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Explicit feedback maintains implicit knowledge

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ABSTRACT

The role of feedback was investigated with respect to conscious and unconscious knowledge acquired during artificial grammar learning (AGL). After incidental learning of training sequences, participants classified further sequences in terms of grammaticality and reported their decision strategy with or without explicit veridical feedback. Sequences that disobeyed the learning structure conformed to an alternative structure. Feedback led to an increase in the amount of reported conscious knowledge of structure (derived rules and recollections) but did not increase its accuracy. Conversely, feedback maintained the accuracy of unconscious knowledge of structure (intuition or familiarity-based responses) which otherwise degraded. Results support a dual-process account of AGL. They suggest that implicit learning of the to-be-rejected structure at test contaminates familiarity-based classifications whereas feedback allows competing familiarity signals to be contextualised, which is incompatible with theories that consider familiarity context-insensitive.

1. Introduction

People often rely on intuitive feelings when performing everyday tasks requiring high levels of expertise, with the underlying processes difficult to introspect (Cleeremans, 2006). Knowledge is said to be implicit or unconscious (here, the terms are used interchangeably) when one is unaware of its presence or nature despite its ongoing influence on behaviour (e.g. Dienes, 2008a, 2012). Many skills thought to have an implicit component rely on repeated practice or exposure rather than direct instruction. This is thought to minimise explicit learning of the material and the intention to learn is not required (e.g. Allen & Reber, 1980; Berry & Dienes, 1993; Dienes & Berry, 1997a, 1997b; Domangue, Mathews, Sun, Roussel, & Guidry, 2004; Higham, Vokey, & Pritchard, 2000; Mathews, 1997; Reber, 1989; Rebuschat & Williams, 2009; Sallas, Mathews, Lane, & Sun, 2007; Scott & Dienes, 2010a; Ziori & Dienes, 2006, 2008). During the acquisition of implicit knowledge – 'implicit learning' – one may not be aware of learning anything at all. Such learning episodes may also result in feelings of intuition or familiarity or experiences of "rightness" or "wrongness" without knowing directly from where those feelings stem (e.g.: Dienes, 2012; Mangan, 2003; Neil & Higham, 2012; Norman, Price, Duff, & Mentzoni, 2007).

One of the most common experimental paradigms used to investigate implicit learning and the resultant knowledge is artificial grammar learning (AGL; Reber, 1967), where participants are exposed to a series of letter sequences generated by a rule-based system. After several minutes exposure, they are informed of the presence of rules before going on to classify further novel sequences in terms of conformity to or violation of the studied structure. Performance is often around 65% accuracy (with a 50% baseline). However, successful worldly discrimination does not allow inference of the conscious status of knowledge that led to that behaviour. Further, it is perfectly possible for someone to be confident that a sequence is (un)grammatical – which entails awareness that the *judgment* itself constitutes knowledge – but this does not necessitate

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awareness of that sequence's features which make it (un)grammatical, i.e.: the underlying *structural* knowledge which led to the grammaticality judgment (Dienes, 2012).

This structural and judgment knowledge distinction motivated the use of structural knowledge attributions in implicit learning (Chen et al., 2011; Dienes, Baddeley, & Jansari, 2012; Dienes & Scott, 2005; Fu, Dienes, & Fu, 2010; Guo et al., 2011; Jiang et al., 2012; Kemeny & Luckacs, 2013; Kiyokawa, Dienes, Tanaka, Yamada, & Crowe, 2012; Neil & Higham, 2012; Rebuschat & Williams, 2009; Scott & Dienes, 2008, 2010a, 2010b, 2010c, 2010d; Wan, Dienes, & Fu, 2008). Structural knowledge attributions reflect different metacognitive experiences of knowledge (see Fig. 1). Rules and recollection responses index conscious structural knowledge where one can explicitly represent the aspects of a given stimulus which motivate the grammaticality judgment. Intuition and familiarity responses index conscious judgment of unconscious structural knowledge when one has a metacognitive feeling related to grammaticality (or accuracy) but not knowledge of its source. Random selection responses reflect the phenomenology of mere guesses, where both judgment and structural knowledge are unconscious. Structural knowledge can be incidentally learned during a standard AGL training phase where participants are unaware of any structure to learn. See Dienes (2012) for a discussion on the conscious vs. unconscious status of knowledge in relation to the learning of statistical and other regularities.

1.1. Unconscious structural knowledge

Laboratory-based empirical studies suggest that unconscious knowledge is weak compared to conscious knowledge in terms of its performance (e.g.: Dienes & Scott, 2005; Scott & Dienes, 2008, 2010a, 2010b, 2010c; contrast Scott & Dienes, 2010d). However, outside of the experimental context, unconscious structural knowledge of one's native language is of better quality than one's conscious structural knowledge (Dienes, 2008a). Mathews (1997) suggests that low confidence in unconscious knowledge (and perhaps its relatively poor performance) obtained during AGL and other implicit learning tasks may be characteristic of the early stages of implicit knowledge acquisition, whereas with sufficient practice implicit knowledge can be used with high levels of confidence and accuracy (Cleeremans, 2006; see also Allen & Reber, 1980). Of course, it is beyond the scope of many laboratory-based single session or small scale studies to train participants to 'expert' levels of unconscious knowledge however one may reasonably define 'expert'. Nevertheless, one feature of natural language acquisition and its use is that speakers are consistently given feedback about the accuracy of their judgment knowledge by virtue of being understood and responded to by others (Demetras, Post, & Snow, 1986). Yet, feedback on judgment knowledge is not given in typical AGL studies after the point that participants are instructed to apply their knowledge, which may detract from ecological validity when drawing conclusions beyond the experimental methodology.

In one of the few published studies to provide feedback in AGL, Mathews et al. (1989) trained one group of participants under typical memorisation instructions. This group proceeded to classify 800 sequences (with feedback) over a number of sessions and after each 10-trial block reported their subjectively derived classification rules. A second untrained group of participants used these rules to classify sequences themselves, thereby assessing their validity. These participants showed above baseline performance, suggesting the first group reported some relevant conscious structural knowledge. Both groups also showed improvement over the course of the experiment. However, the performance of the second group did not reach the level attained by the first, evidence that not all of the first group's knowledge was subsequently reported. However, it is

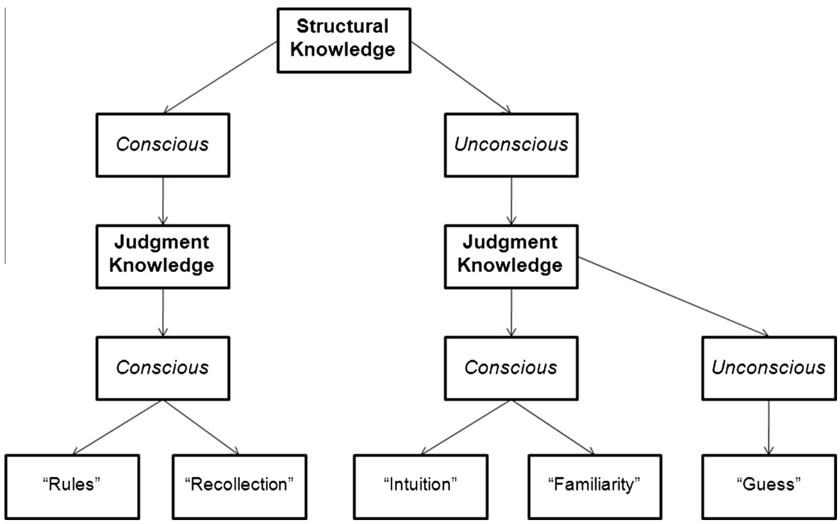

Fig. 1. The relationship between the conscious status of structural and judgment knowledge. The bottom row represents self-reported awareness of knowledge. "Rules" and "recollection" reflect explicit knowledge. "Intuition", "familiarity" and "guess" reflect degrees of awareness of implicit knowledge (Scott and Dienes, 2010a).

uncertain whether this is due to the potential issue of withholding information in free report (see Berry & Dienes, 1993) or if some of the structural knowledge that the first group had was unconscious, thus not available to introspection. Consequently the influence of feedback upon structural knowledge types remains uncertain (see also Dolan & Fletcher, 1999).

AGL studies are frequently conducted in a single session, rather than over weeks as in the Mathews et al. (1989) case. In many cases multiple testing sessions may simply be impractical or beyond the scope of the project. In a separate single session study that provided feedback about responses in AGL, Scott and Dienes (2008, experiment 2) encouraged participants to be more confident in their grammaticality judgments. They showed that confidence encouragement (suggesting to the participant that their grammar judgments were generally correct) reduced the number of responses attributed to random selection (guessing) and increased intuition and memory (recollection) attributions. It also reduced the quality of responses attributed to guessing to chance levels, through a process of familiarity calibration (Scott & Dienes, 2010a). However, it remains unclear what role veridical feedback regarding accuracy plays with respect to the conscious status of structural knowledge.

1.2. Conscious structural knowledge

Scott and Dienes (2010a) present a dual process theory of knowledge acquisition in AGL. At test, participants undergo a process of familiarity calibration in which grammaticality decisions become more tightly linked to the subjective mean familiarity of test sequences encountered thus far. Further exposure to sequences allows for increasingly reliable estimates of mean familiarity and smaller discrepancies from mean familiarity to be taken as a reliable method to determine grammaticality; allowing for conscious judgments of unconscious structural knowledge to be made (intuition, familiarity). Additionally, once participants are able to make these feeling-based distinctions, conscious structural knowledge can be derived. For example, an explicit rule is developed when the realisation is made that all preceding sequences containing a particular element had been classified as (un)grammatical. The results of Scott and Dienes (2008) suggest that encouraging confident convictions accelerates this process. However, this feedback was non-veridical as it was provided regardless of accuracy. Providing feedback about the actual accuracy of grammaticality decisions should allow conscious structural knowledge to be derived rapidly.

The dual process model predicts that under deliberate learning ("rule-search") conditions, conscious structural knowledge would emerge earlier in the test phase than through incidental learning through considered effort to learn subjectively pertinent sequence elements. Dienes and Scott (2005) found rule-search instructions increased the amount of reported conscious structural knowledge but without increasing its accuracy and Reber (1976) found that explicit rule-search instructions led to worse performance than memorise instructions, in part driven by the consistent application of erroneous rules. Reber, Kassin, Lewis, and Cantor (1980) argue that accuracy differences stemming from rule-search vs. standard memorise instructions likely depend on the complexity of the learning materials (see also Berry & Dienes, 1993). Here we make the prediction that feedback should serve much the same purpose as rule-search instructions. However, the key distinction is that derived conscious structural knowledge should develop over the course of the experiment after incidental learning; that is when the intention to learn is absent. Using the same materials as Dienes and Scott, who detected an increased reliance on conscious structural knowledge but not in its accuracy, we can derive the prediction that there should be an increase in the number of conscious structural knowledge attributions due to feedback, without necessarily increasing its accuracy.

1.3. Familiarity contamination vs. familiarity decay

A different prediction regarding unconscious structural knowledge can be derived through AGL methodological considerations. One common method thought to ensure adequate control is the grammar cross-over design. One group is trained on grammar A and another on grammar B. Ungrammatical sequences for use at test are then selected from the opposing grammar. This method has been used in a number of studies (e.g. Brooks & Vokey, 1991; Dienes & Altmann, 1997; Dienes & Scott, 2005; Scott & Dienes, 2008, 2010b, 2010c, 2010d). However, the dual-process theory of Scott and Dienes (2010a) allows for learning at test, which may extend to implicit learning of the regularities of to-be-rejected sequences. Increasing familiarity with the to-be-rejected grammar would result in their subjective familiarity distributions being drawn together, resulting in reduced sensitivity to grammaticality and impairing discrimination as test trials progressed. Wan et al. (2008) demonstrated strategic application of unconscious structural knowledge of two grammars when given the appropriate intention to do so. Importantly, people could use familiarity to distinguish the grammars, showing feelings of familiarity can be contextualised. Feedback could similarly aid participants to contextualise familiarity signals, helping discrimination between the grammars to be maintained.

An alternative, but not mutually exclusive, prediction stems from dual process theory of recognition. There is an emerging literature postulating that the processes underlying classification in AGL are similar (although not identical) to those which contribute to performance in recognition memory tests (e.g.: Higham, 1997; Higham et al., 2000; Mealor & Dienes, 2013; Scott & Dienes, 2010b; Tunney, 2007, 2010; Vokey & Higham, 1999). Dual process theories of recognition memory posit a qualitative difference between recollection and familiarity processes, reminiscent of the dual process theory of AGL under consideration here (for reviews, see e.g.: Diana, Reder, Ardnt, & Park, 2006; Wixted & Mickes, 2010; Yonelinas, 2002; Yonelinas, Aly, Wang, & Koen, 2010). Over the long term (e.g. over 24 h), forgetting associated with recollection occurs to a greater extent than forgetting associated with familiarity (Jacoby, Kelley, Brown, & Jasechko, 1989a; Jacoby, Woloshyn,

& Kelley, 1989b). However, over the course of an intermediate term delay (such as an experimental setting), forgetting associated with familiarity occurs more rapidly than forgetting associated with remembering (Hockley, 1992; Hockley & Consoli, 1999; Yonelinas & Levy, 2002; see also Yonelinas, 2002, for review). Thus, a familiarity signal driving unconscious structural knowledge sequence classification could decay over the test phase. The lag in the participant realising that the distributions have shifted will lead to a lowering of the endorsement rate of sequences generally when structural knowledge is unconscious, i.e. a more conservative criterion. As AGL classifications are dependent on similarity to exemplars, feedback could maintain a familiarity signal that would otherwise degrade.

1.4. Hypotheses

In sum, we will test the following hypotheses. Considering unconscious structural knowledge, contaminated familiarity with to-be-rejected sequences predicts a reduction in discrimination without feedback (whereas contextualisation through feedback maintains grammaticality sensitivity). Familiarity decay predicts a shift to more conservative responding without feedback. Furthermore, feedback should increase the development of conscious structural knowledge over the test phase to a greater extent than without feedback, according to the dual-process model of Scott and Dienes (2010a).

2. Method

2.1. Design and participants

Eighty-seven members of the University of Sussex participated (47 in the feedback group and 40 in the no feedback group). The two grammar cross-over design of Dienes and Altmann (1997) was used. Participants were trained and tested on either grammar A or B. At test, sequences from grammar A were used as ungrammatical sequences for grammar B and vice versa.

2.2. Materials

The set of testing and training sequences were the same as used by Dienes and Scott (2005, experiment 2). Sequence length was between five and nine characters. The training lists were comprised of 15 training sequences from each grammar, combined and repeated three times in a random order. Thirty novel testing sequences from each grammar were used, combined in a random order meaning participants viewed sixty testing sequences, 50% of which conformed to their respective training grammar. EPrime 2.0 software was used to display the stimuli and record responses. A fixed counterbalanced order was used in training and testing, with half of the subjects shown the list in reverse order.

2.3. Procedure

Participants were tested individually at a computer. During the training phase, training sequences appeared centrally in black text (font Arial, point size 66) for 5000 ms followed by a blank screen for 5000 ms. During this time the participant was required to write down the sequence as accurately as possible before the next sequence appeared on a sheet of paper provided. This sheet was then removed and participants were then informed the sequences obeyed a complex set of rules and they were to classify further new sequences in terms of grammaticality, half of which obeyed the same rules. At test, each sequence required three judgments: grammaticality, attribution and confidence. For the grammaticality decision, participants indicated their choice by pushing the 1 (yes – the sequence is grammatical and conforms to the rules) or 0 key (no – the sequence is not grammatical and does not conform to the rules). Secondly, they were asked from where they felt their response arose (knowledge attribution) from five options based on Scott and Dienes (2008), corresponding to five numbers on the keyboard: random selection (1), intuition (3), familiarity (5), rules (7), recollection (9). The definition of these categories was as follows: *Random selection* – There is no basis for your response whatsoever. You may as well have flipped a coin to decide. *Intuition* – You feel your response is correct but have no idea why. *Familiarity* – Your response is based on a feeling of something seen earlier, or a feeling that something has changed or is missing, but you have no idea what. *Rules* – Your response is based on some rule(s) you learned earlier and you could say what these rules are if asked. *Recollection* – Your response is based on the fact you could or could not recollect seeing (parts of) the sequence earlier. Finally they were asked to type their confidence in their grammar judgment choosing any number between 50% and 100% (where 50% corresponds to a complete guess and 100% to complete certainty). After these three decisions, participants in the feedback group would see a message box before the next sequence reading 'Your grammar judgment was CORRECT' or 'Your grammar judgment was INCORRECT' based on accuracy. Participants in the no feedback condition did not see a message box.

3. Results

Intuition and familiarity responses both reflect instances where sequence classification is based on unconscious structural knowledge accompanied with conscious judgment knowledge and as such, were pooled into an 'unconscious structural knowledge' category for the purposes of analysis, where 'gut-feelings' drive the grammaticality decision. Rules and recollection responses reflect instances where structural knowledge is conscious and as such were pooled into a 'conscious structural knowledge' category, where the grammaticality decision can be explicated (see Fig. 1). Random selection responses are instances where both structural and judgment knowledge are unconscious, and therefore form their own 'guess' category where no preference for grammaticality is available to metacognition (the conscious status of judgment knowledge is the key difference between the 'guess' and 'unconscious structural knowledge' categories used here). In order to investigate effects over the course of the experiment, trials 1–30 were pooled into block 1 and trials 31–60 were pooled into block 2. Note the degrees of freedom throughout: not all participants used all category types in the relevant block of the experiment, thus could not be entered into the corresponding analyses (two blocks were considered appropriate in order to maximise use of the data). Mean confidence in conscious structural knowledge responses was 78%, and in unconscious structural knowledge was 67%. Neither feedback group nor block significantly impacted upon confidence, thus this measure is not discussed further.

3.1. Distribution of response types

Analyses of the percentages of responses attributed to each category required the use of separate ANOVAs as these percentages sum to 100%. Thus, three 2 × 2 (Block [block 1 vs. block 2] × Feedback [feedback vs. no feedback]) mixed ANOVAs ($N = 87$) were conducted on the percentage of guess, unconscious and conscious structural knowledge responses respectively (see Table 1 for descriptive statistics). No significant main effects or interactions were found for guess responses, $Fs < 1$. The ANOVA on unconscious structural knowledge responses revealed a marginal effect of block, with more unconscious structural knowledge responses in block 1 ($M = 55$, $SE = 2.49$) than block 2 ($M = 52$, $SE = 2.64$), $F(1,85) = 3.80$, $p = .055$. The main effect of feedback failed to reach significance, $F < 1.15$, as did the feedback × block interaction, $F(1,85) = 2.83$, $p = .096$. The ANOVA on the percentage of conscious structural knowledge responses revealed no significant main effect of block, $F(1,85) = 2.80$, $p = .098$, or feedback, $F < 1$. However there was a significant feedback × block interaction, $F(1,85) = 4.01$, $p = .049$. The data were split by feedback group, revealing no significant change in the percentage of conscious structural knowledge responses within the no feedback group, $t < 1$, but a significant increase between experimental blocks within the feedback group, $t(46) = 2.40$, $p = .020$. This supports the notion that feedback would increase the availability of conscious structural knowledge.

3.2. The effect of feedback on accuracy

A 2 × 2 × 2 (Structural knowledge type [conscious vs. unconscious] × Block [block 1 vs. block 2] × Feedback [feedback vs. no feedback]) mixed ANOVA was conducted on the proportion of correct responses ($N = 76$). (As only 43 participants used at least one random selection response, guesses were considered separately.) See Table 2 for descriptive statistics. Conscious structural knowledge responses ($M = .76$, $SE = .03$) outperformed unconscious structural knowledge responses ($M = .69$, $SE = .02$), $F(1,74) = 7.53$, $p = .008$. There was no significant main effect of block, with similar overall performance in block 1 ($M = .74$, $SE = .02$) and block 2 ($M = .71$, $SE = .02$), $F < 1.80$. There was no significant main effect of feedback, $F < 1$. There were no significant two-way interactions, $Fs < 2.99$, $ps > .088$. However, there was a significant knowledge type × block × feedback interaction, $F(1,74) = 4.47$, $p = .036$.

In order to follow up this interaction, mean accuracy of block 1 was subtracted from mean accuracy of block 2 for both response types (henceforth 'block difference'). Descriptive statistics are reported in Table 3 (positive values indicate an increase in accuracy across the experimental blocks). Independent samples t-tests were conducted, revealing a significant difference in the block difference of unconscious structural knowledge between the feedback and no feedback conditions, $t(74) = 2.48$, $p = .015$. The same difference was not found for conscious structural knowledge responses, $t < 1$. One sample t-tests were conducted against a value of zero (indicating no change in accuracy across experimental blocks). The block difference of unconscious structural knowledge responses without feedback was significantly less than zero, $t(33) = 3.20$, $p = .003$. The block difference of this response type with feedback was not detectibly different from zero, $t < 1$. For conscious structural knowledge responses, there was no detectible decrease in accuracy either under feedback or no feedback conditions, $ts < 1$. Thus, there was a relative decrease in accuracy of unconscious structural knowledge without feedback which was not the case when feedback was provided or for conscious structural knowledge irrespective of feedback.

Table 1
Percentage of trials per experimental block attributed to guess, unconscious and conscious structural knowledge attributions as a function of feedback condition. Standard errors appear in parentheses.

	Feedback		No feedback	
Structural knowledge	Block 1	Block 2	Block 1	Block 2
Guess	11 (2.41)	11 (2.79)	10 (1.63)	11 (1.82)
Unconscious	54 (3.38)	48 (3.58)	56 (3.66)	56 (3.88)
Conscious	35 (3.66)	41 (3.81)	34 (3.97)	33 (4.14)

Table 2
Proportion of correct responses as a function of knowledge type, block and feedback. Standard errors appear in parentheses.

Structural knowledge	Feedback		No feedback	
	Block 1	Block 2	Block 1	Block 2
Guess	.56 (.07)	.56 (.04)	.68 (.04)	.56 (.06)
Unconscious	.69 (.02)	.69 (.03)	.75 (.03)	.63 (.03)
Conscious	.73 (.04)	.72 (.04)	.77 (.04)	.80 (.04)

Table 3
Block difference scores as a function of knowledge type and feedback. Standard errors appear in parentheses.

	Feedback	No feedback
Unconscious	.00 (.03)	−.11 (.04)
Conscious	−.01 (.04)	.03 (.04)

Note: Positive values indicate an increase in accuracy in block 2.

Table 2 shows the accuracy of guesses. An orthogonal analysis revealed no significant effects, $Fs < 1.25$. However, it is of interest that the only condition under which random selection responses satisfied the guessing criterion – that is when above chance accuracy is displayed when both judgment and structural knowledge are unconscious (Dienes, Altmann, Kwan, & Goode, 1995) – was in the first block without feedback, $t(26) = 3.71$, $p = .001$ (all other $ts < 1.01$), a result predicted by the familiarity calibration process of Scott and Dienes (2010a).

3.3. The effect of feedback on discrimination (d′) and response criterion (C)

The contaminated familiarity and familiarity decay hypotheses were tested through signal detection measures, d' (indexing discrimination between grammatical and ungrammatical sequences) and C (indexing response criterion). Hit rates (HR) and false alarm rates (FAR) were calculated via the formulae HR = (hits + 0.5)/(hits + misses + 1); and FAR = (false alarms + 0.5)/(false alarms + correct rejections + 1), where the terms inside of the parentheses refer to frequencies. Note values of 1 or 0 are problematic for calculating d' and C (Snodgrass & Corwin, 1988, recommend the procedure of adding 0.5 to each cell as an arbitrary patch; but it can be justified from a Bayesian perspective as the implementation of a prior belief that d' is near zero, worth one observation for HR and one observation for FAR, i.e. it is a unit information prior for each, corresponding to the belief that with 95% probability HR lies between 5% and 95% and FAR the same; cf. Baguley, 2012; Kass & Wasserman, 1995; Laplace, 1814). See Table 4 for descriptive statistics. Only the analyses of d' and C are reported as the analyses on HR and FAR were consistent with findings for these measures or non-significant.

Thus, d' and C were entered into separate 2 × 2 × 2 (Structural knowledge type [conscious vs. unconscious] × Block [block 1 vs. block 2] × Feedback [feedback vs. no feedback]) mixed ANOVAs ($Ns = 71$). Considering d', there was a significant main effect of knowledge type, with conscious structural knowledge resulting in greater sensitivity ($M = 1.25$, $SE = .12$) than unconscious structural knowledge ($M = 0.98$, SE = .09), $F(1,69) = 5.64$, $p = .020$. The main effect of block approached significance, with marginally greater sensitivity in block 1 ($M = 1.19$, $SE = .09$) than block 2 ($M = 1.04$, $SE = .10$), $F(1,69) = 3.79$, $p = .056$. The main effect of feedback was non-significant, $F < 1$. The only two-way interaction to reach significance was knowledge type × block, $F(1,69) = 4.29$, $p = .042$ (other $Fs < 1$). However, as the three-way interaction was marginally significant, $F(1,69) = 2.81$, $p = .098$, the data were split by feedback group. Within the feedback group, there was no partial

Table 4
Hit rate (HR), false alarm rate (FAR), discrimination (d') and response criterion (C) for conscious and unconscious structural knowledge responses as a function of feedback and block. Standard errors appear in parentheses.

Structural knowledge		HR	FAR	d'	C
Feedback					
Conscious	Block 1	.63 (.03)	.27 (.03)	1.18 (.17)	.14 (.06)
	Block 2	.64 (.04)	.30 (.03)	1.12 (.17)	.14 (.08)
Unconscious	Block 1	.63 (.03)	.31 (.03)	1.02 (.13)	.09 (.07)
	Block 2	.64 (.04)	.34 (.04)	0.89 (.15)	.03 (.07)
No feedback					
Conscious	Block 1	.71 (.04)	.32 (.04)	1.28 (.20)	−.05 (.08)
	Block 2	.71 (.05)	.28 (.04)	1.40 (.20)	.03 (.09)
Unconscious	Block 1	.68 (.04)	.27 (.03)	1.26 (.20)	.11 (.08)
	Block 2	.61 (.04)	.40 (.04)	0.75 (.17)	.03 (.09)

Note: Values of C reflect response criterion where positive values indicate a conservative response bias and negative values indicate a liberal bias.

two-way interaction between knowledge type and block, $F < 1$. However, within the no feedback group, there was a significant partial knowledge type × block interaction, $F(1,29) = 4.89$, $p = .035$. There was a significant reduction in the sensitivity of unconscious structural knowledge responses between blocks 1 and 2, $t(36) = 2.71$, $p = .010$; the same was not true of conscious structural knowledge responses, $t < 1$. This offers support for the contaminated familiarity hypothesis outlined in Section 1.3.

In terms of *C*, the three-way ANOVA revealed no significant main effects or interactions, *Fs* < 1.26, *ps* > .267. Thus, in the absence of feedback, the sensitivity of unconscious structural knowledge towards grammaticality was reduced; there was no evidence that the same was true for unconscious knowledge when feedback was provided, nor for conscious structural knowledge generally, whereas changes in response criteria were not detected.

Next, Bayes factors were conducted to assess whether the accuracy and discrimination data for conscious structural knowledge and the response criterion data for unconscious structural knowledge reflect evidence for the null or merely insensitive evidence. Bayes factors require a plausible range of effect sizes to be specified for the given comparison. Bayes factors indicate a continuum of support for hypotheses where values less than 1/3 designate substantial evidence for the null; values over 3 substantial evidence for the experimental hypothesis; values around 1 indicate no substantial support either way and suggest insufficient sensitivity in the experimental design (Jeffreys, 1961; see Dienes, 2008b, 2011, for discussions on the relative merits and drawbacks of Bayesian and Orthodox statistics).

Two Bayes factors were calculated for conscious structural knowledge; one for the proportion of correct responses and one for d'. The data were modelled as half normals, with a mode of 0 and *SD*s set to the mean estimate reductions between blocks for unconscious structural knowledge between no feedback and feedback groups for both accuracy ($SD = .115$) and sensitivity ($SD = .374$). The reduction in accuracy for conscious knowledge in the no feedback group was −.042 (*SE* of the difference = .055), yielding a Bayes factor of 0.27, indicating substantial evidence for the null. The reduction in discrimination was −.181 (*SE* of the difference = .236), giving a Bayes factor of 0.34, approaching substantial evidence for the null, i.e. feedback had little impact on the accuracy of conscious structural knowledge.

To calculate the change in *C* in the current study, the difference between blocks in the no feedback condition was subtracted from that of the feedback condition, giving a mean difference of .027 (*SE* of the difference = .113). Yonelinas and Levy (2002, experiment 2) directly investigated reductions in recognition as a function of intermediate term delays (see Yonelinas, 2002, for review). Acceptance rates of targets and lures fell in parallel over an 8- and 32-item lag similar to the thirty trial blocks in the current study, giving a change in *C* estimated at .36. However, this is a likely underestimate in familiarity as all acceptance rates were included, thus an influence of recollection – thought resilient to intermediate term forgetting – cannot be ruled out. The change in *C* in the current study was therefore modelled as a half normal with a mode of 0 and *SD* of .40. This comparison yielded a Bayes factor of 0.33, approaching strong evidence for the null. Note that considering the change in *C* between block 1 and block 2 in the no feedback group in isolation gives a mean difference of −.077 (*SE* of the difference = .084), yielding a Bayes factor of 0.12 indicating strong evidence for the null hypothesis of no change in criterion, contrary to the familiarity decay hypothesis (see Section 1.3).

4. Discussion

We discuss the results first in terms of the effect of feedback on conscious structural knowledge, then unconscious structural knowledge, and finally the implications for ecological validity in implicit learning research.

4.1. The availability of conscious structural knowledge

The hypothesis that feedback would increase the availability of conscious structural knowledge was supported. Feedback led to an increase in the proportion of responses attributed to rules and recollection; thus, external feedback accelerates the process of deriving conscious structural knowledge. This is predicted by the Scott and Dienes (2010a) dual-process model of AGL. According to this model, conscious structural knowledge can be derived through the monitoring of unconscious structural (implicit) knowledge responses (i.e. a form of self-generated feedback). For example, participants may consciously realise never classifying a sequence containing a certain element as grammatical. Such sequences may hitherto have been attributed to intuition or familiarity but once the realisation has been made, they may attribute to rules or recollection instead as their conviction of encountering (or not) a salient element from training increases (an element that may become salient because of feelings of (un)familiarity associated with it). The results presented here show that feedback accelerates this process of hypothesis testing. It is not surprising that this did not occur without feedback in the current study; it could simply be the case that sixty test sequences is not enough for this process to reveal itself under incidental learning. Furthermore, although this theory posits a general shift of increasing metacognition at test, any conscious structural knowledge which was thought unreliable by the participant leads back to a reliance on intuition or familiarity. Feedback allows the veracity of conscious structural knowledge to be independently verified and its use continued.

Feedback appears to affect conscious structural knowledge in a manner parallel to rule-search instructions. For instance, Dienes and Scott (2005) found that instructing participants to search for rules in the training phase of AGL (thought to maximise explicit learning of the grammar) led to a 10% increase in conscious structural knowledge attributions and the current results show an increase of 6% of such attributions as a function of feedback under incidental learning (the same materials were used here as in the Dienes and Scott study). The key difference, however, is that rule-search instructions encourage explicit learning during training whereas feedback encourages greater amounts of conscious structural knowledge to be derived at test from incidentally acquired knowledge.

Importantly, the amount of reported conscious structural knowledge only increased in the second block of the feedback group, showing it was derived gradually as a function of feedback. If the increase in reported conscious structural knowledge was produced simply by demand characteristics, one would expect the difference between feedback and no feedback to appear straightaway. Feedback could have increased the amount of cognitive effort but this would be similar to rule-search instructions; greater effort to derive rules leads to increases in metacognition, consistent with the Scott and Dienes (2010a) model of AGL in that increasing metacognition was shown.

4.2. The accuracy of conscious and unconscious structural knowledge

Without feedback, there was a relative decrease in the accuracy of unconscious structural knowledge, whereas the accuracy of conscious structural knowledge was relatively maintained throughout the test phase regardless of feedback, The source of inaccuracy in unconscious structural knowledge responses was a relative deficit in grammar sensitivity, and not a shift in response criterion; conversely, the feedback manipulation had little effect on conscious structural knowledge accuracy. Two contrasting explanations underlying the effect on unconscious structural knowledge, contaminated familiarity and familiarity decay, are discussed.

Contaminated familiarity is anticipated by a theory that the feeling of familiarity toward a current sequence is dependent on the elements within all preceding exemplars. Here, participants implicitly learned (some of) the regularities of the to-be-rejected grammar at test and this contaminated familiarity was expressed through unconscious structural knowledge. When feedback was provided, encroaching familiarity with to-be-rejected sequences could be contextualised. Familiarity signals became confounded in the participant's mental state when feedback was absent, reducing discrimination (i.e.: the probability distributions relating to grammatical and ungrammatical sequences become drawn together in terms of their subjective familiarity; see also Higham et al., 2000). Sequences that the experimenter considers should, or should not, result in a feeling of familiarity do not necessarily match those of the participant. Importantly, unconscious structural knowledge was not reduced to baseline levels in the absence of feedback. In fact, 63% of unconscious structural knowledge responses in the second block were correct and 65% performance is typical, thus accurate knowledge was still demonstrated despite a relative reduction in the quality of this knowledge (note that although there was an accuracy reduction *within* the no feedback group, the difference *between* groups was not substantial). Wan et al. (2008) discuss the possibility that multiple types of familiarity can be acquired in AGL (e.g.: Type A and Type B reflecting the respective grammars), positing that intentions can increase reliance on one type over the other. Feedback may work in a similar manner through alerting participants to encroaching familiarity from to-be-rejected sequences which allows participants to contextualise competing familiarity signals. Note that contextualisation is inconsistent with the Jacoby (1991) definition of familiarity as a memory process that occurs regardless of intent or context, but is in-line with the Dienes, Scott, and Wan (2011) definition as a continuous indication of 'oldness' emerging from learning. Dienes et al propose the familiarity signal emerges from the goodness-of-fit of context-sensitive neural networks. (See Rohrmeier & Cross, in press, for learning during the test phase when the design is comparing one grammar vs. ungrammatical strings; our results indicate that the two-grammar design may be different in this respect, producing test-phase unlearning of implicit knowledge in neural networks.)

Conversely, the accuracy of conscious structural knowledge was maintained throughout, regardless of feedback (although the number of trials based on conscious structural knowledge increased with feedback). This suggests the quality of conscious structural knowledge cannot easily be improved simply through providing feedback (evidence approached the null for discrimination and strongly supported the null for accuracy), which appears curious at first glance.

If a participant uses inaccurate conscious knowledge (e.g.: a false recollection, mistaken reconstruction or a derived rule which was incorrect), they may erroneously and consistently endorse sequences with that element as grammatical if they are not alerted to which of their particular rules is incorrect, which may also account for the lack of a detectible feedback effect on confidence (cf. Dienes, Kurz, Bernhaupt, & Perner, 1997; Dienes & Scott, 2005; Reber, 1976, 1989; Reber et al., 1980). This shows the virtue of including subjective measures of awareness in implicit learning studies, where the decision process itself can become the object of study as opposed to simply the ability of a process to make worldly discriminations, i.e.: measuring the extent to which people think they know as opposed to how they perform (cf. Dienes, 2012).

Further, contaminated familiarity was not reflected in recollection or rule-based conscious knowledge which goes beyond familiarity. When structural knowledge is conscious, the decision is likely a binary one (perhaps based on a subjectively defined decision criterion), and there is relatively little noise in the decision making process compared to using continuous familiarity signals to guide responding. The predicted dissociation between knowledge types supports the structural knowledge attribution methodology.

The recognition memory literature states that a familiarity signal decays under the medium term (as in an experimental setting) but recollection is largely maintained (see Yonelinas, 2002, for review), which predicts a shift toward conservative responding through a reduction in overall endorsement as opposed to a reduction in discrimination. However, the data approached strong evidence for the null comparing the feedback groups (and substantial evidence considering the no feedback group in isolation), thus the contaminated familiarity explanation is a better fit of the data, which suggests implicit learning continues at test. However, theoretically response criterion and discrimination are not mutually exclusive and future research could investigate changes in these measures using alternatives to the classic AGL protocol (see e.g., Chen et al., 2011; Jiang et al., 2012; Neil & Higham, 2012; Rebuschat & Williams, 2009; Rohrmeier, Fu & Dienes, 2012).

The accuracy of random selection responses was only significantly above baseline (satisfying the guessing criterion of Dienes et al., 1995) in the first block of trials without feedback. On the Scott and Dienes (2010a) model of unconscious structural knowledge AGL classifications based on guess and intuition/familiarity responses exist on a continuum. Test sequences which exceed a baseline level of familiarity are endorsed as grammatical and those which fall short of baseline are rejected as ungrammatical. Initially, only sequences on the extremities of the familiarity axis give rise to confidence and conscious judgment knowledge; those closer to the baseline give rise to accurate guess responses. As the test phase proceeds, the baseline estimate becomes settled and evaluating discrepancies from baseline more reliable, thereby decreasing the boundary under which accurate guesses arise. As this calibration proceeds, guesses are based on sequences with familiarity least predictive of grammaticality and therefore accuracy. False feedback that the participant is being very accurate appears to accelerate this process (cf. Scott & Dienes, 2008, who encouraged more confident responses).

4.3. Ecological validity in AGL

The results presented here potentially contradict those of Mathews et al. (1989), who found feedback increased accuracy rather than maintain it. However, the current study used only one session of sixty trials, which is not comparable with the 800 trials over multiple sessions used by Mathews et al. Rather, the setting was similar to the majority of AGL studies (including subjective measures of awareness) and single session studies are certainly vital to researchers in the field by virtue of their practicality. It is plausible that repeating the current study with a larger number of trials or testing sessions would show feedback increases, rather than merely maintains the accuracy of unconscious structural knowledge which would be a worthwhile area for future research, particularly if analogies wish to be drawn between AGL and natural language learning. Achieving the highest levels of expertise in language learning requires both immersion in that language environment as well as formal training in proper use of the language such as spelling, language use, appropriate conversational use and so on (Ellis & Laporte, 1997).

Domangue et al. (2004) and Sallas et al. (2007) investigated the role of different AGL training techniques on participants' ability to generate grammatical sequences, finding that a synergy of bottom-up exemplar and top-down model-based learning resulted in rapid, accurate responding reflecting learning in natural settings (see also Kovic, Westermann, & Plunkett, 2008). Replicating these studies with respect to structural knowledge attributions would reveal the relative contributions of conscious and unconscious structural knowledge to performance in the learning of structured regularities under different forms of training and could potentially provide a model of how structural knowledge develops over longer time periods than used in standard AGL tasks.

AGL provides a simplified analogy of how implicit learning can lead to conscious and unconscious knowledge in everyday contexts. Clearly, natural language learning is a much richer learning experience. Cleeremans (2006) states that repeated practice leads to higher quality representations and Mathews (1997) argues that practice and greater exposure can lead to expert levels of unconscious knowledge. Yet, feedback often accompanies performance based on the products of implicit learning in everyday settings, which is often not the case in laboratory studies. Nonetheless, the notion that feedback supports unconscious knowledge and leads to the development of conscious structural knowledge was borne out in a standard AGL task. Without feedback, unconscious structural knowledge shows a relative deterioration in the gradually contaminated familiarity signal (but note that reasonable accuracy was found for this knowledge type). On the other hand, conscious structural knowledge accuracy was not detectibly affected by feedback, demonstrating a theoretically expected difference between the natural kinds of conscious and unconscious structural knowledge (cf. Dienes, 2012).

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