Measuring unconscious knowledge: Distinguishing structural knowledge and judgment knowledge

Zoltán Dienes & Ryan Scott

Department of Psychology

University of Sussex

Psychological Research, vol 69, pp 338-351.

RUNNING HEAD: MEASURING UNCONSCIOUS KNOWLEDGE

Correspondence to

Zoltán Dienes, Department of Psychology, University of Sussex, Brighton, BN1 9QH, UK.

E-mail: dienes@sussex.ac.uk

Tel: 00 44 1273 678550

Home page: http://www.lifesci.sussex.ac.uk/home/Zoltan_Dienes/

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 awaareness 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. Further, 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.

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 which 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 e.g. 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 one is 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 higher order thought theory that any method for 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 on 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) 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, and 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), people 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. People are informed of the existence of the rules only at the end of the training phase, and are then asked to classify new strings as obeying the rules or not. Depending on the grammar, people 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, people 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 also no relationship between confidence and accuracy (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, people 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, people acquire knowledge of the structure of the training items. Call this structural knowledge. Structural knowledge might 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, people 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.

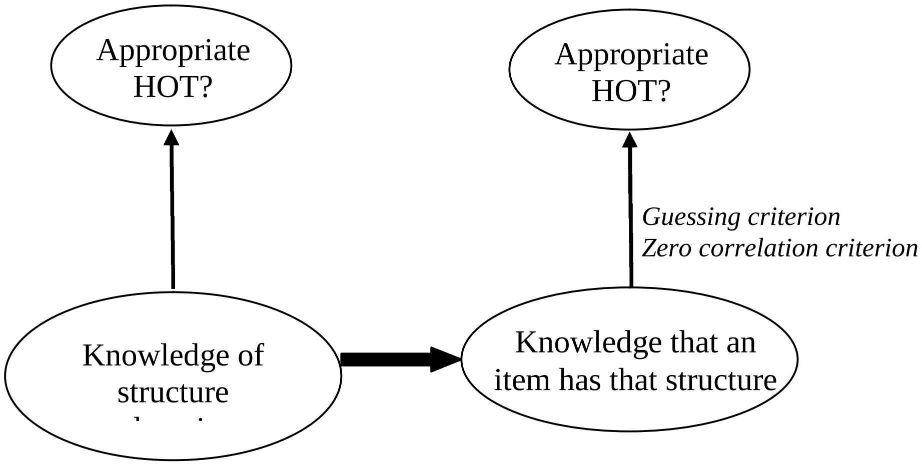


Figure 1: Structural knowledge and judgment knowledge. When structural knowledge is unconscious, judgement knowledge can be conscious or unconscious. In knowledge of natural language, for example, one can have knowledge of structure with no relevant higher order thought making that knowledge conscious; but one might know whether a sentence has that structure, and also have the higher order thought that one knows this. (See text.)

Both structural knowledge and judgment knowledge can be conscious or unconscious, depending on the existence of relevant higher order thoughts. If the person'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 person 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.

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 one 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 might 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 structural knowledge. Knowing the conscious or 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 might be characteristic of implicit learning only at 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. Further, 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 compliment the existing measures for judgment knowledge (cf Lau, 2002). In this paper, we will ask people 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 rather from knowledge they had anyway concerning letter patterns. The rules category indicated the participant felt they based their answer on some rule or rules acquired from the training phase and which they could state if asked. The memory category indicated that the person felt the judgment was based on memory for particular items or parts of items from the training phase.

The “guess” and “intuition” responses were taken to indicate those cases where structural knowledge was likely unconscious. The “rules” and “memory” responses were taken to indicate those cases where structural knowledge was likely 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. People were tested twice on the test phase in immediate succession. Redington et al (1996) speculated that with practice with a domain, for example an artificial grammar, people 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 might 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 as compared to 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

Method

Design and participants. The two-grammar design of Dienes and Altmann (1997) was used. Specifically, participants were trained on one of two grammars, grammar A or Grammar B, and all participants were tested on the same test items, consisting of an equal mixture of grammar A and grammar B items. For participants trained on grammar A, the grammar A test items were the grammatical items and the grammar B test items were the non-grammatical items; and vice versa for participants trained on grammar B. Twenty-five volunteers from the University of Sussex were used, such that 12 participants were trained on grammar A and 13 on 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 Figure 2.

Grammar A Grammar B

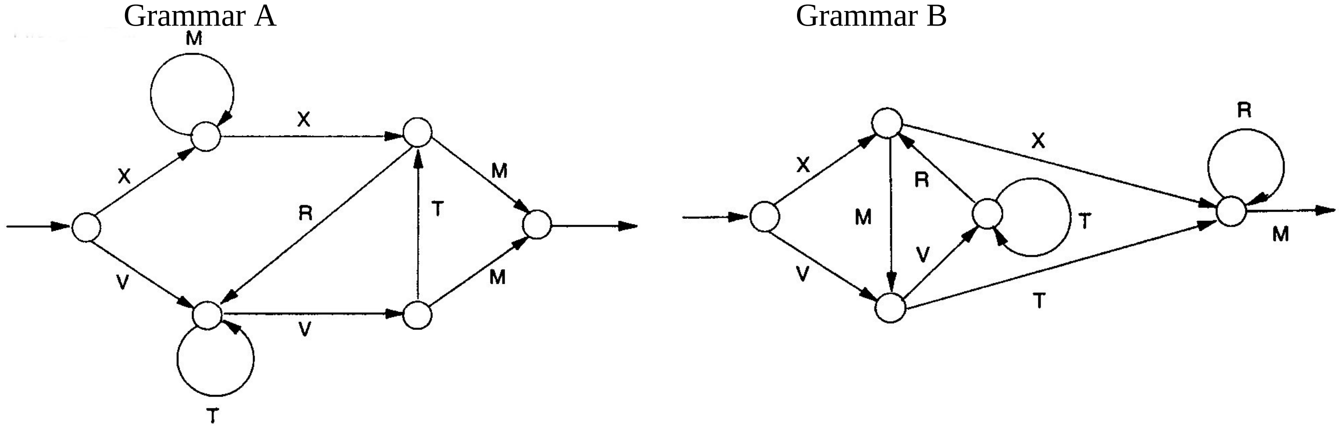


Figure 2 The two grammars used in experiments 1 and 2

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 to 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 comprised of 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 five seconds 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 judgement by ticking one of: 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 on (grammar A vs grammar 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. No participant 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 X 2 (attribution [guess vs intuition vs rules vs memory] by time [first half of testing vs 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; nor 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 knowledge (explicit responses). There was a greater proportion of implicit rather than explicit responses (81% vs 19%), $t(24) = 7.33$, $p < .0005$.

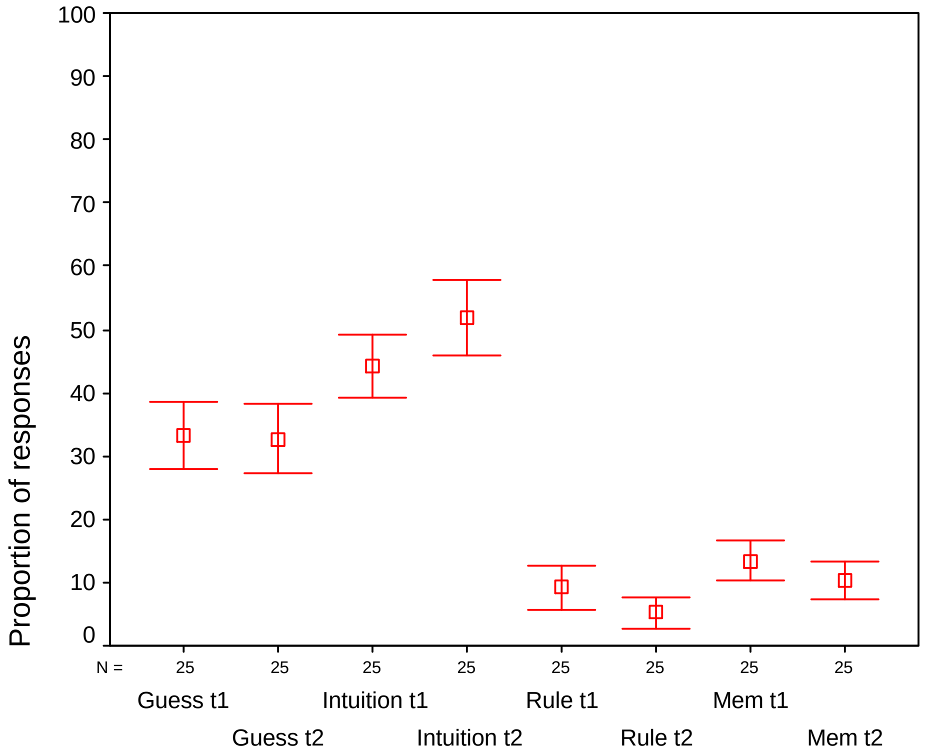


Figure 3. Proportion of different attribution types for first half (t1) and second half (t2) of testing in experiment 1. Bars indicate plus and minus one standard error.

It can be seen from figure 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 X 2 (attribution [guess vs intuition vs rules vs memory] by time [first half of testing vs second half]) repeated measures ANOVA on percentage 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 X 2 (attribution [guess vs 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 X 2 (attribution [rules vs 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 X 2 (attribution [implicit vs explicit] by time) repeated measures ANOVA indicated only a significant effect of attribution (N= 15), $F(1,14) = 7.93$, $\underline{p} = .014$, with people being more correct when there was conscious (76%) rather than unconscious (65%) structural knowledge.

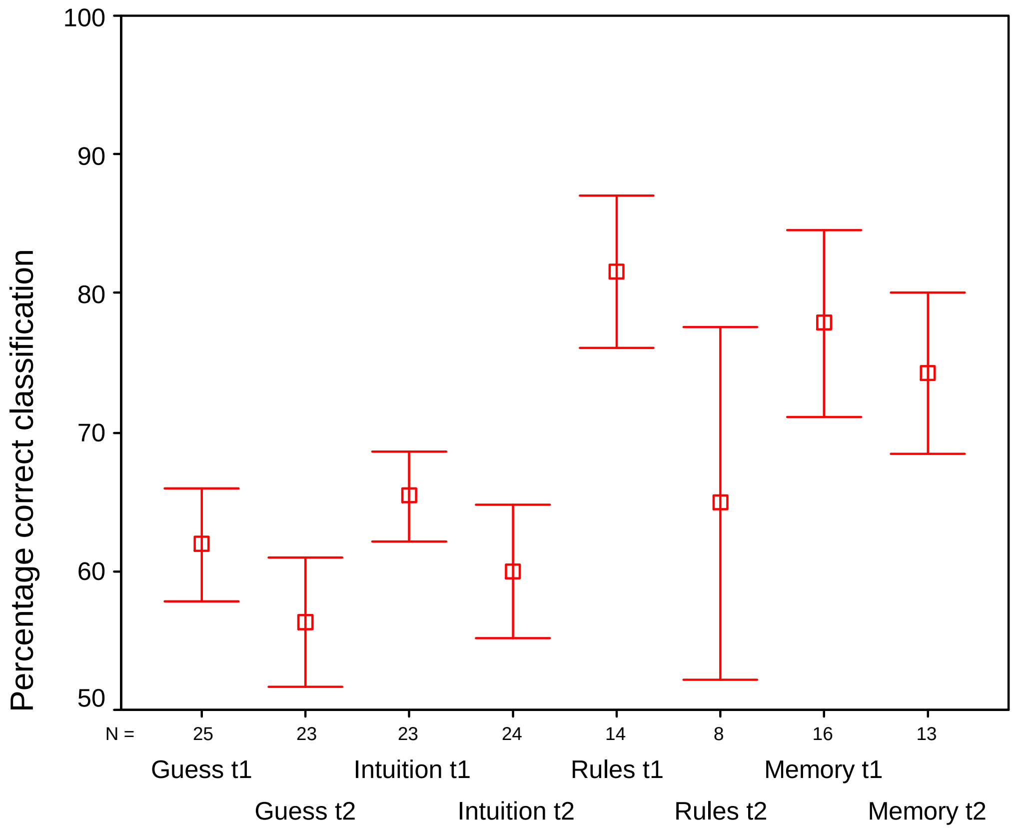


Figure 4. Percentage of correct grammaticality judgments in first half (t1) and second half (t2) of testing in experiment 1. Bars indicate plus and minus one standard error.

Figure 5 shows the 95% confidence intervals, collapsing over time. It can be seen that when subjects believed they were literally guessing they were classifying above baseline (50%) indicating unconscious judgment knowledge by the guessing criterion. In addition, when subjects indicated the judgement was based on intuition, they were classifying significantly above baseline, indicating significant amounts of unconscious structural knowledge when judgment knowledge was conscious.

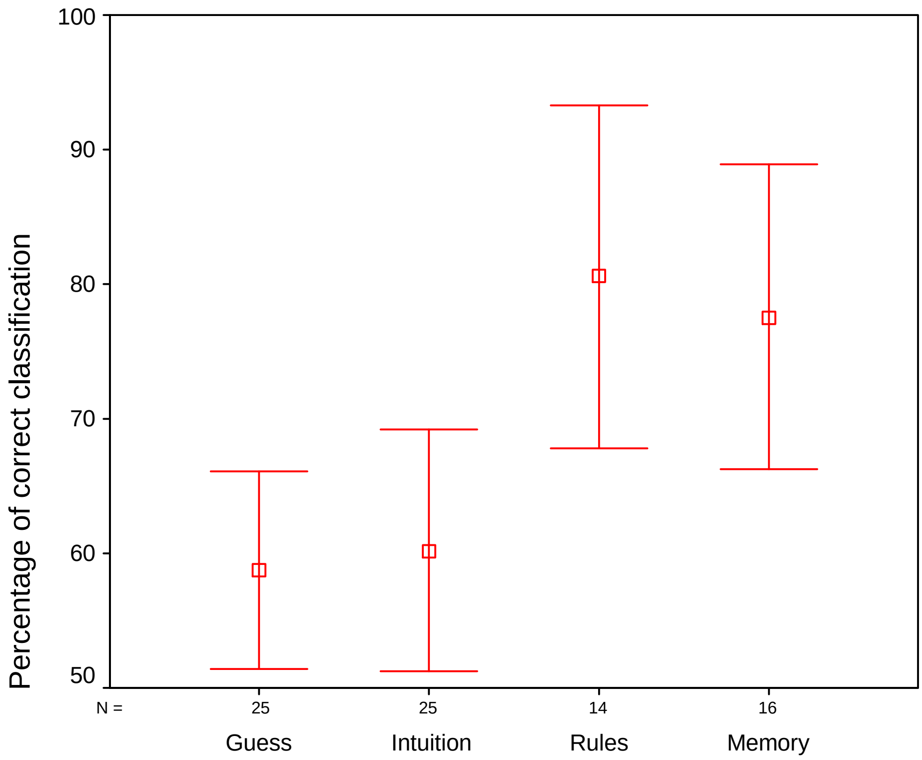


Figure 5. 95% confidence intervals for percentage of correct grammaticality judgments in experiment 1

<u>Consistency and awareness of structural knowledge</u>. Reber (e.g. 1989) suggested that the application of conscious knowledge would be revealed in the consistency of responding when people are 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 to compare EE against is the average proportion of items classified correct then in error (CE) and in error then correct (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 6 subjects 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 Figure 6. For the 10 subjects 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, 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.

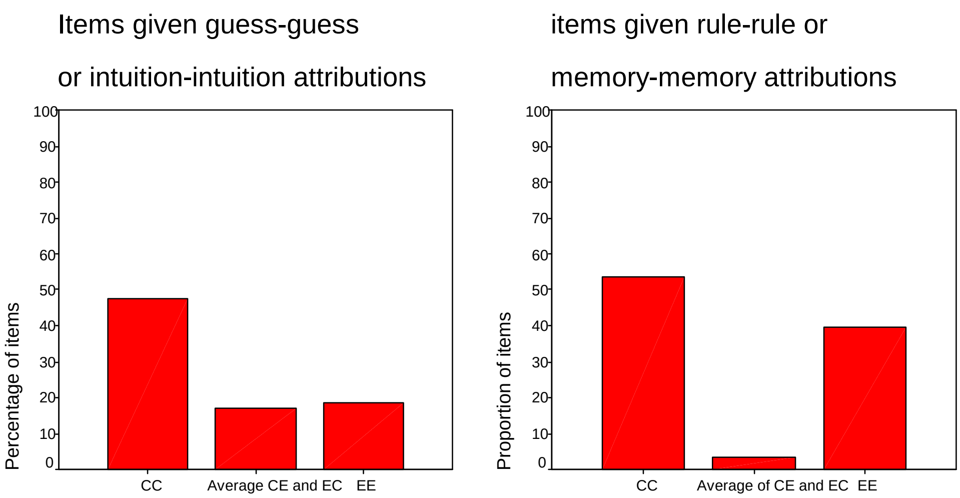


Figure 6 Pattern of consistency in experiment 1

Discussion

Experiment 1 showed that people made use of the guess, intuition, rules, and memory categories. Furthermore, for each of these categories, people 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 judgement 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 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 might 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 behavioural 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 on 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, people will acquire more conscious structural knowledge when asked to search for rules in the training phase than when asked to memorise strings (e.g. cf Reber, Kassin, Lewis and 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 and Ashby, 2001; Ziori & Dienes, in press; contrast Shanks, 2003; see Jimenez, 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 & Berry (1991) and Dienes et al (1995) as a secondary task with artificial grammar learning.

Experiment 2

Method

Design. The two main between-participant independent variables were: Training (search for rules vs memorize) and attention when training (full vs 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 male and 40 female). Ages ranged from 19 to 35 years with a mean of 23.30 (SD=3.25). There were twenty participants in each of the four training by attention cells.

Materials. The same grammars were used as experiment 1, but different specific items. Forty-five unique grammatical strings between 5 and 9 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 A. 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 seconds followed by a blank screen for a further 5 seconds. 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 memorise training condition participants were required to memorise 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 non-random 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 50-100%) and the source of their knowledge according to the 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 performance for the different conditions. A 2 X 2 (training [rule search vs memorization] x attention [full vs 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.

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

Table 1. Percentage of correct classifications in experiment 2. Standard errors in parentheses.

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 X 2 (training [rule search vs memorization] x attention [full vs divided]) between-participants ANOVA on each of the guessing criterion 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 one might expect no effects on the guessing criterion, one would expect these manipulations to affect the relative amount of conscious knowledge, as measured by the Chan difference score (cf Dienes et al, 1995).

		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)

Table 2. Measure of the conscious status of judgment knowledge in experiment 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.

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)

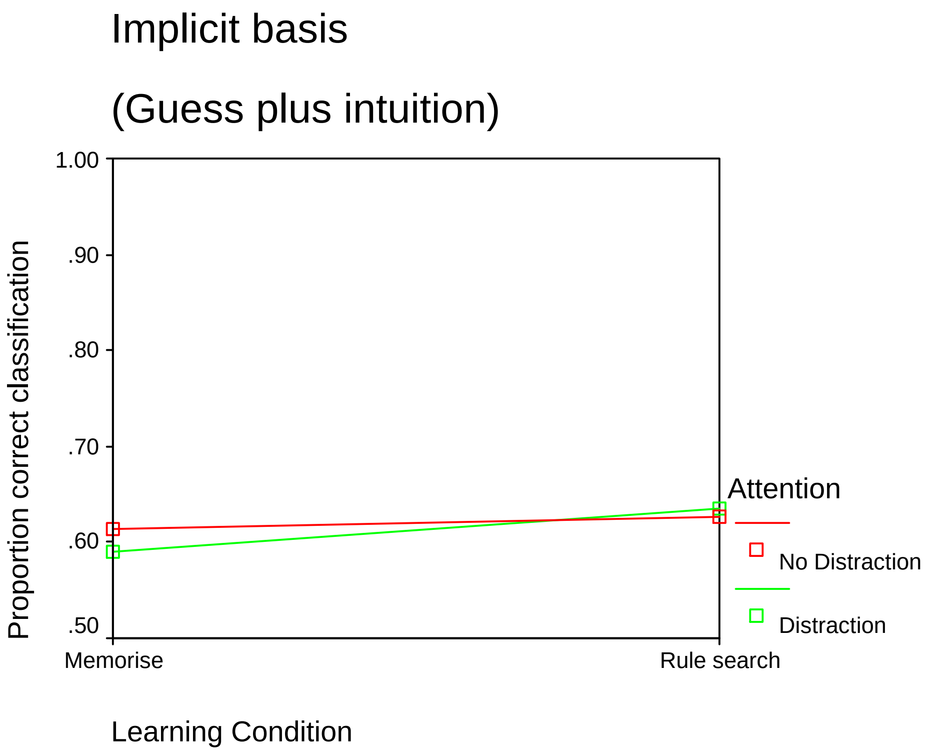
Table 3. Proportion of different attributions in experiment 2. Standard errors appear in parentheses.

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 X 2 X 2 (attribution [guess vs intuition vs rules vs memory] by training [rule search vs memorization] x attention [full vs 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%), $F(1,76) = 3.57$, $p = .049$ (1 tailed) (and correspondingly increased the proportion of implicit attributions). Further the effect of the secondary task did not differ significantly for the proportion of guess vs intuition attributions, $p > .10$; however, the effect of the secondary task did differ for the proportion of rules vs 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 focussed 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%), $F(1,76) = 3.93$, $p = .026$ (1 tailed) (and correspondingly decreased the proportion of explicit attributions). Note that instructions to memorize rather than search for rules actually (non-significantly) decreased the proportion of memory attributions. The effect of training was not significantly different for guess vs intuition, nor rules vs memory, ps > .10.

Attributions and classification accuracy. Only 42 of the 80 participants used all four attributions. Comparing the two implicit attributions, a 2 X 2 X 2 (attribution [guess vs intuition] by attention [full vs divided] by training [memorize vs 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 vs 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 X 2 X 2 (attribution [implicit vs explicit] by attention [full vs divided] by training [memorize vs 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 figure 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 non-significant for implicit attributions, $p > .10$, but was significant for explicit attributions, $F(1, 76) = 4.02$, $p = .049$. This two way interaction was analysed 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.



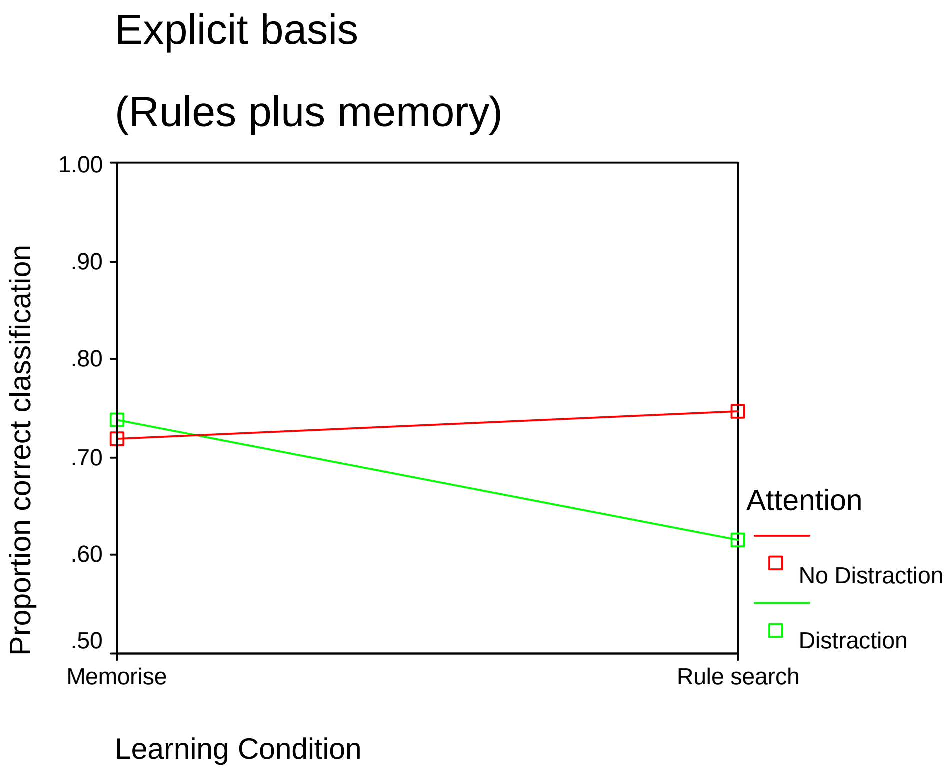


Figure 7. Proportion of correct classifications in experiment 2

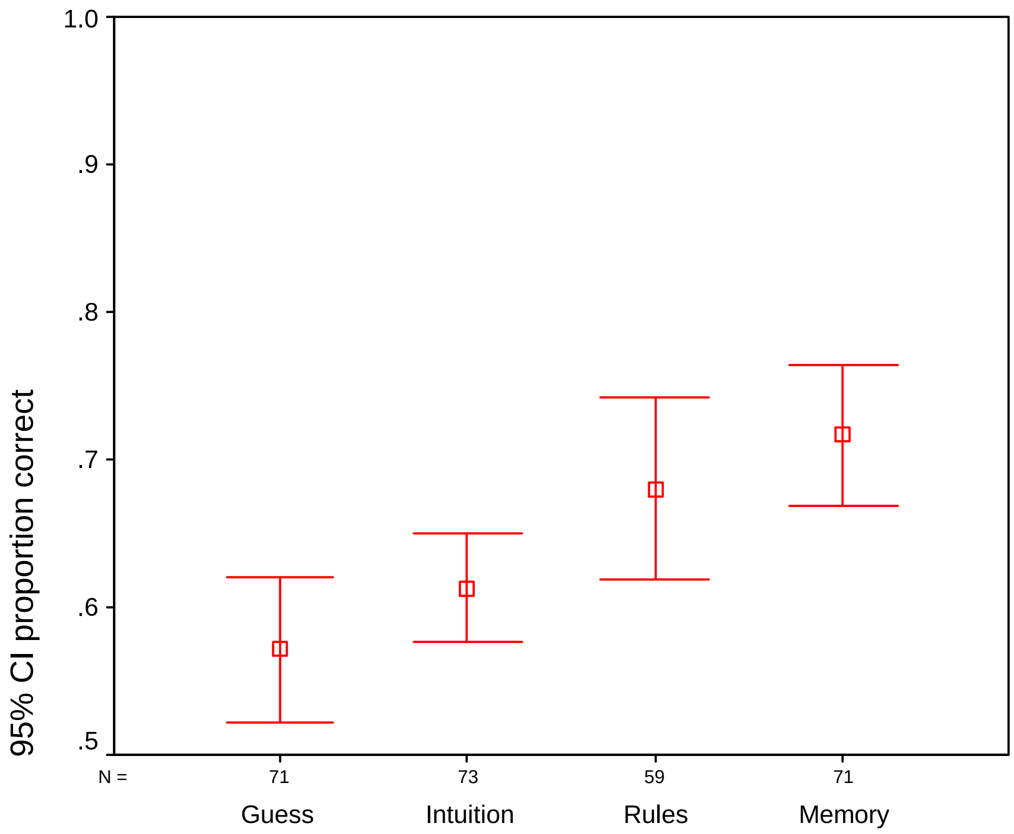


Figure 8. Ninety-five percent confidence intervals for the proportion correct classifications for different attributions in experiment 2.

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 having confidence in one's answer. Participants also gave higher confidence to memory than 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) $t(76) = 15.64$, $p < .0005$.

	Guess	Intuition	Rules	Memory
Confidence	56 (0.8)	66 (0.9)	74 (1.2)	76 (1.2)

Table 4. Confidence for each attribution in experiment 2. Standard errors appear in parentheses.

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, one could just as well have flipped a coin. It could be "guess" was taken as having a looser everyday meaning; or that when people were given a more fine grained scale (50-100 vs guess non-guess) they made more fine 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 = 0.52, 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. Further when people 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 people give a confidence of 50% indicating that they were literally guessing, that may mean the answer "grammatical" or "non-grammatical" just popped into their head as if out of nowhere. But it might 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 one 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.

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)

Table 5. The distribution of 50% confidence responses over attributions in experiment 2. 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 conditions; 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 subjects to search for rules rather than memorise and requiring subjects 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 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 memorise 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 behaviour. Thus, it is not surprising 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 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 memorise and full attention cell, the proportion of responses attributed to unconscious structural knowledge was 56%; the corresponding figure in experiment 1 was 81%. This is a large difference and significant, $t(43) = 4.29$, $p < .0005$. (The overall percentage correct classifications were virtually identical; 66% compared to 64%). The materials were slightly different across the two experiments. Another factor is that in the memorise condition in experiment 2 people looked at a string and then copied it down once it had disappeared; in experiment 1 people copied the string down as it was presented. In experiment 1 the task was not presented even as a memorisation task. It may be that such simple exposure encourages maximally implicit learning compared to memorisation (cf Reber & Allen, 1978); this could be explored in future better controlled studies.

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 overall number of correct responses was higher), consistent with the theoretical claims of Reber (1989). Experiment 2 showed that rule search rather than memorise 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 first-pass real division between conscious and unconscious structural knowledge. However future research may tease out more complicated boundaries 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, Camponi, & 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 people 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 might 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 (one knows that one has 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). Further, in some cases it is difficult for people to become aware of the existence of structural knowledge even when they try. Using the same grammars as in this paper, Tymann & Dienes (submitted) told people in a test phase that they were being underconfident. These warnings reduced the number of guess responses used (on a 50-100 confidence scale) but people could not choose which guess responses to give a higher confidence rating to: The percentage correct classifications when guessing remained unaltered whether underconfidence 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; Destrebecqx & 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 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. Desterebecqz and Cleeremans exposed people to a sequential regularities in a serial reaction time task, and then informed people of the existence of such regularities and asked them to generate a sequence that did not have the same structure as the one they were just 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 on the exclusion task. For example, one can readily generate strings of words that are non-grammatical 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.

References

Allwood, C. M., Granhag, P. A., Johansson, H. (2000). Realism in confidence judgements of performance based on implicit learning. European Journal of Cognitive Psychology, 12, 165-188.

Baddeley, A. (1986). Working memory. Oxford: Clarendon Press.

Block, N. (2001). Paradox and cross purposes in recent work on consciousness. Cognition, 79, 197-219

Chan, C. (1992). Implicit cognitive processes: theoretical issues and applications in computer systems design. Unpublished D.Phil thesis, University of Oxford

Boucher, L., & Dienes, Z. (2003). Two ways of learning associations. Cognitive Science, 27, 807-842.

Channon, S., Shanks, D., Johnstone, T., Vakili, K., Chin, J., & Sinclair, E. (2002). Is implicit learning spared in amnesia? Rule abstraction and item familiarity in artificial grammar learning. Neuropsychologia, 40, 2185-2197.

Destrebecqz, A. & Cleeremans, A**.** (2001). Can sequence learning be implicit? New evidence with the process dissociation procedure. Psychonomic Bulletin & Review, 8, 343-350.

Destrebecqz, A., & Cleeremans, A. (2003). Temporal effects in sequence learning. In Jiménez, L. (Ed.), Attention and Implicit Learning. John Benjamins, pp. 181-213.

Dienes, Z. (2004). Assumptions of subjective measures of unconscious mental states: Higher order thoughts and bias. Journal of Consciousness Studies.

Dienes, Z., & Altmann, G. (1997). Transfer of implicit knowledge across domains? How implicit and how abstract? In D. Berry (Ed.), How implicit is implicit learning? (pp 107-123). Oxford: Oxford University Press.

Dienes, Z., Altmann, G., Kwan, L, Goode, A. (1995) Unconscious knowledge of artificial grammars is applied strategically. Journal of Experimental Psychology: Learning, Memory, & Cognition, 21, 1322-1338.

Dienes, Z., & Berry, D. (1997). Implicit synthesis. Psychonomic Bulletin and Review, 4, 68-72

Dienes, Z., Broadbent, D. E., & Berry, D. C. (1991). Implicit and explicit knowledge bases in artificial grammar learning. Journal of Experimental Psychology: Learning, Memory, & Cognition, 17, 875-882.

Dienes, Z., Kurz, A., Bernhaupt, R., & Perner, J. (1997). Application of implicit knowledge: deterministic or probabilistic? Psychologica Belgica, 37, 89-112.

Dienes, Z., Longuet-Higgins, H. C. (2004). (2004). Can musical transformations be implicitly learned? Cognitive Science, 28, 531-558.

Dienes, Z., & Perner, J. (1999) A theory of implicit and explicit knowledge. Behavioural and Brain Sciences, 22, 735-755.

Dienes, Z., & Perner, J. (2003). Unifying consciousness with explicit knowledge. In Cleeremans, A. (Ed.) The unity of consciousness: binding, integration, and dissociation. Oxford University Press. (pp 214-232).

Dienes, Z., & Perner, J. (2004). Assumptions of a subjective measure of consciousness: Three mappings. In R. Gennaro (Ed.), Higher order theories of consciousness. John Benjamins Publishers: Amsterdam (pp 173-199).

Dulany, D.E., Carlson, R.A. & Dewey, G.I. (1984). A case of syntactical learning and judgement: How conscious and how abstract? Journal of Experimental Psychology: General, 113, 541-555.

Frensch PA, Wenke D, and Ruenger D. (1999) A secondary tone-counting task suppresses expression of knowledge in the serial reaction task. Journal of Experimental Psychology: Learning, Memory, & Cognition, 25, 260-274

Gardiner, J. M.,& Parkin, A. J.(1990). Attention and recollective experience in recognition memory. Memory & Cognition, 18, 579-583.

Gardiner, J. M., Ramponi, C., & Richardardson-Klavehn, A. (1998). Experiences of remembering, knowing, and guessing. Consciousness and Cognition, 7, 1-26.

Jacoby, L. L.,& Hay, J. F. (1998). Age-related deficits in memory: Theory and application. In M. A. Conway (Ed.), Theories of memory II. Mahwah, NJ: Erlbaum. (pp.111-134)

Jiménez, L. (Ed.) (2003). Attention and implicit learning. John Benjamins: Amsterdam.

Kelley, C. M.,& Jacoby, L. L. (2000). Recollection and familiarity: Process-dissociation. In E. Tulving & F. I. M. Craik (Eds.), The Oxford handbook of memory (pp. 215–228). Oxford, England: Oxford University Press.

Kinder, A., Shanks, D. R., Cock, J., & Tunney, R. J. (2003). Analytic and nonanalytic strategies and the explicit/implicit distinction in artificial grammar learning. Journal of Experimental Psychology: General, 132, 551-565.

Lau, K. K. (2002). Metacognitive measures of implicit learning in a dynamic control task. Unpublished D.Phil thesis, University of Sussex.

Mathews, R. C. (1997). Is research painting a biased picture of implicit learning? The danger of methodological purity in scientific debate. Psychonomic Bulletin & Review, 4, 38-42.

Mathews, R.C., Buss, R.R., Stanley, W.B., Blanchard-Fields, F., Cho, J R. & Druhan, B. (1989). The role of implicit and explicit processes in learning from examples: A synergistic effect. Journal of Experimental Psychology: Learning, Memory, and Cognition, 15, 1083-1100.

Pacini, R., & Epstein, S. (1999). The Relation of Rational and Experiential Information Processing Styles to Personality, Basic Beliefs, and the Ratio-Bias Phenomenon. Journal of Personality and Social Psychology, 76, *972-987.*

Parkin, A. J., Reid, T. K.,& Russo, R.(1990). On the differential nature of implicit and explicit memory. Memory & Cognition, 18, 507-514.

Perruchet, P., & Pacteau, C. (1990). Synthetic grammar learning: Implicit rule abstraction or explicit fragmentary knowledge? Journal of Experimental Psychology: General, 119, 264-275.

Perruchet, P., Vinter, A., & Gallego, J. (1997). Implicit learning shapes new conscious percepts and representations. Psychonomic Bulletin & Review, 4, 43-48.

Reber, A.S. (1967). Implicit learning of artificial grammars. Journal of Verbal Learning and Verbal Behaviour, 6, 855-863.

Reber, A. S. (1969). Transfer of syntactic structures in synthetic languages. Journal of Experimental Psychology, 81, 115-119.

Reber, A.S. (1989). Implicit learning and tactic knowledge. Journal of Experimental Psychology: General, 118, 219-235.

Reber, A. S., & Allen, R. (1978). Analogic and abstraction strategies in synthetic grammar learning: A functionalist interpretation. Cognition, 6, 189-221.

Reber, A. S., Kassin, S. M., Lewis, S., & Cantor, G. (1980). On the relationship between implicit and explicit modes in the learning of a complex rule structure. Journal of Experimental Psychology: Human Learning & Memory, 6, 492-502.

Redington, M., Friend, M. & Chater, N. (1996). Confidence judgements, performance, and practice, in artificial grammar learning. In G. W. Cottrell (Ed.), Proceedings of the Eighteenth Annual Conference of the Cognitive Science Society, (pp. 649-654). Mawah, NJ: Erlbaum.

Roberts, P.L., & MacLeod, C. (1995). Representational consequences of two modes of learning. Quarterly Journal of Experimental Psychology, 48A, 296-319.

Rosenthal, D.M. (1986). Two concepts of consciousness. Philosophical Studies, 49, 329-359.

Rosenthal, D. M. (2005). Consciousness and mind. Oxford: Clarendon Press.

Rotello, C. M.,Macmillan, N. A., Reeder, J. A. **(**2004). Sum-difference theory of Remembering and Knowing: A two-dimensional signal-detection model. Psychological Review, 111, 588-616

Shanks, D. R. (2003). Attention and awareness in “implicit” sequence learning. In L. Jiménez (Ed.), Attention and implicit learning (pp. 11-42). Amsterdam & Philadelphia: John Benjamins

Tunney, R. J. (in press). Sources of confidence judgments in implicit cognition. Psychonomic Bulletin & Review.

Tunney, R. J., & Altmann, G. T. M. (2001). two modes of transfer in artificial grammar learning. Journal of Experimental Psychology: Learning, Memory, & Cognition, 27, 1322-1333.

Tunney, R. J., & Shanks, D. R. (2003). Subjective measures of awareness and implicit cognition. Memory and Cognition, 31, 1060-1071.

Waldron, E.M., & Ashby, F.G. (2001). The effects of concurrent task interference on category learning: Evidence for multiple category learning systems. Psychonomic Bulletin & Review, 8, 168-176.

Whittlesea, B. W. A., & LeBoe, J. P. (2000). The heuristic basis of remembering and classification: Fluency, generation, and resemblance. Journal of Experimental Psychology: General, 129, 84-106.

Wilkinson, L., & Shanks, D. R. (2004). Intentional control and implicit sequence learning. Journal of Experimental Psychology: Learning, Memory, and Cognition, 30, 354-369.

Ziori, E., & Dienes, Z. (in press). Subjective measures of unconscious knowledge of concepts. Mind & Society.

Appendix A Training and test strings in order of presentation

The training sets include 15 unique strings from the chosen grammar repeated 3 times in different random orders. The test set includes 30 unique strings from each grammar randomly combined.

Grammar A: Training strings		**Grammar B: Training strings**		**Grammar A & B: Testing strings**		(Grammar)
1	XMXRTVTM	1	VVRXRRRM	1	XMXRVM	A
2	VVTRTTVTM	2	VVTTTRXRM	2	VTTTVM	A
3	VTTTTVM	3	VTRRRRM	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
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