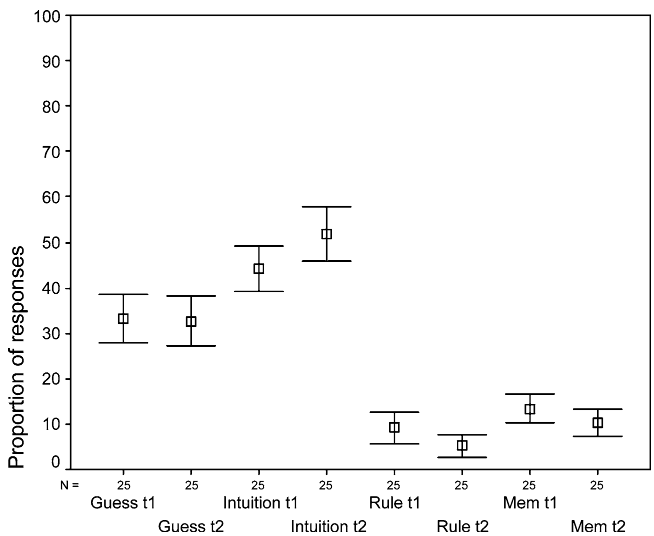

Fig. 3 Proportion of different attribution types for first half (*t1*) and second half (*t2*) of testing in Experiment 1. *Bars* indicate plus and minus one standard error

knowledge (explicit responses). There was a greater proportion of implicit rather than explicit responses (81 vs. 19%), $t(24) = 7.33$, $p < .0005$.

It can be seen from Fig. 3 that there was no tendency for guess attributions to decrease; that is, the data do not support the hypothesis that guess attributions might become converted to intuition attributions over time.

Classification accuracy for different attribution types

Figure 4 shows the classification accuracy for the four attribution types and two time periods. A 4×2 (attribution [guess versus intuition versus rules versus memory] by time [first half of testing versus second half]) repeated measures ANOVA on percentage of correct responses was not conducted because only five participants had complete data for all eight cells. Just comparing the two implicit attribution types, a 2×2 (attribution [guess versus intuition] by time) repeated measures ANOVA indicated no significant main effects nor an interaction ($n = 20$). Similarly, just comparing the two explicit attribution types, a 2×2 (attribution [rules versus memory] by time) repeated measures ANOVA indicated no significant main effects nor an interaction ($n = 6$). The guess and intuition categories were thus collapsed to make an implicit category and the rules and memory attributions were collapsed to make an explicit category. Comparing implicit and explicit attribution types, a 2×2 (attribution [implicit versus explicit] by time) repeated measures ANOVA indicated only a significant effect of attribution ($n = 15$), $F(1, 14) = 7.93$, $p = .014$, with participants being more correct when there was conscious (76%) rather than unconscious (65%) structural knowledge.

Figure 5 shows the 95% confidence intervals, collapsed over time. It can be seen that when participants

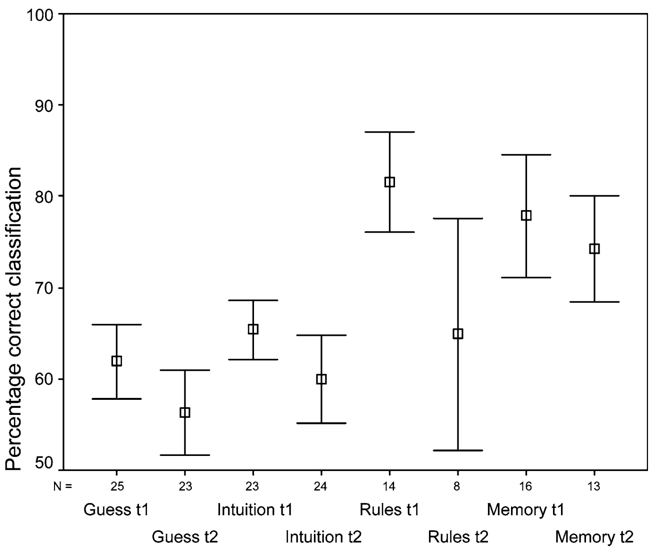

Fig. 4 Percentage of correct grammaticality judgments in the first half (*t1*) and second half (*t2*) of testing in Experiment 1. *Bars* indicate plus and minus one standard error

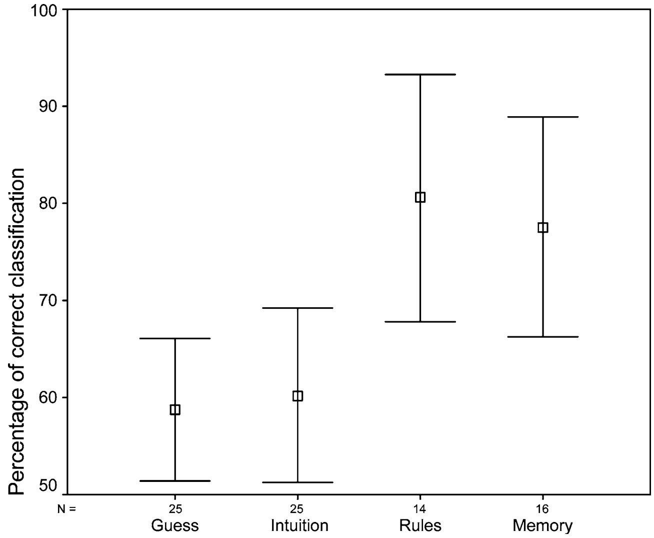

Fig. 5 Ninety-five percent confidence intervals for percentages of correct grammaticality judgments in Experiment 1

believed they were literally guessing, they were classifying above baseline (50%), indicating unconscious judgment knowledge by the guessing criterion. In addition, when participants indicated that the judgment was based on intuition, they were classifying significantly above baseline, indicating significant amounts of unconscious structural knowledge when judgment knowledge was conscious.

Consistency and awareness of structural knowledge

Reber (1989) suggested that the application of conscious knowledge would be revealed in the consistency of responding when people were tested twice on the same item (see also Dienes et al., 1997, for further analysis). Specifically, he suggested that conscious knowledge relative to implicit knowledge would lead to a high level of errors twice in a row (call this proportion EE), even for the same overall level of correct classifications. A baseline against which to compare EE is the average proportion of items classified correctly, then in error (CE), and in error, then correctly (EC); with random responding, EE is expected to be the same as the average of EC and CE.

The pattern of consistency was investigated only for items that were classified with the same structural knowledge attribution on both classifications. Because only six participants classified any item twice with a rule attribution, the rule and memory attributions were combined to form an explicit category, and guess and intuition attributions were combined to make an implicit category. The pattern of consistency is shown in Fig. 6. For the ten participants who had data for both implicit and explicit patterns, the difference between EE and the average of EC and CE was found to be greater for explicit rather than implicit knowledge, $F(1, 9) = 11.05$,

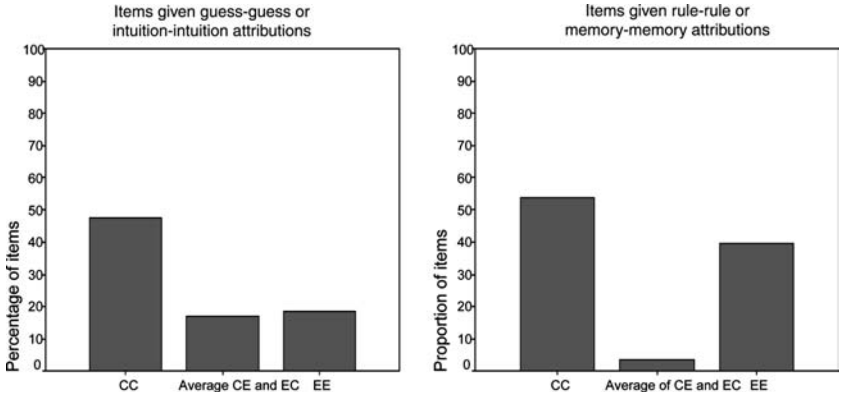

Fig. 6 Pattern of consistency in Experiment 1

$p = .009$, in striking accordance with Reber's claim. In detail, EE was greater for explicit rather than implicit knowledge, $F(1, 9) = 7.30$, $p = .024$, and the average of EC and CE was lower for explicit rather than implicit knowledge, $F(1, 10) = 19.10$, $p = .001$.

Discussion

Experiment 1 showed that participants made use of the guess, intuition, rules, and memory categories. Furthermore, for each of these categories, participants classified above baseline, prima facie indicating significant amounts of both conscious and unconscious judgment knowledge and conscious and unconscious structural knowledge.

Over the course of roughly 100 classification decisions, time had little effect on the proportions of these different attributions, thus not supporting the suggestion that the acquisition of unconscious structural knowledge might be associated with judgment knowledge becoming increasingly conscious (Redington et al., 1996; Mathews, 1997). However, the time periods in this experiment scarcely match the periods involved in the implicit learning in everyday life of languages, music, or motor skills, and it may be that more realistic periods are needed in order to see the effect of time emerge (Mathews, 1997). This will be an interesting issue for future research.

In terms of both proportions used and associated correct grammaticality judgments, the intuition and guess categories behaved similarly, and also the rules and memory categories behaved similarly. Indeed, it may be hard for a person to distinguish the rule and memory categories on occasion. If I remember that a string started with XX, clearly XX can start a string. That is both a memory and a rule. But the distinction between memory and rule is not important for determining the conscious status of structural knowledge: Either way of construing the knowledge is a case of conscious structural knowledge.

Experiment 1 also provided evidence that these subjective attributions were providing a grip on something psychologically real in that they had behavioral consequences. When people made conscious rather than unconscious structural knowledge attributions they had a strikingly higher level of consistent errors, in accordance with Reber's (1989) claim about the nature of conscious and unconscious structural knowledge (see also Dienes et al., 1997; Dienes & Perner, 2004). Our system that acquires unconscious structural knowledge may be specifically adapted for learning certain structures, including the *n*-gram structures provided by simple finite state grammars; thus, when encountering such grammars, the system rarely systematically misclassifies. On the other hand, our system for acquiring conscious structural knowledge can acquire knowledge of any rule we can conceive of; this very flexibility may also make it liable to forming firmly held incorrect as well as correct rules, and hence liable to systematic misclassification.

Experiment 2 had two main aims. First, the relationship between the attributions assessing structural knowledge and the normal measures of the conscious status of judgment knowledge using confidence ratings was assessed by asking participants to give both a confidence rating and an attribution of structural knowledge in each trial. Second, manipulations were introduced to provide converging evidence on the validity of the measures of the conscious or unconscious status of structural knowledge. Putative measures of the conscious or unconscious status of knowledge only prove their worth by participating in theory-driven research, as illustrated in Experiment 1 by the relationship between knowledge attribution and consistency. Only by behaving sensibly in a theoretical context do proposed measures pick themselves up by the bootstraps, validating both themselves as measures (with whatever finite accuracy) of what they say they measure and also validating the theories involved (Dienes, 2004). Thus, two further manipulations were introduced in Experiment 2. Plausibly, participants will acquire more conscious structural knowledge when asked to search for rules in the training phase than when asked to memorize strings (e.g., cf. Reber, Kassin, Lewis, & Cantor, 1980; Mathews et al., 1989). Thus, half the participants were asked to search for rules in the training phase and half were asked to memorize strings. Plausibly, the acquisition and application of conscious structural knowledge also requires central executive or working memory resources. Loading working memory should disrupt the acquisition of specifically conscious structural knowledge and leave the acquisition of unconscious structural knowledge relatively intact (e.g., cf. Dienes et al., 1995; Roberts & MacLeod, 1995; Frensch, Wenke, & Ruenger, 1999; Waldron & Ashby, 2001; Ziori & Dienes, in press; contrast Shanks, 2003; see Jiménez, 2003, for critical discussion). Thus, half the participants generated random numbers during the training phase, and half did not. Baddeley (1986) regarded random number generation as a way of loading the central executive, and it was used by Dienes, Broadbent, and Berry (1991) and Dienes et al. (1995) as a secondary task with artificial grammar learning.

Experiment 2

Methods

Design

The two main between-participants independent variables were: Training (search for rules versus memorize) and attention when training (full versus divided). Experiment 2 also used the same two-grammar design as Experiment 1.

Participants

Eighty volunteers were recruited from the University of Sussex library (40 men and 40 women). Ages ranged from 19 to 35 years with a mean of 23.30 ($SD = 3.25$). There were 20 participants in each of the four training by attention cells.

Materials

The same grammars were used as in Experiment 1, but there were different specific items. Forty-five unique grammatical strings between five and nine characters in length were selected for each grammar. Fifteen of the 45 strings from each grammar, repeated three times in different random orders, made up each of the two training sets. The remaining 30 strings from each grammar were randomly combined to form the test set. The selection of strings was made such that the same numbers of strings of each length were contained in both training sets and that the proportion of strings of each length was the same for training and test sets. The strings used in the training and test sets are included in Appendix 1. A fixed order of test items was used; half the participants received the test items in that order, and half in the reverse order.

Microsoft PowerPoint was used to present both training and test strings. Each string was presented on a separate slide displayed centrally in black text (Times New Roman font size 40) on a white background. The PowerPoint presentation for the training phase was configured to display each string for 5 s followed by a blank screen for a further 5 s. The PowerPoint presentation for the testing phase was configured to allow participants to advance through the strings at their own pace. An electronic metronome at a setting of 45 beats per minute was used to prompt the generation of random numbers during the divided attention condition.

Procedure

Each participant was given a questionnaire measuring intuitive and analytical styles (the Rational-Experiential Inventory of Pacini & Epstein, 1999) to complete immediately prior to the main experiment; this questionnaire will not be discussed further.

For the memorize training condition participants were required to memorize each string while it was displayed and to write down what they could remember while the screen was blank. For the rules-search learning condition participants were required to attempt to discern the rules governing the order of letters in the strings while each string was displayed and to again write down what they could remember while the screen was blank. Only instructions for the rules-search condition made participants aware that the order of letters in the strings conformed to a set of rules.

Participants in the divided attention condition had additional instructions to announce random numbers between 1 and 10 in time with an electronic metronome. The metronome was only used in this condition and was played throughout the presentation. The experimenter gave appropriate prompts to participants if they paused or began generating obviously nonrandom sequences.

For the test phase, participants were informed that the order of letters in the strings seen during the training phase had obeyed a complex set of rules and that exactly half of the strings they were about to see obeyed the same rules. For each string participants were required to indicate whether or not it obeyed the same rules as those in the training phase, their confidence in their judgement (between 50 and 100%), and the source of their knowledge according to the following categories: Guess, intuition, pre-experimental knowledge, rules, or memory. Participants were not permitted to refer back to the strings they had written down during the training phase.

Results

Overall learning

The overall percentage of correct grammaticality classifications was 66% ($SD = 11\%$), which was significantly greater than a baseline of 50%, $t(79) = 12.65$, $p < .0005$. That is, the training phase did produce learning. Table 1 displays the mean classification

Table 1 Percentage of correct classifications in Experiment 2

	Full attention	Divided attention
Memorize	66 (2.5)	65 (2.5)
Rule search	69 (2.5)	63 (2.5)

Standard errors appear in parentheses

performance for the different conditions. A 2×2 (training [rule search versus memorization] × attention [full versus divided]) between-participants ANOVA on percentage of correct classifications revealed no significant effects. Without separating conscious and unconscious knowledge, the manipulations appear to have had no effect.

Guessing and zero correlation criteria

When participants gave a confidence rating of 50%, their classification performance was 57% (SD = 23%), significantly above 50%, $t(68) = 2.58$, $p = .012$. That is, the guessing criterion for unconscious judgment knowledge was satisfied.

One way of measuring the relationship between confidence and accuracy is the Chan-difference score (Dienes et al., 1995), namely the difference in average confidence between when the participant makes a correct and incorrect classification. The average confidence for correct answers was 69% and the average confidence for incorrect answers was 66%; the difference was significant, $t(79) = 5.29$, $p < .0005$. That is, there was conscious judgment knowledge according to the zero correlation criterion; participants to some extent knew the degree of knowledge that they had when making judgments.

Table 2 displays the mean guessing criterion and Chan-difference scores for the different conditions. A 2×2 (training [rule search versus memorization] × attention [full versus divided]) between-participants ANOVA on each of the guessing criteria and Chan-difference scores revealed no significant effects. The training and secondary task manipulations would appear to have had no effect, just looking at measures of the conscious or unconscious status of judgment knowledge. While no effects on the guessing criterion might be expected, these manipulations would be expected to affect the relative amount of conscious knowledge, as measured by the Chan difference score (cf. Dienes et al., 1995).

Table 2 Measure of the conscious status of judgment knowledge in Experiment 2

		Full attention	Divided attention
Memorize	Guessing criterion	58 (5.0)	53 (4.8)
	Chan difference	2.9 (1.2)	3.5 (1.2)
Rule search	Guessing criterion	56 (5.0)	62 (5.3)
	Chan difference	4.9 (1.2)	1.6 (1.2)

The guessing criterion is the percentage of correct grammaticality classifications when the participant gave a confidence rating of 50%. The Chan-difference score is the difference in average confidence between when correct and incorrect classifications were given. Standard errors appear in parentheses

Proportion of different structural knowledge attributions

Table 3 shows the overall proportions of the different attributions. Only three people ever used the pre-experimental knowledge attribution and this will not be analyzed further.

The secondary task manipulation was expected to decrease the proportion of explicit structural knowledge attributions (rules and memory) relative to the implicit types (guess and intuition), and rule searching rather than memorizing in training was expected to increase the proportion of explicit types relative to implicit types. A $4 \times 2 \times 2$ (attribution [guess versus intuition versus rules versus memory] by training [rule search versus memorization] × attention [full versus divided]) mixed model ANOVA indicated a significant main effect of attribution, $F(2.9, 216.8) = 7.52$, $p < .0005$, which was qualified by a significant attribution by attention interaction, $F(2.9, 216.8) = 3.88$, $p = .011$. The interaction indicated that the use of a secondary task reduced the proportion of rules attributions, $F(1, 76) = 9.75$, $p = .003$, and marginally increased the proportion of intuition attributions, $F(1, 76) = 3.66$, $p = .059$. Combining rules and memory attributions together to make a total proportion of explicit attributions, the secondary task decreased the overall proportion of explicit attributions (from 49 to 40%), $F(1, 76) = 3.57$, $p = .049$ (one tailed), and correspondingly increased the proportion of implicit attributions. Furthermore, the effect of the secondary task did not differ significantly for the proportion of guess versus intuition attributions, $p > .10$; however, the effect of the secondary task did differ for the proportion of rules versus memory attributions, $F(1, 76) = 7.22$, $p = .009$, significantly affecting rules but not memory.

Although the 3 df source by training interaction was not significant, a more focused planned comparison indicated that the memorize rather than rules search training condition increased the proportion of implicit attributions (guess plus intuition; from 50 to 60%), $F(1, 76) = 3.93$, $p = .026$ (one tailed), and correspondingly decreased the proportion of explicit

Table 3 Proportion of different attributions in Experiment 2

Training	Attention	Guess	Intuition	Rules	Memory
Memorize	Full	22 (3.9)	34 (3.9)	22 (4.2)	20 (3.5)
	Divided	22 (3.4)	41 (3.9)	11 (3.1)	26 (3.3)
Rule search	Full	19 (4.3)	26 (3.6)	31 (5.1)	24 (3.9)
	Divided	17 (3.6)	37 (6.6)	15 (4.2)	28 (5.4)

Standard errors appear in parentheses

attributions. Note that instructions to memorize rather than search for rules actually (nonsignificantly) decreased the proportion of memory attributions. The effect of training was not significantly different for guess versus intuition, nor for rules versus memory, $ps > .10$.

Attributions and classification accuracy

Only 42 of the 80 participants used all four attributions. Comparing the two implicit attributions, a $2 \times 2 \times 2$ (attribution [guess versus intuition] by attention [full versus divided] by training [memorize versus rule search]) mixed model ANOVA on percentage of correct classifications indicated no effects involving attribution ($n = 67$), $ps > .10$. A similar ANOVA comparing the explicit attributions (rules versus memory) also found no effects involving attribution ($n = 50$), $ps > .10$. Thus, the two implicit categories were collapsed and the two explicit categories were collapsed, allowing an ANOVA with $n = 77$ participants. A $2 \times 2 \times 2$ (attribution [implicit versus explicit] by attention [full versus divided] by training [memorize versus rule search]) mixed model ANOVA on percentage of correct classifications indicated a significant attribution by training interaction, $F(1, 73) = 4.13$, $p = .046$, itself qualified by a significant attribution by training by attention interaction, $F(1, 73) = 6.12$, $p = .016$. The three-way interaction is illustrated in Fig. 7. The three-way interaction was analyzed by considering the partial training by attention interaction separately for implicit and explicit attributions. The partial interaction was nonsignificant for implicit attributions, $p > .10$, but was significant for explicit attributions, $F(1, 76) = 4.02$, $p = .049$. This two-way interaction was analyzed by simple effects of attention for each training group; there was no effect of the secondary task for explicit attributions in the memorize group, but there was in the rule search group, $F(1, 38) = 6.65$, $p = .014$.

Figure 8 shows the 95% confidence intervals for the proportion of correct classifications for each attribution, collapsed over groups. Overall, participants classified significantly above baseline for all attributions. The above chance performance when participants believed they were guessing satisfies the guessing criterion for the existence of unconscious judgment knowledge, the above chance performance for guessing and intuition indicate the existence of unconscious structural knowledge, and the above chance performance for rules and memory indicate the existence of conscious structural and judgment knowledge.

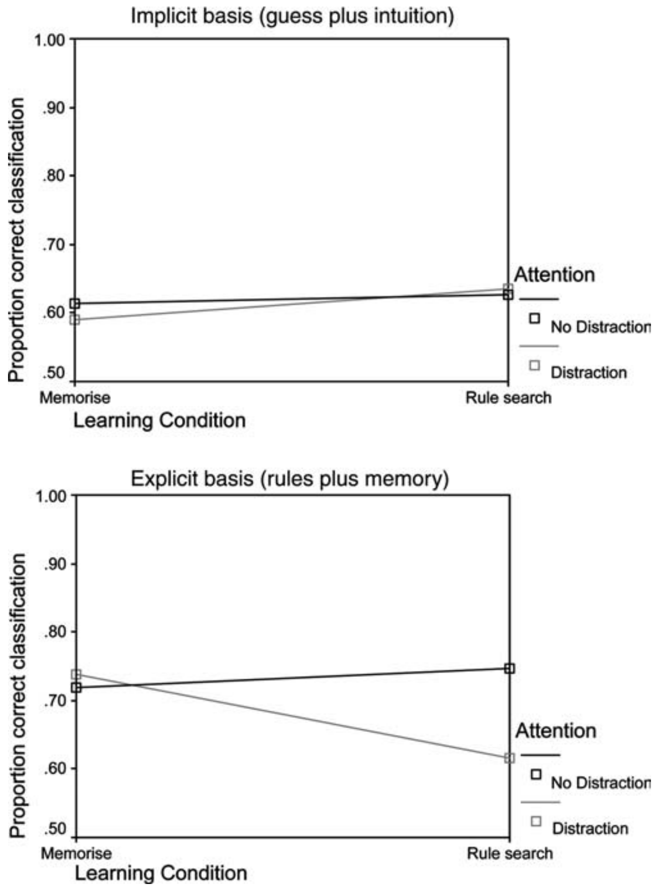

Fig. 7 Proportion of correct classifications in Experiment 2

Relation between attributions and confidence ratings

Table 4 shows the confidence ratings given to each attribution. In order to keep n high, pair-wise comparisons were conducted. Participants gave higher confidence ratings for intuition than guess attributions, $t(66) = 13.08$, $p < .0005$, which is as expected as intuition was defined as being different from guess by virtue of the participants having confidence in their answer. Participants also gave higher confidence to memory than

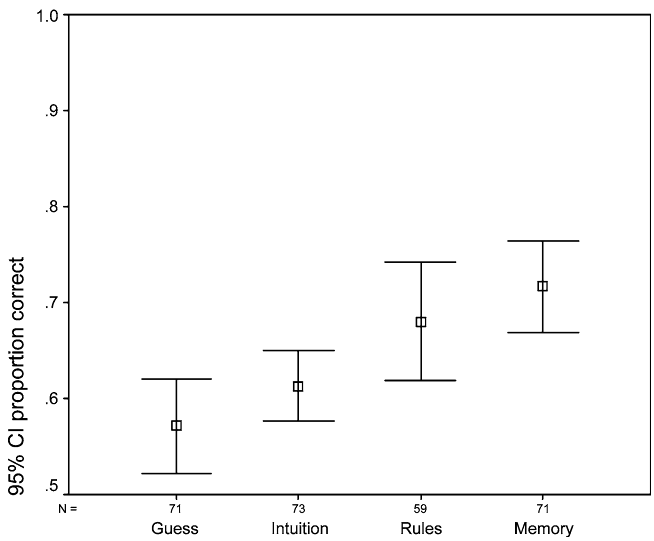

Fig. 8 Ninety-five percent confidence intervals for the proportion of correct classifications for different attributions in Experiment 2

Table 4 Confidence for each attribution in Experiment 2

	Guess	Intuition	Rules	Memory
Confidence	56 (.8)	66 (.9)	74 (1.2)	76 (1.2)

Standard errors appear in parentheses

rule attributions, $t(49) = 2.08$, $p = .043$, and higher confidence to attributions indicating conscious structural knowledge (rules and memory) than unconscious structural knowledge (guess and intuition) $t(76) = 15.64$, $p < .0005$.

It is striking that participants gave confidence ratings above 50% to the guess category, as "guess" was defined as a judgment having absolutely no basis, they could just as well have flipped a coin. It could be "guess" was taken as having a looser everyday meaning; or that when participants were given a more finely grained scale (50–100 vs. guess/nonguess) they made more finely grained distinctions; or that the exact content of higher order thoughts fluctuate even over short time scales. In any case, for the guess attribution, there was no relationship between confidence and accuracy (Chan-difference score = .52, SD = 4.65, not significantly different from zero, $t(64) = .90$, $p = .37$), indicating that knowledge in the guess category was unconscious by the zero correlation criterion. Furthermore, when participants said they were guessing and their confidence was 50%, the average classification performance was 57%, significantly different from baseline, $t(63) = 2.15$. $p = .036$.

When participants give a confidence of 50% indicating that they were literally guessing, that may mean the answer "grammatical" or "nongrammatical" just popped into their head as if out of nowhere. But it may also mean that the answer was based on, e.g., a rule, and it was the rule that just popped into the head and appeared to be based on nothing at all. That could still be a case of having knowledge without knowing that they did, i.e., unconscious knowledge, if in fact the rule was induced by a reliable learning process. Table 5 shows how the 50% confidence responses were distributed over the attributions, averaged over participants. The majority of 50% confidence responses were in the guess category. Their appearance in the intuition category indicates a contradiction; intuition was defined as meaning having some confidence. Only very small numbers of 50% confidence responses were associated with either rules or memory attributions.

Table 5 The distribution of 50% confidence responses over attributions in Experiment 2

Percentage of 50% confidence responses that were based on			
Guesses	Intuition	Rules	Memory
78 (3.9)	11 (2.6)	4 (1.4)	7 (1.9)

Standard errors (over participants) appear in parentheses

Discussion

Experiment 2 combined subjective assessments of judgment knowledge, based on a confidence rating, and subjective assessments of structural knowledge, based on reporting the type of knowledge the judgment appeared to be based on. Experiment 2 found that the subjective reports of the type of structural knowledge used picked out knowledge states differentially sensitive to the type of learning condition; this sensitivity was not achieved just looking at overall classification or just looking at the measures of the conscious status of judgment knowledge. That is, the subjective reports of structural knowledge proved their worth as measuring something objectively real by discriminating knowledge states that behaved in qualitatively different ways. Importantly, the qualitative differences were not arbitrary but fitted into a theoretical context.

Urging participants to search for rules rather than memorize and requiring participants to generate random numbers in the training phase rather than give full attention to learning had no effect on overall classification levels. The lack of an effect of rule search instructions on overall performance replicates Reber et al. (1980), Dulany, Carlson, and Dewey (1984), Mathews et al. (1989), Perruchet and Pacteau (1990), and Dienes et al. (1991). However, Dienes et al. did find an effect of random number generation on overall classification. It may be the case that participants took the secondary task less seriously in Experiment 2 than in the Dienes et al. experiment. Neither manipulation affected the relationship between confidence and accuracy, as measured by the Chan-difference score. Chan (1992) found that rule search rather than memorize instructions increased the relationship between confidence and accuracy. Experiment 2 did not use a strong manipulation for encouraging rule searching, however; participants still had to memorize and in fact did not have to demonstrate rule searching in any overt behavior. Thus, it is not surprising that Chan's finding was not replicated. The important point is that despite the weakness of each manipulation, the manipulations did affect knowledge differentially when the structural knowledge attributions were taken into account. The relative weakness of the manipulations is thus the strength of the study, because it shows the sensitivity provided by the structural knowledge attributions.

The secondary task decreased the proportion of attributions to conscious structural knowledge and rule search increased the proportion of attributions to conscious structural knowledge. Importantly, when judgments were attributed to unconscious structural knowledge, the manipulations had no effect on the percentage of correct classifications; this percentage stayed around 60%. However, when judgments were attributed to conscious structural knowledge, rule search and the secondary task affected performance. Specifically, while performance associated with conscious structural knowledge was generally above 70%, when participants both searched for rules and performed a secondary task, performance fell to 60%.

In the memorize and full attention cell, the proportion of responses attributed to unconscious structural knowledge was 56%, but the corresponding figure in Experiment 1 was 81%. This is a large difference and significant, $t(43) = 4.29$, $p < .0005$. (The overall percentages of correct classifications were virtually identical; 66% compared with 64%). The materials were slightly different across the two experiments. Another factor is that in the memorize condition in Experiment 2, participants looked at a string and then copied it down once it had disappeared whereas in Experiment 1 participants copied the string down as it was presented. In Experiment 1 the task was not presented even as a memorization task. It may be the case that such simple exposure encourages maximally implicit learning compared with memorization (cf. Reber & Allen, 1978); this could be explored in future, better controlled studies.

General discussion

Two experiments showed that the subjective assessment of the knowledge used to make a judgment appear to pick out different knowledge types, namely structural knowledge that is conscious or unconscious. Experiment 1 showed that conscious rather than unconscious structural knowledge was associated with greater consistency in making errors (even though the overall number of correct responses was higher), consistent with the theoretical claims of Reber (1989). Experiment 2 showed that rule search rather than memorize instructions in training and divided rather than full attention in training had no influence on the classification accuracy associated with unconscious structural knowledge, but did affect classification accuracy associated with conscious structural knowledge. These theoretically coherent dissociations help to validate the distinction between conscious and unconscious structural knowledge as measured by the simple attributional categories used.

Broadly, the intuition and guess attributions behaved similarly (i.e., those attributions corresponding to unconscious structural knowledge) and different from the memory and rules attributions (corresponding to conscious structural knowledge), which themselves behaved similarly. Thus, there exists a real division between conscious and unconscious structural knowledge. However, future research may tease out boundaries more complicated in nature. In the memory literature, Gardiner and colleagues have been exploring the use of subjective reports of memorial experience to distinguish different types of memory (e.g., Gardiner, Ramponi, & Richardson-Klavehn, 1998). Recognition judgments associated with remembering (recollecting) are affected by secondary tasks, unlike recognition judgments associated with knowing (feelings of familiarity; Gardiner & Parkin, 1990; Parkin, Reid, & Russo, 1990; Jacoby & Hay, 1998). When our participants made memory attributions they were not asked to distinguish recollective memory from familiarity; both are cases of being conscious of remembering and hence examples of conscious memory and conscious structural knowledge. However, it would be a useful sub-division in the list of attributions. In the artificial grammar learning paradigm, secondary tasks may leave unimpaired performance associated with guesses and intuition (unconscious structural knowledge) and also with familiarity (conscious structural knowledge) while impairing performance associated with attributions of rules and recollection of items (conscious structural knowledge). Kinder, Shanks, Cock, and Tunney (2003) showed that participants performing the test phase of an artificial grammar learning task are partially sensitive to fluency, i.e., the speed with which an item is perceived. Such speed may reflect how tuned neural pathways are to relevant structure, i.e., the speed is evidence for the existence of relevant structural knowledge. In some contexts, fluency is taken to be an indication that an item or part of an item is old; in that case, the participant feels familiarity (Kelly & Jacoby, 2000). Thus, fluency can provide both conscious judgment knowledge (participants know that they have relevant structural knowledge), and in an appropriate context, a feeling of what that structural knowledge is (e.g., memory). If structural knowledge generally leads to enhanced processing speed (contrast Whittlesea & LeBoe, 2000), this speed does not generally lead to feelings of familiarity: Our results show that relevant structural knowledge is sometimes used either without participants being aware of it at all (guess attribution) or having no idea what it is (intuition attribution). Furthermore, in some cases it is difficult for participants to become aware of the existence of structural knowledge even when they try. Using the same grammars as in this paper, Tymann and Dienes (2004) told participants in a test phase that they were being under-confident. These warnings reduced the number of guess responses used (on a 50–100 confidence scale), but participants could not choose which guess responses to give a higher confidence rating to: The percentage of correct classifications when guessing remained unaltered whether under-confidence warnings were given or not. Nonetheless, it may be the same sort of structural knowledge that typically leads to the three different phenomenologies of guess, intuition, and familiarity (perhaps knowledge embedded in a connectionist network, e.g., Boucher & Dienes, 2003; Destrebecqz & Cleeremans, 2003), and rather different structural knowledge, perhaps involving working memory and executive function, that typically leads to the phenomenologies of recollection and rule application (cf. Waldron & Ashby, 2001). Unlike fluency, the phenomenologies of recollection and rule application do not typically involve awareness of a single varying dimension but rather complex conscious contents (cf. Gardiner et al., 1998; Rotello, Macmillan, & Reeder, 2004).

This paper has introduced a means of exploring the conscious or unconscious status of structural knowledge by using subjective reports. Subjective measures based on confidence ratings, like the guessing and zero correlation criteria, assess the conscious status of judgment knowledge. Other than free report, there have not been any general procedures for assessing the conscious or unconscious status of structural knowledge. Jacoby's (1991) process dissociation methodology applied to implicit learning (Destrebecqz & Cleeremans, 2001, 2003; Wilkinson & Shanks, 2004), for example, is, like the guessing and zero correlation criteria, also at heart a way of testing for the conscious status of judgment knowledge. Destrebecqz and Cleeremans exposed participants to sequential regularities in a serial reaction time task, and then informed participants of the existence of such regularities and asked them to generate a sequence that did not have the same structure as the one they had just been exposed to (this is called an exclusion task). The logic is that if a person generates the structure at above baseline levels when they are trying to avoid doing so, the knowledge must be unconscious. For this logic to work, structural knowledge must be brought to bear in initially generating a possible answer. But even if the structural knowledge were unconscious, conscious judgment knowledge could then be used to exclude a possible answer, allowing below baseline performance in the exclusion task. For example, we can readily generate strings of words that are nongrammatical according to English because despite lacking conscious structural knowledge of English, a native speaker typically has conscious judgment knowledge. (In perception all these issues are simpler because in perception we are only interested in judgment knowledge.)

In sum, we recommend the use of the simple methodology in this paper for assessing structural knowledge as a useful addition to existing methodologies for assessing judgment knowledge.

Appendix 1

The training sets include 15 unique strings from the chosen grammar repeated three times in different random orders. The test set includes 30 unique strings from each grammar randomly combined (Table 6).

Table 6 The training and test strings in order of presentation

Grammar A: Training strings	Grammar B: Training strings	Grammar A and B: Testing strings	Grammar
1. XMXRTVTM	1. VVRXRRRM	1. XMXRVM	A
2. VVTRTTVTM	2. VVTTTRXRM	2. VTTTVM	A
3. VTTTTVM	3. VTRRRM	3. XMVRXRM	B
4. XXRTTTVM	4. XMVTRMTM	4. VVTRXRRRM	B
5. VTTTVTRVM	5. VVTTTRMTM	5. XMTRRM	B
6. XXRVTM	6. XXRRRM	6. VVRXRRM	B
7. XMMMMXM	7. VVTRXRM	7. XMMMXRVM	A
8. XMXRTTTVM	8. XMVTRMTRM	8. XXRTTVTM	A
9. XMMXRTVM	9. XMVRMTRM	9. VTRRM	B
10. XMMMXRVTM	10. XMVRMTRRM	10. XMVTTRXM	B
11. XXRTVTM	11. XMVTRXM	11. VTTVTM	A
12. VTVTRVTM	12. VVTRXRRM	12. XMVRMVRXM	B
13. XMMMXRTVM	13. XMVTTRMTM	13. VVTRVTM	A
14. VVTRVM	14. VVRXRM	14. XMMXRVM	A
15. XMMXM	15. XXRRM	15. XMXRTTVTM	A
16. VVTRTTVTM	16. VVTTTRXRM	16. VVTRTTVTM	A
17. XMXRTTTVM	17. XMVTRMTRM	17. XMVTRXRM	B
18. VVTRVM	18. VVRXRM	18. VTVTRTVM	A
19. XMMMXRTVM	19. XMVTTRMTM	19. XMMMXM	A
20. XXRVTM	20. XXRRRM	20. VTTTVTRVM	A
21. XMMMXRVTM	21. XMVRMTRRM	21. VVTTRMTM	B
22. XMMMMXM	22. VVTRXRM	22. XMVRXM	B
23. VTVTRVTM	23. VVTRXRRM	23. VVRMVTRXM	B
24. VTTTTVM	24. VTRRRRM	24. XXRTTVM	A
25. XXRTTTVM	25. XMVTRMTM	25. VVRMVRXM	B
26. XXRTVTM	26. XMVTRXM	26. XMVRXRRM	B
27. XMXRTVTM	27. VVRXRRRM	27. VTVTM	A
28. VTTTVTRVM	28. VVTTTRMTM	28. XMMXRTTVM	A
29. XMMXRTVM	29. XMVRMTRM	29. XMVRXRRRM	B
30. XMMXM	30. XXRRM	30. XXRVTRVM	A
31. VVTRVM	31. VVRXRM	31. XMTRRRM	B
32. XMMXRTVM	32. XMVRMTRM	32. VVTRMTM	B
33. XMMXM	33. XXRRM	33. XMXRVTRVM	A
34. XXRTVTM	34. XMVTRXM	34. XMXRTTVM	A

Table 6 (Contd.)

Grammar A: Training strings	Grammar B: Training strings	Grammar A and B: Testing strings	Grammar
35. XMMMXRTVM	35. XMVTTRMTM	35. XMTRM	B
36. XMXRTVTM	36. VVRXRRRM	36. VTTTVTM	A
37. XMMMXRVTM	37. XMVRMTRRM	37. VVTRMTRRM	B
38. XXRVTM	38. XXRRRM	38. VVTTRMTRM	B
39. VVTRTTVTM	39. VVTTTRXRM	39. XMVRMTM	B
40. XXRTTTVM	40. XMVTRMTM	40. VTTVTRTVM	A
41. VTTTVTRVM	41. VVTTTRMTM	41. VTVTRVM	A
42. VTVTRVTM	42. VVTRXRRM	42. XXRVM	A
43. VTTTTVM	43. VTRRRRM	43. XXRTVTRVM	A
44. XMMMMXM	44. VVTRXRM	44. VTRRRM	B
45. XMXRTTTVM	45. XMVTRMTRM	45. VVTTRXRM	B
		46. VVRMTRRM	B
		47. VTTVTRVM	A
		48. VVTTRXRRM	B
		49. VVRMTRM	B
		50. VVRMVRXRM	B
		51. VTVTRTVTM	A
		52. VTRRRRRM	B
		53. XMXRTVM	A
		54. XXRTTTVTM	A
		55. VVTRTVTM	A
		56. VVRMTM	B
		57. VTVTRTTVM	A
		58. VTTTTVTM	A
		59. VVTRMVRXM	B
		60. XMVTRXRRM	B

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