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How does prior knowledge affect implicit and explicit concept learning?

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Two experiments investigated the effect of prior knowledge on implicit and explicit learning. Implicit as opposed to explicit learning is sometimes characterized as unselective or purely statistical. During training, one group of participants was presented with category exemplars whose features could be tied together by integrative knowledge, whereas another group saw category exemplars with unrelated feature combinations. Half of the participants in each group learned these categories under a secondary-task condition (meant to discourage explicit learning), and the remaining half performed the categorization task under a single-task condition (meant to favour explicit learning). In a test phase, participants classified only the individual features of the training exemplars. Secondary- as opposed to single-task conditions impaired explicit but not implicit knowledge (as determined by subjective measures). Importantly, prior knowledge resulted in increased amounts of both implicit and explicit knowledge.

The present research attempts to investigate the effect of people's prior knowledge on implicit and explicit concept learning. According to some theories (e.g., Hayes & Broadbent, 1988), implicit learning is an unselective and passive process of learning, involving only aggregation of frequently co-occurring features with no room for any interpretive processes based on declarative knowledge. Prominent existing models of implicit learning also involve pure statistical associative processes (Cleeremans, 1993b; Dienes, Altmann, & Gao, 1999). On the other hand, it has been suggested (e.g., Frick & Lee, 1995; Sun, 2000; Sun, Merrill, & Peterson, 2001) that implicit learning may interact with prior knowledge and expectations. The current experiments, unlike most implicit-learning experiments, use highly meaningful material—thus corresponding more closely to concept learning in the real world—in order to activate participants' prior knowledge and investigate its relationship with implicit and explicit concept learning. Initially, it is useful to clarify the definition of the terms *implicit* and *explicit*. Then we discuss the effects of prior knowledge on category learning in general and on implicit category learning in particular. Next we

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introduce the particular methods and measures of implicit and explicit learning that we are using before describing our overall methodology.

The explicit–implicit distinction

Explicit knowledge is knowledge that one is aware of having and hence is easily verbalized; conversely, implicit knowledge is knowledge that one is not aware of having. The implicit–explicit distinction can also refer to the corresponding *methods* of acquiring knowledge. In general, explicit learning is thought to occur when people learn using analytical strategies, such as conscious hypothesis testing. Thus, implicit learning may be facilitated when the use of deliberate strategies is blocked—for example, it may occur more readily than explicit learning under dual-task conditions, where attention is distracted by a secondary task. The present article uses a dual-task methodology as a means of discouraging an analytical mode of processing. Some researchers have assumed that learning proceeds in the absence of conscious hypotheses testing if participants cannot report verbally what they have learned (e.g., Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Frick & Lee, 1995; Lewicki, Hill, & Sasaki, 1989); we tighten up on this criterion by using other subjective measures based on confidence ratings, described in detail below (Ziori & Dienes, 2006).

We use a standard concept-learning paradigm, in which trial-by-trial feedback is provided, and learning conditions are intentional, potentially facilitating explicit rather than implicit learning. Similar learning conditions have been used in many other category-learning tasks that have provided evidence of implicit category learning (e.g., Ashby, Maddox, & Bohil, 2002; Roberts & MacLeod, 1995; Waldron & Ashby, 2001). That is, the conditions of learning do not entirely dictate whether implicit or explicit knowledge is formed. Thus, we use ways of separately measuring implicit and explicit knowledge when, as is typical, tasks are not process pure. These methods enable us to investigate how processes of concept learning affect implicit and explicit knowledge.

Prior knowledge effects in concept learning

Standard similarity-based theories of concept learning (i.e., the classical, the family resemblance, and the exemplar views) assume that a novel object is considered a member of the category only if it is similar to existing category instances or to a summary representation of the concept such as a prototype or a rule (for an extensive description of these views, see Komatsu, 1992; Medin, 1989; Smith & Medin, 1981). These views rely mainly on similarity as an explanatory principle of categorization without taking into account people's prior knowledge about the world or about categories. More recently, however, psychologists developed the *theory-based* view, which argues that categorization depends largely on people's background knowledge (e.g., Carey, 1985; Medin, 1989; Murphy, 1993; Murphy & Medin, 1985; Rips, 1989).

There has been a growing bulk of research on various specific effects that prior knowledge has on category learning (see Heit, 1997, for an extensive review of such effects). For example, Murphy and Allopenna (1994; see also Kaplan & Murphy, 2000; Spalding & Murphy, 1996, 1999) showed that prior knowledge generally facilitates category learning by making the categories more meaningful and coherent. They found that categories whose features were interconnected by prior knowledge and therefore fit with people's common knowledge were much easier to learn than incoherent categories whose features had no preexisting connections among them, despite the fact that the two kinds of categories had the same family resemblance structure.

Researchers have proposed different views as to the explicitness or implicitness of prior knowledge. On one view, theory-based knowledge is considered as explicit knowledge (e.g., McRae, 2004; Pothos, 2005; Sloman, 1996; Smith & Sloman, 1994). In particular, a deliberative and analytical mode of categorization that is associated with analysing causal relationships between features is distinguished from an intuitive associative mode that is used for processing correlations of features not necessarily causally related. On the other hand, it has been argued that prior knowledge may reflect expectations based on previously experienced exemplars (Heit, 1994, 1998; see also Heit, 2001). Such a similarity-based account might associate prior knowledge with implicit memories of exemplars. The present experiments are not designed so as to investigate the content of prior knowledge. Instead, the question that is raised in this article is whether implicit learning is unselective or biased by people's prior knowledge.

Can implicit category learning be affected by prior knowledge?

By contrast to early categorization theories that assumed a single learning system, an increasing number of recent theories have proposed separate category-learning systems (e.g., Ashby et al., 1998; Ashby & Ell, 2001, 2002; Erickson & Kruschke, 1998; Reber, Stark, & Squire, 1998; but see e.g., Nosofsky & Johansen, 2000; see also Love, 2003). Most of these theories were not originally interested in the implicit/explicit distinction per se, and so far only a few of them explicitly hypothesize the existence of an explicit (rule-based) system and a system that involves some form of implicit (statistical- or similarity-based) learning.

A question that remains open is whether or not implicit category learning is pure statistical learning based on the overall similarity of stimuli and unaffected by conceptual prior knowledge. Some concept formation paradigms have shown that people tend to ignore implicitly acquired information derived from the stimuli, when highly strong beliefs or theories are available (e.g., Chapman & Chapman, 1967; Hamilton & Rose, 1980). Moreover, Smith and Sloman (1994) argue that the use of background knowledge in the categorization of common objects is deliberative and analytic, and they place it in opposition to a similarity-based categorization that is more automatic and holistic. Existing computational models in the implicit-learning literature rarely include possible effects of prior knowledge (e.g., Boucher & Dienes, 2003; Cleeremans, 1993a; Dienes, 1992; Servan-Schreiber & Anderson, 1990) with a few exceptions (Dienes & Fahey, 1995; Sun, 2000). Determining whether prior knowledge does affect implicit learning is crucial to developing adequate models of implicit learning. Conversely, recent models of categorization that incorporate prior knowledge effects (e.g., Heit, 1994; Heit & Bott, 2000; Pazzani, 1991; Rehder & Murphy, 2003) could benefit from work on the relationship of prior knowledge with the implicit/explicit distinction. Currently, these models do not address questions regarding the implicit/explicit distinction. There is a need to determine the relationship between the models and concepts in the implicit-learning literature and those in the concept-learning literature. For instance, if prior knowledge takes the form of rules, it would be interesting to know how it interacts with an implicit-learning system (cf. Ashby et al., 1998).

Measures and methods of implicit and explicit learning

Dienes and Berry (1997) proposed the use of subjective measures as a direct way of measuring conscious and unconscious knowledge. People's knowledge is unconscious by subjective measures when people do not know that they know something—that is, when they lack metaknowledge. According to Dienes, Altmann, Kwan, and Goode (1995), this lack of metaknowledge may be expressed in two ways. First, participants may think that they are guessing when in fact they perform above chance (they called this the *guessing criterion*; cf. Cheesman & Merikle, 1984; Weiskrantz, 1997). Second, there may be a lack of relationship between participants' confidence and accuracy (they called this the *zero-correlation criterion*; see also Kunimoto, Miller, & Pashler, 2001, for its application to subliminal perception). The guessing criterion is used to assess whether participants make more accurate than inaccurate classification judgements when they believe they have no confidence at all—that is, when they believe they are guessing. The zero-correlation criterion is a measure of the relationship between confidence and accuracy. A lack of metaknowledge in terms of this criterion is demonstrated when participants are equally confident for accurate and inaccurate decisions. The present experiments used the zero-correlation and guessing criteria as the basic measures of implicit learning (for a discussion of the assumptions of these measures see Dienes, 2004; Dienes & Perner, 2001, 2004; and Dienes & Scott, 2005). In contrast to subjective measures, objective measures test whether people are aware of stimuli or relations in the environment, but not whether people are consciously aware of them—that is, aware of having knowledge. It is the subjective measures that form a direct way of providing evidence about subjective states including conscious awareness (though not without assumptions of their own, as mentioned above).

Further, a strength of the zero-correlation and guessing criteria is that they do not assume that people have only implicit or only explicit knowledge in any one condition (cf. Jacoby, 1991). A guessing criterion analysis resulting in a percentage of correct guesses that is significantly greater than chance indicates the presence of some implicit knowledge, but it does not rule out the existence of explicit knowledge on other trials. Conversely, a zero-correlation criterion analysis that provides evidence of significantly greater confidence for correct than for incorrect decisions indicates the presence of some explicit knowledge, but it does not rule out the existence of implicit knowledge in the same trials. If both criteria are statistically significant then there is evidence for both implicit and explicit knowledge.

Researchers have suggested several features according to which implicit and explicit knowledge are qualitatively different (see Dienes & Berry, 1997). The present article is concerned only with one such feature, namely the relative resistance of implicit knowledge to secondary tasks. It has been suggested that implicit learning and knowledge should be less affected by the imposition of some secondary tasks than is explicit knowledge (contrast Shanks & Channon, 2002; see the chapters in Jiménez, 2003, for critical discussion). For example, Roberts and MacLeod (1995), who used the same secondary task as the one used in the present research, found that the dual-task condition interfered with participants' ability to report the criterial elements of a conceptual rule. In addition, Waldron and Ashby (2001) found that a secondary task interfered with the learning of simple explicit conceptual rules, whereas it did not impair the learning of complex implicit rules. Moreover, in an artificial-grammar-learning study, Dienes et al. (1995) found that a secondary task interfered with classification of novel strings only in those cases in which participants were confident about their responses, not when they gave guess responses. Performance is robust to the imposition of secondary tasks when people have the least metaknowledge.

The secondary task manipulation helps to validate the use of the guessing and zero-correlation criteria. There is no methodology for measuring conscious and unconscious knowledge where the methodology self-evidently measures what it purports to measure in a theory-free way. On the one hand, a common criticism of subjective measures is that they may be affected by response biases (a person may say they are guessing when they actually feel slightly confident; e.g., Merikle & Reingold, 1992); on the other hand, response biases may be a minimal problem in a given experimental context—that is, the measures may largely track what they claim to track. The way to resolve this issue is to show that the measures provide the pattern of results expected by a theory of conscious and unconscious knowledge. On the common theory that the acquisition of conscious knowledge requires the use of working memory, a secondary task that loads working memory should be able to impair the acquisition of conscious knowledge while leaving the acquisition of implicit knowledge intact. Finding this pattern would provide evidence for the validity of the subjective measures (Dienes, 2004). (This logic is exactly the same as that used by Jacoby, 1991, where dissociations of measured processes are used to validate the way of measuring the processes.) The measures could then be used with some confidence to assess the effect of prior knowledge on implicit and explicit learning. As mentioned above, an issue that current implicit learning and categorization models and research have not managed to resolve is whether or not implicit category learning may be affected by conceptual prior knowledge. This question was the motivation for the present research.

OVERVIEW OF EXPERIMENTS

Both current experiments used Murphy and Allopenna's (1994) experimental paradigm in order to study the effect of prior knowledge on concept learning. In this paradigm, participants had to learn two different kinds of category structure, which had the same family resemblance structure and identical features, but differed in the relations among features. Each exemplar of each category structure consisted of five descriptions taken from familiar everyday domains (i.e., animals, vehicles, and buildings). During training, participants had to distinguish between categories of a category pair. In one condition, the category features were meaningful, but had no preexisting connections among them, whereas in the other condition, the same features were combined such that they described a coherent kind of object. For example, in the first condition, participants saw exemplars that contained features, such as "Made in Africa" and "Drives in jungles" in one category and "Made in Norway" and "Drives on glaciers" in the other category, that were integrated by people's general knowledge about different kinds of vehicles. In the second condition, however, participants saw category exemplars with unrelated features, such as "Made in Africa" and "Lives alone" in one category and "Made in Norway" and "Lives in groups" in the other category. Murphy and Allopenna (1994) found that the coherent categories that were consistent with prior knowledge were easier to learn than the incoherent categories that consisted of semantically rich but unrelated features.

Accordingly, in the present experiments the comparison between the *coherent* and the *incoherent* condition is used to study the comparison between the existence and the absence of a facilitative effect of prior knowledge. One might argue that the coherent/incoherent manipulation is not very strong, because even the incoherent categories involve some prior knowledge, since their features' semantic content renders them quite meaningful. However, Murphy and Allopenna (1994) tested this possibility and showed that it is the relations among features rather than the familiarity or the semantic content of features that have the strongest effect. Thus, the coherent/incoherent manipulation can satisfactorily address questions regarding prior knowledge as studied in most concept-learning experiments.

The effect of prior knowledge on implicit and explicit learning was evaluated using the zero-correlation and guessing criteria as measures of implicitness. If prior knowledge affects implicit learning, the coherent condition will provide evidence of greater implicit knowledge in terms of at least one of the two metaknowledge criteria.

The dual-task methodology was used to investigate how a secondary task affects the measures of implicit and explicit learning. The secondary task that was used in the present experiments was the one that was originally designed by Hitch and Baddeley (1976) and was shown to interfere with a verbal reasoning task. Thus, it is expected that participants in the dual-task condition will demonstrate less explicit knowledge (as measured by the zero-correlation criterion) than will participants in the single-task condition.

EXPERIMENT 1

Method

Participants

A total of 96 students from Sussex University participated for payment in Experiment 1. Each participant was randomly assigned to one of the four conditions.

Experimental design

The experiment followed a 2 (prior knowledge: coherent vs. incoherent) × 2 (task load: single vs. secondary) between-subjects design and included two phases, the *acquisition phase* and the *test* *phase*. In the first phase, participants were presented with category exemplars, each containing five features. Performance in this phase was scored by calculating the number of exemplars required until participants reached the learning criterion—that is, until they were able to correctly categorize 22 consecutive exemplars or until 32 blocks of 22 exemplars had been presented. The difference between the present criterion and Murphy and Allopenna's (1994) criterion is that in Murphy and Allopenna's study training stopped when participants were able to correctly categorize all 22 exemplars of a block. By contrast, in the present research, training stopped when participants were able to correctly classify 22 exemplars in a row in an attempt to reduce the time of training, which (especially in the dual-task condition) could be quite long. Following Murphy and Allopenna (1994, Exp. 2), the test phase involved a timed categorization task on single-feature exemplars, which allowed a test of participants' implicit and explicit knowledge of individual features. Performance in this phase was measured in terms of the percentage of correct responses.

Stimuli

Participants learned a pair of categories, called Category 1 and Category 2. The categories of the present experiment were identical to those used by Murphy and Allopenna (1994, Exp. 2). An example of the structure of the category members in the coherent and incoherent conditions can be found in Table 1. The features of the remaining coherent categories can be found in the Appendix.

The features of all categories were short phrases (e.g., "Made in Africa" and "Has wheels"). The categories in the coherent and the incoherent condition were constructed from the same features. What differentiated the two conditions, however, was the relations among features. In both conditions, participants had to learn one out of three category pairs that were constructed from features taken from three domains: vehicles, buildings, and animals. The features of the coherent categories, however, were combined such that they matched up with people's common knowledge about familiar categories (i.e., either vehicles, or buildings or animals). One example of a coherent category pair was "Made in Africa, Drives in jungles, Uses gasoline, Has wheels, Licence plate in front" (Category 1) and "Made in Norway, Drives on glaciers, Uses diesel, Has treads, Licence plate in front" (Category 2). As can be noticed from the above example, the coherent categories consisted of features, all of which were taken from the same domain (e.g., the domain of vehicles) and were thus expected to activate participants' prior knowledge of that domain. In the incoherent condition, however, the features were collected together from all three domains and were thus completely unrelated to each other. Accordingly, the incoherent categories could not activate useful prior knowledge. In the incoherent condition, the three category pairs were constructed by using each feature of each of the three domains only once, combined with features of the other domains. One example of an incoherent category pair was: "Lives alone, Made in Africa, Fish kept there as pets, Four door, Modern furniture" (Category 1) and "Lives in groups, Made in Norway, Birds kept there as pets, Four door, Victorian furniture" (Category 2).

Each category pair in both conditions was structured in the same way. In particular, each pair was constructed from nine binary stimulus dimensions, six of which were called *characteristic* because their features described a specific category and always appeared in that category. The remaining three dimensions were called *random* because their features appeared about equally often in the two contrasting categories. The features of 5 (out of the 6) characteristic dimensions were called *frequent* because they occurred many times within a category. The features of the sixth characteristic dimension were called *infrequent* as they appeared only once in a category.

Training exemplars. A total of 22 exemplars (11 in each category) were constructed for the acquisition phase. Each of the 20 out of the 22 exemplars contained three frequent features and two random features. For instance, in the coherent category exemplar that was provided above, the

Table 1. *The structure of one of the three category pairs in each knowledge condition*

	Category 1		*Category 2*
Condition	*Characteristic features*	*Random features*	*Characteristic features*
Incoherent	Lives alone	Two door, Four door	Lives in groups
	Made in Africa	Hibernates, Doesn't hibernate	Made in Norway
	Thick heavy walls	Victorian furniture, Modern furniture	Thin light walls
	Has a barbed tail		Has a furry tail
	Fish kept there as pets		Birds kept there as pets
	Convertible[a]		Nonconvertible[a]
Coherent	Made in Africa	Two door, Four door	Made in Norway
	Drives in jungles	Licence plate in front, Licence plate in back	Drives on glaciers
	Green	Uses gasoline, Uses diesel	White
	Lightly insulated		Heavily insulated
	Has wheels		Has treads
	Convertible[a]		Nonconvertible[a]

Note: This table presents only the features of one of the three category pairs that were constructed in each knowledge condition. As can be seen, only a few features are common in the category pairs of the two conditions. The majority of the features of the present incoherent category pair are derived from the other two coherent category pairs that are provided in the Appendix.
[a]Infrequent features.

features "Made in Africa", "Drives in jungles", and "Has wheels" are frequent characteristic features of Category 1, whereas the remaining two features are random. In the incoherent category exemplar provided, the features "Lives alone", "Made in Africa", and "Fish kept there as pets" are frequent characteristic features of Category 1, with the other two being random. The number of all possible combinations of three out of the five frequent features for a given category is 10. Each of these 10 combinations was used only once within each category. Each of the remaining 2 (out of the 22) exemplars contained an infrequent feature combined with two frequent features and two random features. One of these two exemplars belonged to Category 1 and the other one to Category 2. Overall, some frequent features appeared in 6 and others in 7 training exemplars of the block of 22 exemplars, whereas each of the two infrequent features appeared only in 1 exemplar of the block. In addition, some random features occurred seven times and others eight times within a category. Category learning proceeded in blocks of 22 exemplars, though learning could stop before the end of a block if the learning criterion was reached.

Test exemplars. The test phase consisted of 36 single-feature exemplars. Each feature was tested twice to increase the sensitivity of analyses involving the individual features. This procedure resulted in 20 exemplars, each consisting of one of the frequent features of a given category, 12 exemplars, each consisting of one of the random features, and 4 exemplars, each consisting of one of the infrequent features. Performance in the test phase was measured only in terms of participants' accuracy on the characteristic features. The feature frequency manipulation was used to address issues not taken up here and are not analysed further.

Procedure

Participants were randomly assigned to one of the four conditions and were instructed to distinguish between examples of two categories. Each participant learned only one out of the six (i.e., three coherent and three incoherent) pairs of categories. The assignment of participants to category pairs was random. In the acquisition phase, participants were shown exemplars presented one at a time and were requested to indicate whether they thought they belonged to Category 1 or Category 2. They had 7 seconds to give each response and provide a confidence rating on a scale from 50 (complete guessing) to 100 (complete certainty). In cases where they exceeded this time limit, their response was considered as a missed trial. After each response and confidence rating, feedback was provided for 2 seconds. Exemplars were presented in a random order within a block. The order in which the features appeared in each exemplar was also random. Participants were required to continue responding until they were able to correctly categorize 22 exemplars in a row or until 32 blocks of 22 exemplars had been presented.

Participants allocated to the dual-task conditions were instructed to respond as accurately as possible on an additional task. Prior to each category exemplar, they were shown a six-digit string for 3 seconds, which they had to rehearse aloud until a second string was presented at the end of each trial (i.e., after each response on the category-learning task and the feedback that was provided). At that point, they were asked to decide whether the two strings were exactly the same or not. Each string contained the digits 1 to 9 presented in a random order. Only half of the strings that followed the category examples were exactly the same as the strings that preceded the examples. In the remaining half of these strings, two of the digits were changed with equal probability in each position of the string. Feedback about participants' accuracy on the secondary task was provided immediately after each response.

After the acquisition phase, the last half of participants run were presented with the *intermediate* phase—that is, an extra block of 22 exemplars, in which no feedback was provided, and which allowed an unbiased test of participants' level of learning. Moreover, participants did not perform the secondary task in this phase. After the acquisition (or the intermediate) phase, all participants entered the test phase, in which they were asked to categorize exemplars that contained only descriptions of single features. Participants were required to respond as quickly and accurately as possible and give their confidence rating for each response, without, however, having the chance to receive any feedback about their accuracy. The order of test exemplars was randomized for each participant. Only the data of participants that managed to correctly categorize 22 consecutive exemplars in the acquisition phase were analysed in this phase to ensure equivalent levels of learning had been achieved in the different groups. Participants did not perform the secondary task in the test phase.

Results

Acquisition phase

Table 2 shows the number of trials required for reaching the learning criterion. A 2(prior knowledge: coherent vs. incoherent) $\times$ 2 (task load type: single vs. secondary) analysis of variance (ANOVA) showed that the coherent group required fewer trials than the incoherent group ($M = 112$, $SD = 97$ vs. $M = 307$, $SD = 218$), $F(1, 92) = 38.14$, $p < .001$, $\eta_p^2 = .293$.

Thus, Experiment 1 replicated Murphy and Allopenna's (1994) finding that the interrelation of features and their consistency with prior knowledge facilitates concept learning. In addition, the single-task group required significantly fewer trials to reach criterion than did the dual-task group ($M = 140$, $SD = 169$ vs. $M = 280$, $SD = 194$), $F(1, 92) = 19.51$, $p < .001$, $\eta_p^2 = .175$. The interaction of the two variables was not statistically significant, $F < 1$, $\eta_p^2 = .002$. A total of 6 participants (2 in the incoherent single-task condition and 4 in the incoherent dual-task condition) were presented with all 32 blocks of 22 exemplars without managing to correctly categorize 22 consecutive exemplars.

Table 2. *The average mean number of trials required for reaching the learning criterion in Experiment 1*

Knowledge types	*Task load types*	*M*	*SD*
Incoherent	Single	230	202
	Secondary	384	210
Coherent	Single	50	27
	Secondary	175	101

Intermediate phase

Performance in this phase was measured in terms of the number of correct responses in the block of 22 exemplars for only the last half of participants (see Table 3). The scores of 2 participants who had exhausted all 32 blocks without being able to correctly categorize 22 exemplars in a row were eliminated from this analysis.

Performance in the single-task condition did not differ significantly from performance in the dual-task condition ($M = 20.3$, $SD = 1.8$ vs. $M = 20.9$, $SD = 1.2$), $F(1, 42) = 2.16$, $p = .149$; 95% CI: $-1.54 \leq \mu_1 - \mu_2 \leq 0.23$; $\eta_p^2 = .049$. Moreover, the performance of the coherent group did not differ significantly from the performance of the incoherent group ($M = 21.0$, $SD = 1.0$ vs. $M = 20.1$, $SD = 1.9$), $F(1, 42) = 3.16$, $p = .083$; 95% CI: $-1.71 \leq \mu_1 - \mu_2 \leq 0.06$; $\eta_p^2 = .070$. Similarly, the interaction of the two variables was not statistically significant, $F < 1$, $\eta_p^2 = .019$. Thus, participants in all conditions learned the categories equally well.

Test phase

A two-way ANOVA, with prior knowledge and task load type entered as variables, was used to analyse the percentage of correct responses for the single-feature items. As shown in Table 4, the 6 participants who saw 32 blocks without being able to correctly categorize 22 consecutive exemplars in the acquisition phase were excluded from the analysis. The secondary task interfered with participants' ability to learn the individual features ($M = 75.9$, $SD = 18.4$ in the dual-task condition vs. $M = 84.9$, $SD = 13.4$ in the single-task condition), $F(1, 86) = 13.19$, $p < .001$, $\eta_p^2 = .133$.

Moreover, the coherent group performed better than the incoherent group ($M = 89.8$, $SD = 12.1$ vs. $M = 69.8$, $SD = 14.6$), $F(1, 86) = 57.96$, $p < .001$, $\eta_p^2 = .403$. The interaction of the two variables was not statistically significant, $F < 1$, $\eta_p^2 = .007$.

Confidence rates in the acquisition phase

To measure the amount of explicit knowledge in terms of the zero-correlation criterion, an ANOVA on the difference in confidence between correct and incorrect responses was used. A total of 3 participants who did not give any incorrect responses were not included in this analysis.

The secondary task did decrease the amount of explicit knowledge, as expected (see Table 5). The single-task group demonstrated a significantly greater difference in confidence between correct and incorrect responses than did the dual-task group ($M = 18.7$, $SD = 9.5$ vs. $M = 9.4$, $SD = 6.3$), $F(1, 89) = 34.82$; $p < .0005$, one-tailed; $\eta_p^2 = .281$. Prior knowledge did not affect the amount of explicit knowledge, $F(1, 89) = 1.30$, $p = .257$, $\eta_p^2 = .014$. However, the prior knowledge by task load interaction was statistically significant, $F(1, 89) = 8.48$, $p = .005$, $\eta_p^2 = .087$. In particular, prior knowledge increased the amount of explicit knowledge only in the single-task condition, $F(1, 43) = 5.78$, $p = .021$, $\eta_p^2 = .118$, and not in an attention-demanding condition—namely, the dual-task condition, $F(1, 46) = 2.50$, $p = .121$; 95% CI: $-0.78 \leq \mu_1 - \mu_2 \leq 6.45$; $\eta_p^2 = .051$. The fact that all 3 participants who gave no incorrect responses, and were thus dropped from this analysis, belonged to the coherent single-task condition is in line with the above finding. Assuming

Table 3. *Mean number of correct responses in the intermediate phase*

Knowledge types	*Task load types*	*M*	*N*	*SD*
Incoherent	Single	19.7	12	2.2
	Secondary	20.7	10	1.5
Coherent	Single	20.8	12	1.1
	Secondary	21.1	12	0.8

Note: For only the last half of participants run in Experiment 1.

Table 4. *Mean percentage of correct responses in the test phase of Experiment 1*

Knowledge types	*Task load types*	*M*	*N*	*SD*
Incoherent	Single	75.4	22	12.5
	Secondary	63.8	20	14.6
Coherent	Single	93.6	24	6.6
	Secondary	85.9	24	15.0

Table 5. *The mean values of metaknowledge in the acquisition phase of Experiment 1, as measured by the zero-correlation and guessing criteria*

Metaknowledge criteria	*Knowledge types*	*Task load types*	*Confidence difference*	*M*	*N*	*SD*
Zero-correlation[a]	Incoherent	Single	80.5 − 64.8	15.6	24	7.1
		Secondary	80.3 − 69.5	10.9	24	6.9
	Coherent	Single	83.8 − 61.7	22.1	21	10.8
		Secondary	73.1 − 65.1	8.0	24	5.5
Guessing[b]	Incoherent	Single		50.2	24	11.1
		Secondary		63.6	24	14.8
	Coherent	Single		56.2	23	24.2
		Secondary		63.9	24	16.8

[a]Difference between confidence when correct and confidence when incorrect. [b]Percentage of guesses that were correct.

that a lack of incorrect responses is associated with an increased amount of explicit knowledge, the missing values in the coherent single-task condition imply increased conscious awareness in that condition. The mean value of the explicit knowledge of participants of the coherent group allocated to the dual-task condition (8.0) was greater than zero, $t(23) = 7.16$, $p < .001$, $r^2 = .691$. Further, this experiment provided evidence of explicit knowledge overall, since the mean value of explicit knowledge ($M = 13.9$, $SD = 9.2$) was significantly greater than zero, $t(92) = 14.55$, $p < .001$, $r^2 = .697$, a result that makes perfect sense considering the high learning criterion to which participants were trained. Moreover, evidence of explicit knowledge was found even in the dual-task condition, $t(47) = 10.36$, $p < .001$, $r^2 = .696$.

Implicit knowledge in terms of the guessing criterion was measured by analysing the percentage of guess responses (i.e., responses accompanied by a confidence rating of exactly 50%) that were correct. One participant was excluded, as he did not guess at all.

Table 6 shows the number of correct and incorrect guesses given by participants in the four conditions. As shown in Table 5, the dual-task group was significantly more accurate when they thought they were guessing than was the single-task group ($M = 63.8$, $SD = 15.6$ vs. $M = 53.1$, $SD = 18.7$), $F(1, 91) = 8.89$, $p = .004$, $\eta_p^2 = .089$. A t test showed that the overall percentage of guesses that were correct ($M = 58.5$, $SD = 18.0$) was significantly greater than chance, $t(94) = 4.62$, $p < .001$, $r^2 = .185$, providing evidence of implicit knowledge. Moreover, evidence of implicit knowledge was provided only in the dual-task condition, $t(47) = 6.10$, $p < .001$, $r^2 = .442$, and not in the single-task condition $t(46) = 1.15$, $p = .258$ (the 95% CI for the percentage of correct guesses went from 47.6% to 58.6%), $r^2 = .028$. However, the coherent group did not differ significantly from the incoherent group ($M = 60.1$, $SD = 20.9$ vs. $M = 56.9$, $SD = 14.6$), $F < 1$, $\eta_p^2 = .008$. Similarly, the interaction of prior knowledge with task load, $F < 1$, $\eta_p^2 = .007$, was not statistically significant. Thus, prior knowledge did not affect the amount of implicit knowledge of the whole exemplars.

Confidence rates in the test phase

The zero-correlation criterion was measured by taking the difference in confidence between correct and incorrect responses for all the characteristic-feature items. Data were missing for 18 participants who gave no incorrect responses and the 6 participants (2 in the incoherent single-task condition and 4 in the incoherent dual-task condition) who had not categorized 22 consecutive training exemplars correctly.

The dual task decreased explicit knowledge of the test items, as measured by the zero-correlation criterion, $F(1, 68) = 3.29$; $p = .037$, one-tailed; $\eta_p^2 = .046$ ($M = 20.5$, $SD = 12.8$ in the single-task group vs. $M = 15.8$, $SD = 11.8$ in the dual-task group; see Table 7). Prior knowledge did not

Table 6. *Mean number of guess responses in the acquisition phase of Experiment 1*

		Number of guesses		Number of correct guesses		Number of incorrect guesses	
Knowledge types	*Task load types*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Incoherent	Single	37.3	51.4	18.8	25.3	18.5	26.4
	Secondary	77.9	117.7	43.3	63.2	34.6	55.4
Coherent	Single	8.0	7.2	4.2	3.4	3.8	4.6
	Secondary	44.9	51.5	26.0	29.5	18.9	22.6

affect participants' explicit knowledge ($M = 19.2$, $SD = 13.7$ in the coherent group vs. $M = 17.3$, $SD = 11.4$ in the incoherent group), $F < 1$, $\eta_p^2 = .009$. Similarly, the interaction of the two variables was not statistically significant, $F(1,\ 68) = 1.95$, $p = .167$, $\eta_p^2 = .028$. The overall mean value of explicit knowledge ($M = 18.1$, $SD = 12.4$) was significantly greater than zero, $t(71) = 12.40$, $p < .001$, $r^2 = .684$, thus providing evidence of explicit knowledge of the test items. Evidence of explicit knowledge was found even in the dual-task condition, $t(35) = 8.06$, $p < .001$, $r^2 = .650$.

As can be noticed from Table 7, most of the missing values occurred in the coherent condition. Assuming that missing values because of a lack of incorrect responses are associated with an increased amount of explicit knowledge, the coherent group's increased number of missing data suggests that this group might have acquired more explicit knowledge of the test items than did the incoherent group.

Participants' percentage of guesses that were correct while classifying the test items was used to measure implicit learning in terms of the guessing criterion. Data were missing for 15 participants, 6 of whom (2 in the incoherent single-task condition and 4 in the incoherent dual-task condition) were the participants who had not managed to correctly categorize 22 training exemplars in a row. The remaining 9 participants did not guess at all in the test phase. As can be seen in Table 7, the number of missing values was virtually the same in both knowledge groups as well as in both task load groups.

Table 8 presents the overall number of guesses in the four conditions. As Table 7 shows, the coherent group was significantly more accurate when they thought they were literally guessing than was the incoherent group ($M = 73.4$, $SD = 27.6$ vs. $M = 50.8$, $SD = 23.6$), $F(1,\ 77) = 15.57$, $p < .001$, $\eta_p^2 = .168$. The overall percentage of guess responses that were correct ($M = 61.9$, $SD = 27.9$) was significantly greater than chance, $t(80) = 3.84$, $p < .001$, $r^2 = .156$, providing evidence of implicit knowledge in the test phase. Further, the percentage of guesses that were

Table 7. *The mean values of metaknowledge in the test phase of Experiment 1, as measured by the zero-correlation and guessing criteria*

Metaknowledge criteria	*Knowledge types*	*Task load types*	*Confidence difference*	*M*	*N*	*SD*
Zero-correlation[a]	Incoherent	Single	78.7 − 60.9	17.8	21	11.4
		Secondary	77.5 − 60.9	16.6	19	11.7
	Coherent	Single	84.8 − 60.6	24.2	15	14.1
		Secondary	78.1 − 63.2	14.9	17	12.2
Guessing[b]	Incoherent	Single		53.2	22	23.0
		Secondary		47.9	19	24.6
	Coherent	Single		68.3	19	32.3
		Secondary		78.0	21	22.5

[a]Difference between confidence when correct and confidence when incorrect. [b]Percentage of guesses that were correct.

Table 8. *Mean number of guess responses in the test phase of Experiment 1*

		Number of guesses		*Number of correct guesses*		*Number of incorrect guesses*	
Knowledge types	*Task load types*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Incoherent	Single	6.5	5.3	3.6	3.4	3.0	2.4
	Secondary	8.6	5.7	3.9	2.8	4.7	3.3
Coherent	Single	3.9	2.5	2.8	2.0	1.1	1.0
	Secondary	6.2	5.7	4.7	5.3	1.5	1.7

correct was significantly greater than chance only in the coherent condition, $t(39) = 5.35$, $p < .001$, $r^2 = .424$, and not in the incoherent condition, $t(40) = 0.205$, $p = .84$, $r^2 = .001$ (the 95% CI for the percentage of correct guesses went from 43.3% to 58.2%). Participants acquired implicit knowledge of the individual features only when they were aided by prior knowledge. The effect of task load ($M = 60.2$, $SD = 28.4$ in the single-task condition vs. $M = 63.7$, $SD = 27.7$ in the dual-task condition), $F < 1$, $\eta_p^2 = .002$, and its interaction with prior knowledge, $F(1, 77) = 1.74$, $p = .192$, $\eta_p^2 = .022$, were not statistically significant. Thus, prior knowledge increased implicit knowledge in both task load conditions, which implies that the task load type did not affect the coherent group's strategies while learning the individual features.

Discussion

Experiment 1 replicated Murphy and Allopenna's (1994) finding that interfeature relations that are consistent with prior knowledge or a theory facilitate concept learning. In addition, the current results confirmed the hypothesis that the secondary task discourages explicit learning (e.g., Roberts & MacLeod, 1995). In particular, the secondary task decreased explicit learning (as measured by the zero-correlation criterion) in both phases, but not implicit learning (as measured by the guessing criterion) in either the learning or the test phase. This pattern helps validate the use of the zero correlation and guessing criteria to measure conscious and unconscious knowledge.

The main issue addressed by the present experiment is the effect of prior knowledge on implicit and explicit learning. The most interesting finding is that prior knowledge promoted implicit knowledge in the test phase, which contradicts the argument that implicit learning is a passive process independent of any theory-based knowledge. We discuss this as well as all other findings concerning the effect of prior knowledge on implicit and explicit learning below. But first, we briefly consider the categorization performance results in the three phases.

Categorization performance in the three phases

The learning data showed that coherent categories, whose features could be tied together by integrative knowledge, were easier to learn than incoherent categories with unrelated feature combinations. Moreover, the dual-task group had a significantly longer learning phase than that of the single-task group, a result that makes perfect sense considering the attentional load of the former group. By the end of the learning phase, however, all participants, irrespective of the condition they were allocated to, had learned the whole category exemplars equally well, as evidenced from the fact that the intermediate-phase results revealed no significant differences between the different groups.

On the other hand, the test results showed that the coherent group was more accurate while categorizing the single-feature items than was the incoherent group, despite the fact that the two groups had learned the whole category exemplars to an equivalent degree. Similarly, Murphy and

Allopenna (1994, Exp. 2) found an advantage of the group that learned the coherent categories over the group that learned the incoherent categories while categorizing the single-feature items, despite the fact that the two groups performed fairly similarly (in their Experiment 1) while categorizing different types of five-feature test exemplars (including some of the exemplars that were presented during learning). However, according to Murphy and Allopenna, the coherent group did not learn much about the individual features (despite their overall advantage in categorizing them). This interpretation is based on their finding that the coherent group demonstrated less sensitivity to frequency information about the individual features than did the incoherent group (but see Spalding & Murphy, 1999). The authors concluded that the coherent group did not pay much attention to the individual features, as they could also form and rely more on abstract descriptions of the categories, which do not necessarily include all specific feature–category associations. (We discuss below how this interpretation relates to the differences in implicit and explicit knowledge between the two groups.)

The test results also showed that the single-task group categorized the single-feature items more accurately than did the dual-task group, despite the fact that the two groups had learned the whole exemplars equally well. Similarly, Roberts and MacLeod (1995), who used the same secondary task as the present one (in a different concept-learning paradigm), found that the secondary task impaired participants' ability to decompose a conceptual conjunction into its constituent properties, even though the single- and dual-task groups had learned the categories equally well. The authors explained their results in terms of a qualitative difference in knowledge representation under the two task load conditions (see the General Discussion for a more detailed description of this explanation). Further, the present results are in line with Smith and Shapiro's (1989) finding that, under dual-task conditions, participants used holistic—that is, family-resemblance-based—relations among category exemplars, whereas participants in the single-task condition were strongly analytic. The authors concluded that the secondary task destroys participants' capacity to analyse, in that it reduces the cognitive resources that are available to perform the task. Thus, the impaired ability to classify the individual features that the dual-task group demonstrated may be explained in terms of the fact that they focused on family resemblance relations among exemplars rather than on the individual features.

Prior knowledge effects on explicit and implicit learning

In the learning phase, prior knowledge increased explicit learning as measured by the zero-correlation criterion, only in the single-task condition. Thus, it seems that the emergence of explicit knowledge is allowed only when attentional resources are available. The metaknowledge results of the learning phase also showed that prior knowledge did not influence implicit learning during training.

On the other hand, prior knowledge promoted implicit knowledge, as measured by the guessing criterion, in the test phase. In fact, only the coherent (and not the incoherent) group's knowledge of the individual features satisfied the guessing criterion of implicitness. One possible interpretation of the finding that prior knowledge promoted implicit knowledge only in the test phase and not in the learning phase is that the knowledge representations in the two phases may be of different quality. In particular, knowledge of individual features (like the knowledge in the test phase) may not be of a sufficiently good quality to support conscious awareness, whereas representations formed on the basis of a number of semantically interrelated features (like the representations in the learning phase) may be good enough to support conscious awareness. Most interestingly, the finding that the coherent group acquired implicit knowledge of the individual features prima facie contradicts the argument that implicit learning is independent of prior theory-based knowledge (e.g., Hayes & Broadbent, 1988) and is more supportive of the view that implicit knowledge may be affected by prior knowledge (e.g., Sun, 2000).

Another possible explanation of the coherent group's implicit knowledge of the individual features is in terms of participants' reliance on a general theme and the overall similarity of whole exemplars to that theme rather than on individual features. Murphy and Allopenna (1994) suggested that the coherent group could infer the correct response once they saw a feature in the test phase by relying on its relevance to their schema or theory, even if they never accessed that feature during learning. This explanation is in line with the interpretation proposed above, because, if the coherent group did not pay much attention to the individual features while learning the categories, it is highly likely that their knowledge of individual features was not sufficiently good to support conscious awareness.

One might be tempted to argue that the coherent group's inferences in the test phase were explicit inferences. But if participants' theories allowed them to make explicit inferences while classifying the single-feature items, then they should feel some confidence about their responses and not rate them as pure guesses—participants were clearly instructed that a guess meant that their response was based on no information whatsoever. Prior knowledge may have allowed participants to make implicit inferences about the individual features, which explains the coherent group's increased implicit knowledge in the test phase.

Summary

The main finding of Experiment 1 was that prior knowledge facilitated the acquisition of implicit knowledge of individual features. However, one might argue that the coherent group acquired implicit knowledge of the features in contrast to the incoherent group who acquired explicit knowledge because the former had reached the learning criterion fairly soon and, accordingly, saw a limited number of exemplars in comparison with the latter. Maybe the relevant factor is number of training trials rather than coherent versus incoherent structure per se. This possibility is tested in the following experiment. Thus, unlike Experiment 1, Experiment 2 does not aim at equating learning among all participants. Instead, Experiment 2 aims at equating the number of times that participants were exposed to the category features.

EXPERIMENT 2

Method

Participants

A total of 96 undergraduates from Sussex University participated in this experiment for payment. Each participant was randomly assigned to one of the four conditions.

Experimental design

Like Experiment 1, this experiment followed a 2 (prior knowledge: coherent vs. incoherent) $\times$ 2 (task load: single vs. secondary) between-subjects design and consisted of two phases, the *acquisition phase* and the *test phase.* The differences between the two phases of the present experiment and those of Experiment 1 are described below.

Stimuli and procedure

The stimuli of this experiment were the same as those used in Experiment 1. The total of 22 exemplars used in Experiment 1 was randomly divided in two sets of 11 exemplars: Set A and Set B. Each set contained 10 exemplars with frequent features, some of which belonged to Category 1 and the others to Category 2, and 1 of the two exemplars containing one infrequent feature, which belonged either to Category 1 or to Category 2. Participants were presented with 6 sets of 11 category exemplars, in which feedback about the correct response was provided at the end of each trial. Each of those sets was followed by a set of 11 category exemplars that provided no feedback. Thus, all participants were presented with an overall number of 132 exemplars, only half of which provided feedback. In particular, in order to counterbalance the experiment, half of the participants were first presented with Set A, in which feedback was provided for 2 seconds. Then, these participants were presented with Set B, in which no information about their accuracy was provided. Subsequently, they were shown the exemplars of Set B, but this time they had the chance to see the correct response for each exemplar. Set B was then followed by Set A, in which no feedback was given. This procedure was repeated three times. The remaining participants saw the same sets, but in reverse order. Thus, stimuli presentation now started with Set B (with feedback) and so on. In the first half of participants run, the dual-task group was asked to perform the secondary task only in the sets with feedback, whereas in the last half of participants, the dual-task group had to perform the secondary task in both kinds of sets. The sets with no feedback were introduced in this experiment in order to examine the amount of knowledge acquired after each set of training. Moreover, the separate sets were used because Experiment 2 originally aimed at studying one more issue—namely, the time course of implicit and explicit learning. However, this issue is not examined in the present article. Similarly, the feedback/no-feedback distinction is not analysed further since it did not affect implicit or explicit learning (see the Results section). The procedure in the test phase was the same as that of Experiment 1. However, the last half of participants run in this experiment were presented with 14 single-feature exemplars (i.e., 10 frequent and 4 infrequent features) instead of 36 single-feature exemplars in an attempt to reduce the time of testing, as these participants also classified 28 five-feature exemplars divided in five types. Following Murphy and Allopenna (1994), these exemplars were originally used to test how well participants learned the category structure. (Performance on these exemplars is not analysed here because of space restriction.) All above manipulations were balanced across conditions.

Results

Acquisition phase

Performance was measured in terms of the percentage of correct responses. As expected, the coherent group was more accurate than the incoherent group ($M = 72.5$, $SD = 17.3$, vs. $M = 62.5$, $SD = 15.9$), $F(1, 92) = 12.99$, $p = .001$, $\eta_p^2 = .124$ (see Table 9).

Moreover, the single-task group gave more correct responses than the dual-task group ($M = 77.1$, $SD = 14.2$ vs. $M = 58.0$, $SD = 14.7$), $F(1, 92) = 47.02$, $p < .001$, $\eta_p^2 = .338$. Like in Experiment 1, the interaction of the two variables was not significant, $F < 1$, $\eta_p^2 < .001$. The analysis in which feedback (feedback vs. no-feedback sets) was entered as a within-subjects variable showed that the effect of feedback was also significant, $F(1, 92) = 9.42$, $p = .003$, $\eta_p^2 = .093$, with participants giving a greater percentage of correct responses in the sets without feedback than in the sets with feedback (68.8% vs. 66.2%). This result is most probably due to the fact that each set without feedback followed each set with feedback. None of the interactions of feedback with the other variables was statistically significant, all $ps > .20$.

Test phase

As Table 9 shows, the coherent group gave a significantly greater percentage of correct responses while categorizing the test items than did the incoherent group ($M = 77.1$, $SD = 20.0$ vs. $M = 55.3$, $SD = 17.1$), $F(1, 92) = 36.60$, $p < .001$, $\eta_p^2 = .285$. Moreover, the single-task group was more accurate than the dual-task group ($M = 72.5$, $SD = 18.8$ vs. $M = 60.0$, $SD = 22.4$), $F(1, 92) = 12.13$, $p = .001$, $\eta_p^2 = .116$. The interaction of the two variables was not statistically significant, $F < 1$, $\eta_p^2 = .002$.

Table 9. *Mean percentage of correct categorization in the acquisition and the test phases of Experiment 2*

Percent correct	*Knowledge types*	*Task load types*	*M*	*SD*
Acquisition phase	Incoherent	Single	72.1	13.6
		Secondary	52.8	11.8
	Coherent	Single	82.0	13.2
		Secondary	63.1	15.7
Test phase	Incoherent	Single	62.4	16.9
		Secondary	48.2	14.3
	Coherent	Single	82.6	15.0
		Secondary	71.7	23.1

Confidence rates in the acquisition phase

The amount of explicit knowledge in terms of the zero-correlation criterion was measured by estimating the difference in confidence between correct and incorrect responses. The means are shown in Table 10. As expected, the secondary task decreased the amount of explicit knowledge ($M = 4.9$, $SD = 9.1$ in the dual-task condition vs. $M = 17.4$, $SD = 11.8$ in the single-task condition), $F(1, 92) = 37.76$; $p < .0005$, one-tailed; $\eta_p^2 = .291$. Moreover, the coherent group had a greater difference in confidence between correct and incorrect responses than did the incoherent group ($M = 14.9$, $SD = 13.7$ vs. $M = 7.4$, $SD = 9.3$), $F(1, 92) = 13.42$, $p < .001$, $\eta_p^2 = .127$. The mean values of explicit knowledge in the dual-task condition, $t(47) = 3.72$, $p = .001$, $r^2 = .227$, as well as in the incoherent condition, $t(47) = 5.54$, $p < .001$, $r^2 = .395$, were greater than zero, providing evidence of explicit knowledge in the two conditions. The overall mean value of explicit knowledge ($M = 11.1$, $SD = 12.2$) was also significantly greater than zero, $t(95) = 8.92$, $p < .001$, $r^2 = .456$. Unlike Experiment 1, which showed that prior knowledge increased the amount of explicit knowledge only in the single-task condition, this experiment found no significant interaction between the two variables, $F < 1$, $\eta_p^2 = .008$. (The analysis with feedback as a within-subjects variable found no significant effect of feedback, $F < 1$, $\eta_p^2 = .0003$. Similarly, none of the interactions of feedback with the other variables was significant, all ps $> .20$).

The percentage of guess responses that were correct was analysed to measure implicit knowledge in terms of the guessing criterion. The overall number of correct and incorrect guesses is presented in Table 11.

As can be seen in Table 10, the secondary task significantly increased the percentage of guesses that were correct ($M = 51.5$, $SD = 15.5$ in the dual-task group vs. $M = 43.7$, $SD = 19.3$ in the single-task group), $F(1, 92) = 4.81$, $p = .031$, $\eta_p^2 = .050$. However, the percentage of guesses that were correct in the dual-task condition did not differ significantly from chance, $t(47) = 0.653$, $p = .517$, $r^2 = .009$ (the 95% CI went from 47.0% to 56.0%). Moreover, overall, no evidence of implicit knowledge was found ($M = 47.6$, $SD = 17.8$), $t(95) = -1.34$, $p = .183$, $r^2 = .019$ (the 95% CI went from 44.0% to 51.2%). Like in Experiment 1, prior knowledge did not affect the percentage of guesses that were correct during learning ($M = 46.4$, $SD = 18.6$ in the coherent group vs. $M = 48.7$, $SD = 17.0$ in the incoherent group), $F < 1$, $\eta_p^2 = .004$. The interaction, $F(1, 92) = 2.11$, $p = .149$, $\eta_p^2 = .022$, was not statistically significant either. (The analysis that included feedback as a variable showed that feedback did not affect implicit knowledge, $F(1, 81) = 1.33$, $p = .253$, $\eta_p^2 = .016$. The interactions of feedback with the other variables were not significant either, Fs < 1.)

Table 10. *The mean values of metaknowledge in the acquisition phase of Experiment 2, as measured by the zero-correlation and guessing criteria*

Metaknowledge criteria	*Knowledge types*	*Task load types*	*Confidence difference*	*M*	*SD*
Zero-correlation[a]	Incoherent	Single	76.3 − 63.5	12.8	9.1
		Secondary	69.2 − 67.1	2.1	5.8
	Coherent	Single	86.4 − 64.4	22.0	12.6
		Secondary	75.1 − 67.3	7.8	11.0
Guessing[b]	Incoherent	Single		47.4	16.2
		Secondary		50.0	18.1
	Coherent	Single		40.0	21.6
		Secondary		52.9	12.6

[a]Difference between confidence when correct and confidence when incorrect. [b]Percentage of guesses that were correct.

Table 11. *Mean number of guess responses in the acquisition phase of Experiment 2*

		Number of guesses		*Number of correct guesses*		*Number of incorrect guesses*	
Knowledge types	*Task load types*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Incoherent	Single	23.5	23.6	11.7	12.4	11.8	11.4
	Secondary	30.8	20.8	16.6	11.7	14.3	9.8
Coherent	Single	11.6	11.6	5.5	5.7	6.2	6.1
	Secondary	25.8	23.6	13.7	13.0	12.1	11.2

Confidence rates in the test phase

Explicit knowledge of the test stimuli in terms of the zero-correlation criterion was measured by estimating the difference in confidence between correct and incorrect responses for the individual features. Data were missing for 9 participants who gave no incorrect responses at all. As shown in Table 12, the coherent group acquired more explicit knowledge than did the incoherent group (M = 16.5, SD = 15.2 vs. M = 7.8, SD = 12.4), $F(1, 83) = 9.16$, $p = .003$, $\eta_p^2 = .099$. Like in the test phase of Experiment 1, the fact that the most missing values appear in the coherent condition implies an increased amount of explicit knowledge in that condition. The secondary task decreased the amount of explicit knowledge (M = 6.0, SD = 11.5 in the dual-task group vs. M = 17.5, SD = 14.7 in the single-task group), $F(1, 83) = 16.86$; $p < .0005$, one-tailed; $\eta_p^2 = .169$. Like in the previous phase, the mean values of explicit knowledge of the incoherent group, $t(46) = 4.36$, $p < .001$, $r^2 = .292$, as well as of the dual-task group, $t(42) = 3.43$, $p = .001$, $r^2 = .219$, were greater than zero. Similarly, the overall mean value of explicit knowledge (M = 11.8, SD = 14.4) was greater than zero, $t(86) = 7.69$, $p < .001$, $r^2 = .408$, which provides evidence of explicit knowledge of the test items. The prior knowledge by task load interaction was not statistically significant, $F < 1$, $\eta_p^2 < .0001$.

Participants' implicit knowledge of the test items in terms of the guessing criterion was measured by analysing the percentage of guess responses that were correct. There were missing data for 15 participants (see Table 12) who did not guess at all. The number of correct and incorrect guesses is presented in Table 13.

As can be seen in Table 12, the coherent group was again significantly more accurate when they thought they were guessing than was the incoherent group (M = 61.6, SD = 28.2 vs. M = 48.7, SD = 28.4), $F(1, 77) = 4.34$, $p = .041$, $\eta_p^2 = .053$. Moreover, the percentage of guesses that were correct in the coherent condition was significantly greater than chance, $t(36) = 2.50$, $p = .017$,

Table 12. *The mean values of metaknowledge in the test phase of Experiment 2 as measured by the zero-correlation and guessing criteria*

Metaknowledge criteria	*Knowledge types*	*Task load types*	*Confidence difference*	*M*	*N*	*SD*
Zero-correlation[a]	Incoherent	Single	73.3 − 59.9	13.5	23	13.7
		Secondary	65.9 − 63.4	2.5	24	8.0
	Coherent	Single	83.4 − 61.5	21.9	21	14.7
		Secondary	74.6 − 64.1	10.5	19	13.7
Guessing[b]	Incoherent	Single		48.2	22	30.4
		Secondary		49.2	22	27.0
	Coherent	Single		54.4	19	32.4
		Secondary		69.2	18	21.4

[a]Difference between confidence when correct and confidence when incorrect. [b]Percentage of guesses that were correct.

Table 13. *Mean number of guess responses in the test phase of Experiment 2*

		Number of guesses		*Number of correct guesses*		*Number of incorrect guesses*	
Knowledge types	*Task load types*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Incoherent	Single	6.2	5.1	2.6	2.2	3.6	3.8
	Secondary	6.7	4.9	3.1	2.4	3.7	3.1
Coherent	Single	3.9	2.7	2.2	1.8	1.7	1.6
	Secondary	4.9	4.5	3.1	2.5	1.9	2.2

$r^2 = .148$, whereas the corresponding percentage in the incoherent condition did not differ from chance, $t(43) = -0.31$, $p = .76$, $r^2 = .002$ (the 95% CI went from 40.0% to 57.3%). Again, implicit knowledge of the test items was demonstrated only by the coherent group. Finally, like in Experiment 1, the guessing criterion analysis showed that the effect of task load ($M = 51.1$, $SD = 31.1$ in the single-task condition vs. $M = 58.2$, $SD = 26.4$ in the dual-task condition), $F(1, 77) = 1.58$, $p = .212$, $\eta_p^2 = .020$, and its interaction with prior knowledge, $F < 1$, $\eta_p^2 = .015$, were not statistically significant.

Discussion

The main aim of Experiment 2 was to test whether the reason why the coherent group acquired implicit knowledge of the individual features in contrast to the explicit knowledge of the incoherent group was that the former saw these features for less time than did the latter. In other words, implicit knowledge might become explicit with extensive training. Perhaps at an early stage of learning, both groups had implicit knowledge of the category features, and this knowledge turned into explicit only in the incoherent and not in the coherent group, because of the longer learning phase of the former group. However, the guessing criterion analysis showed that, even when the two knowledge groups saw the individual features equally often, only the coherent group acquired implicit knowledge of these features in contrast to the incoherent group, who acquired explicit knowledge.

Experiment 2 used only 66 learning trials with feedback. Thus, the coherent group might have needed more learning trials before their explicit knowledge of the features emerged. However, the learning trials of Experiment 2 were enough for the development of explicit knowledge in the incoherent (single-task) condition, indicating a difference in the acquisition of explicit knowledge between the coherent and incoherent groups when exposure times are controlled. This difference can be reasonably attributed to the effect of prior knowledge on learning.

Of course, we are not suggesting that the amount of learning in Experiment 2 is comparable to that in Experiment 1. For example, in Experiment 2, the incoherent dual-task group acquired no explicit or implicit knowledge, and their accuracy did not exceed chance levels in either of the two phases, most probably because of the limited number of training trials they were exposed to. Thus, participants in one of the four conditions learned nothing at all. Importantly, even at such an early point of learning, the incoherent group acquired (only) explicit knowledge of the features, which weakens the possibility that their explicit knowledge in Experiment 1 was due to their longer learning phase converting implicit knowledge into explicit knowledge. By contrast, the coherent group acquired implicit knowledge of the features. The fact that this pattern of results was obtained both in Experiment 1, in which learning was equated, and in Experiment 2, in which exposure to features was equated, allows us to conclude that prior knowledge does facilitate the acquisition of implicit knowledge.

Finally, Experiment 2 showed that, once again, the secondary task reduced the amount of explicit knowledge as measured by the zero-correlation criterion, but not the amount of implicit knowledge, as measured by the guessing criterion. This pattern of results helps validate these measures of conscious and unconscious knowledge.

GENERAL DISCUSSION

The current experiments showed that categories whose features were integrated by prior knowledge were easier to learn than incoherent categories with unrelated features. Thus, the present experiments confirmed the well-established finding that prior knowledge facilitates concept learning. The primary aim of this article was to investigate the effect that such knowledge has on implicit and explicit concept learning by comparing the coherent and incoherent groups' implicit and explicit knowledge, as measured by the guessing and zero-correlation criteria. The dual-task methodology was used to examine the effect of a secondary task on the implicit–explicit distinction and to test the validity of the two metaknowledge criteria. As mentioned in the Introduction, the secondary task is expected to interfere only with explicit learning and knowledge and not with implicit learning and knowledge.

Prior knowledge led to the emergence of implicit knowledge (as measured by the guessing criterion) only in the test phases, in which participants had to categorize individual features. In fact, in the test phases, the guessing criterion provided evidence of implicit knowledge only in the coherent condition and not in the incoherent condition. The lack of a prior knowledge effect on the acquisition of implicit knowledge of the whole exemplars is discussed in more detail below. In addition, all zero-correlation criterion results (except for those in the test phase of Experiment 1) showed that prior knowledge enhanced explicit learning, especially in the single-task condition, which is thought to favour explicit learning.

Finally, the secondary task decreased explicit knowledge (in both the training and the test phases) but not implicit knowledge. This pattern of results validates the zero-correlation and guessing criteria as measures of the conscious or unconscious status of knowledge.

The effect of prior knowledge on implicit and explicit learning

Prior knowledge increased the amount of explicit knowledge (as measured by the zero-correlation criterion). In the training phase of Experiment 1, prior knowledge increased explicit learning only in the single-task condition and not in an attention-demanding condition. This finding is in line with Curran and Keele's (1993) results, which showed that a dual-task condition blocked the emergence of explicit knowledge in a sequence-learning task. Consistently, Cleeremans (1993a) proposed a model of sequence learning, in which the acquisition as well as the expression of explicit knowledge depended on the availability of attentional resources. Thus, according to this model (and consistent with the learning-phase results of Experiment 1), explicit knowledge should emerge only under single-task conditions, when attentional resources are available. However, it is not clear why, on such a model, prior knowledge and task load did not interact in Experiment 2.

In terms of the effect of prior knowledge on implicit knowledge (as measured by the guessing criterion), the overall pattern of results showed that prior knowledge did not influence participants' implicit knowledge of the whole exemplars. However, in the test phases, evidence of implicit knowledge of the individual features was found only in the coherent (and not in the incoherent) condition. Why should implicit knowledge emerge in the coherent condition only in the testing and not in the learning phase? The knowledge representations in the learning and test phases may be of different quality. According to Cleeremans and Jiménez (2002), the content of a representation is conscious only if the representation is of a sufficiently good quality. The knowledge of individual features might not be sufficiently good to support conscious awareness, whereas the representations produced by a set of such features that are semantically interrelated might be good enough to support conscious awareness.

There are two possible interpretations for why prior knowledge increased implicit knowledge (of the individual features). The first interpretation equates prior knowledge with explicit knowledge and is, thus, consistent with the influence of explicit knowledge on implicit learning. On this interpretation, the present results have shown that the interaction of explicit and implicit learning should not necessarily be a negative one as Hayes and Broadbent (1988) have argued. Rather, explicit prior knowledge may facilitate the acquisition of implicit knowledge, thus supporting a synergy between explicit and implicit knowledge (e.g., Cleeremans, 1993a; Dienes & Fahey, 1995; Mathews et al., 1989; Sun, 2000). Indeed, the results of the zero-correlation criterion in the learning phases showed that prior knowledge, overall, increased explicit learning (see Frensch et al., 2003, for how implicit knowledge can become explicated), indicating an explicit component (see also Ziori & Dienes, 2006). Participants made use of some explicit prior knowledge consistent with a synergistic interaction between explicit and implicit knowledge.

The coherent group may have been influenced by some implicit prior knowledge. For instance, in Heit's (1994; see also Heit, 2001) integration model, prior knowledge is represented by exemplars from other related categories, which could in principle be part of implicit memory (see Dienes & Fahey, 1998, for an example of implicit learning based on implicit memory). Thus, the coherent group could have made use of implicit memories of previously encountered exemplars of other related categories. Moreover, work on speeded perceptual categorization has shown that background knowledge can influence categorization decisions at an early stage of categorization (e.g., Lin & Murphy, 1997; Luhmann, Ahn, & Palmeri, 2002; Palmeri & Blalock, 2000). These findings were taken as evidence against the view (e.g., Sloman, 1996; Smith & Sloman, 1994) that background knowledge always involves a rule-based conscious process that emerges rather late within the categorization decision.[1] Thus, prior knowledge may involve unconscious knowledge that can be used automatically and unintentionally.

In sum, the two interpretations above suggest that prior knowledge may include both explicit and implicit components.

The effect of the secondary task on the implicit/explicit distinction

The current experiments found that the secondary task decreased the amount of explicit learning (as measured by the zero-correlation criterion), whereas it left implicit learning (as measured by the guessing criterion) unchanged, or increased implicit learning (in the learning phase of Experiment 1). Recently, Waldron and Ashby (2001) have, similarly, found that a secondary task interfered with the learning of simple explicit rules (which participants could verbally report at the end of the experiment), whereas it did not impair the learning of complex rules (which participants could not describe verbally). Although Waldron and Ashby's (2001) study used completely different experimental materials from those in the present research, the similarity between the two studies lies in the fact that they both showed that secondary tasks interfere only with explicit learning and not with implicit learning.

The secondary-task results allow us to draw conclusions about knowledge representation. Our data in Experiment 1, in particular, have implications for the type of knowledge representation induced by the secondary task, following logic used by Roberts and MacLeod (1995). Roberts and MacLeod showed by using a secondary task to discourage explicit learning that implicit

[1] However, as Palmeri and Blalock (2000) point out, the rapid influence of background knowledge on categorization may generalize only in cases where background knowledge has a perceptual basis, and categories consist of perceptual features rather than of verbal descriptions. Instead, when verbal and semantically rich stimuli like Smith and Sloman's (1994) stimuli or like the present stimuli are used, prior knowledge might involve a rather reflective and effortful process.

learning and explicit learning result in qualitatively different knowledge representations. According to Roberts and MacLeod, an atomic knowledge representation is one that fails to contain the constituent elements (e.g., *P* and *Q*) of a conceptual rule with a compositional structure (e.g., *P&Q*) (cf. Dienes & Perner, 1996, and Fodor & Pylyshyn, 1988). If participants learn that all exemplars are *P&Q*, where *P&Q* has compositional structure, they can also infer that all exemplars contain the features *P* and *Q*. Roberts and MacLeod predicted that the dual-task condition, which putatively favours implicit learning (by discouraging explicit learning), would lead to atomic knowledge representations that could not be decomposed into constituent attributes, whereas the condition that favoured explicit learning would result in knowledge representations with a compositional structure. Their results confirmed this prediction, despite the fact that all participants had learned the categories equally well. These results support the hypothesis that implicit learning results in holistic knowledge representations, whereas explicit learning results in analytic knowledge representations (see also Kemler Nelson, 1984, 1989). Experiment 1 allowed a further test of this hypothesis using different materials.

First, we needed to establish that participants in Experiment 1 had learned the categories equally well in the two task load conditions (see Roberts & MacLeod, 1995). The level of initial learning of the two task load groups was directly tested by comparing their performance in the intermediate phase. The finding that performance of the two task load groups did not differ significantly in this phase showed that the differences between the two task load groups in the test phase occurred despite the fact that the two groups had learned the categories equally well. That is, Experiment 1 showed that the secondary task impaired participants' ability to classify the individual features of the concepts. These results are consistent with Roberts and MacLeod's (1995) finding that the secondary task impaired participants' ability to decompose a conceptual conjunction into its constituent properties, even though the single- and dual-task groups had learned the categories equally well. Thus, it may be concluded that the dual-task condition that favoured implicit learning (by discouraging explicit learning) resulted in the acquisition of holistic knowledge.

CONCLUSIONS

To conclude, the present experiments showed that prior knowledge facilitated the acquisition of implicit knowledge. However, the present research leaves open the issue of the relation between the implicit and the explicit component of prior knowledge. Maybe, for example, at an early stage of learning the explicit component dominates, as people try to apply rules and explain conceptual relations, but with increased experience, the implicit component takes over, as past exemplars are easily retrieved from memory (see, e.g., Johansen & Palmeri, 2002). Another possibility is that the explicit and implicit components are tightly coupled within a single categorization task. Future research could clarify these issues by providing more examples of the so far neglected relationship between prior knowledge and implicit learning.

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APPENDIX

Coherent categories

Categories	*Category 1* *Characteristic features*	*Random features*	*Category 2* *Characteristic features*
Animal	Has sharp teeth	Hibernates, Doesn't hibernate	Has flat teeth
	Has a barbed tail	Short snout, Long snout	Has a furry tail
	Eats meat	Lives in Northeast, Lives in Northwest	Eats plants
	Aggressive		Placid
	Lives alone		Lives in groups
	Fast[a]		Slow[a]
Building	Divers live there	Has rugs, Has wall-to-wall carpeting	Astronauts live there
	Get there by submarine	Victorian furniture, Modern furniture	Get there by plane
	Fish kept there as pets	6-month lease, 12-month lease	Birds kept there as pets
	Thick heavy walls		Thin light walls
	Under the water		Floats in the air
	Windows cannot be opened[a]		Windows can be opened[a]

Note: The present stimuli were identical to the stimuli that Murphy and Allopenna (1994, Exp. 2) used.
[a]Infrequent features.