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The time course of implicit and explicit concept learning

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A B S T R A C T

The present experiment investigated the development of implicit and explicit knowledge during concept learning. According to Cleeremans and Jiménez (2002), the content of a representation can be conscious only when the representation is of a sufficiently good quality; on this theory, increasing explicit and decreasing implicit knowledge might be expected with training. The view that implicit knowledge arises from compilation of explicit knowledge makes the opposite prediction. The present research tested these possibilities using subjective measures based on confidence ratings. One group of participants was presented with blocks of category exemplars that activated prior knowledge, whereas another group was presented with blocks of categories that did not elicit any useful prior knowledge. The results showed that, irrespective of the knowledge group participants were allocated to, explicit knowledge increased over the course of learning, whereas implicit knowledge either stayed the same or decreased, consistent with Cleeremans and Jiménez's prediction.

1. Introduction

A dichotomy that has received an increasing interest among cognitive psychologists is the one between explicit and implicit learning. Learning is implicit when people acquire knowledge they are not conscious of, and thus cannot express verbally. In that sense, implicit learning contrasts with explicit learning, which often depends on the use of hypothesis-testing strategies and results in knowledge one is conscious of. The main aim of the present research is to investigate the development of implicit and explicit knowledge over the course of learning. Several possibilities as to the direction of this development seem plausible. For instance, implicit knowledge may be evident only at an early level of processing (see Mathews, 1997). On the other hand, people may apply analytic strategies and thus rely on explicit knowledge only at an early stage of learning, whereas extensive training may turn explicit knowledge into implicit (Anderson, 1983).

1.1. The relationship between explicit and implicit learning

As defined above, implicit learning is the process of acquiring knowledge that people are not conscious of. Researchers have used a variety of experimental paradigms in order to investigate implicit learning, including artificial grammars (e.g., Dienes, Altmann, Kwan, & Goode, 1995; Mathews et al., 1989), concept learning tasks (e.g., Frick & Lee, 1995; Roberts & MacLeod, 1995; Ziori & Dienes, 2008), the control of complex systems (e.g., Berry & Broadbent, 1988; Stanley, Mathews, Buss, & Kotler-Cope, 1989), and sequence learning (e.g., Destrebecqz & Cleeremans, 2001; Nissen & Bullemer, 1987). Implicit category learning, in particular, occurs when people acquire knowledge of categories but are unaware of the knowledge. The area of implicit learning has raised considerable debate among researchers (e.g., Dulany, 2003; Perruchet & Pacteau, 1990;

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Shanks & St. John, 1994), a debate that has resulted in different measures of the inaccessibility of knowledge to conscious awareness. Dienes et al. (1995) proposed the use of two subjective measures of the conscious status of knowledge expressed in a judgment. According to the *guessing criterion*, knowledge is unconscious if participants think they are just guessing when in fact their performance is better than baseline. In other words, knowledge is unconscious in terms of the guessing criterion when the percentage of guesses (i.e., the percentage of responses accompanied by a complete lack of certainty) that are correct is significantly greater than a chance level. According to the *zero-correlation criterion*, knowledge is unconscious when people cannot distinguish when they do or do not have knowledge, i.e., when confidence is not related to accuracy. Thus, the zero-correlation criterion assumes that when knowledge is unconscious then the average difference in participants' confidence between correct and incorrect responses would be zero. By contrast, when this difference is significantly greater than zero, it follows that participants are aware of having knowledge, irrespective of its origin, which may vary. For instance, a person might rely on abstracted rules, whereas someone else might simply remember that a present exemplar was previously associated with a given feedback (cf. Ashby & Casale, 2003; see Dienes & Scott, 2005).

The two above subjective criteria of implicitness have been used in a range of implicit learning studies (e.g., Dienes & Perner, 2003; Dienes & Scott, 2005; Dienes & Seth, 2010; Dienes et al., 1995; Guo et al., 2011; Redington, Friend, & Chater, 1996; Scott & Dienes, 2008; Tunney, 2005; Tunney & Shanks, 2003; Ziori & Dienes, 2008). Unlike subjective measures, objective measures test whether people are (in some minimal sense) aware of stimuli or relations in the environment, but not whether people are consciously aware of them, i.e., aware of having knowledge. It is the subjective measures that provide a direct way of assessing subjective states including conscious awareness (though not without assumptions of their own; see Dienes, 2004, 2008, 2012; Dienes & Perner, 2001, 2004; Dienes & Scott, 2005).

In most learning situations, implicit and explicit learning are likely to co-exist. The advantage of the two above metaknowledge criteria is that they allow for such a co-occurrence of the two types of learning as: (a) the existence of implicit knowledge on guess responses does not exclude the co-existence of explicit knowledge on other trials. (b) the existence of explicit knowledge as measured by the zero-correlation criterion does not exclude the existence of some implicit knowledge in the same trials. The present research used both metaknowledge criteria as measures of implicit learning.

Although in most cases, implicit and explicit learning are likely to co-exist, the temporal relationship between the two types of learning, which is the primary interest of the present article, is not yet clear. On the one hand, some researchers argue that implicit knowledge can only arise late in training because, at an early stage, learning is characterized by declarative knowledge, which, through practice, becomes procedural and implicit (Anderson, 1983; Lewis & Anderson, 1985). The distinction between declarative and procedural knowledge often corresponds to the distinction between conscious and unconscious knowledge in that declarative knowledge can be declared and therefore may have access to conscious awareness, whereas procedural knowledge is generally inaccessible to consciousness. According to Anderson (1983, 1993), at an early stage of skill learning, people rely on declarative knowledge, that is on explicit knowledge or instructions about how one should perform a given task. This explicit knowledge is a prerequisite for successful performance on a task. The application and interpretation of explicit declarative knowledge is a slow process that is prone to errors, which may arise, for instance, when retrieval of the correct knowledge fails or when incorrect knowledge is retrieved. Extensive practice eventually leads to the development of procedural knowledge, which is fast and error free. Procedural knowledge allows people to perform a skill without the use of declarative knowledge and even with no access to conscious awareness of specific aspects of the skill. Procedural knowledge is represented by production systems (i.e., a collection of if-then rules), which form the basis for interpreting various complex cognitive skills, such as language learning and problem solving. Thus, Anderson's theory may capture cognitive skills involving a set of rules. Category learning, in particular, may be viewed as a complex cognitive skill involving behavioral aspects (and even some neural substrates) that can be found in motor skill learning (Gluck, Poldrack, & Keri, 2008). Thus, category learning can draw on skill learning.

On the other hand, other researchers allow implicit knowledge to be formed without prior explicit knowledge (e.g., Berry & Dienes, 1993; Cleeremans & Jiménez, 2002; Fu, Fu, & Dienes, 2008). There are two versions of the view that implicit knowledge can be formed early in training, according to whether one or two learning systems are postulated. Cleeremans and Jiménez (2002) postulate one learning system, with representations becoming conscious depending on their quality so that explicit knowledge emerges from early implicit knowledge (cf Karmiloff-Smith, 1986, 1990; Pascual-Leone, Grafman, & Hallett, 1994). On this view, extended training would lead to a decrease in the amount of implicit knowledge (as it became converted to explicit). On the other version of the view that implicit knowledge can be formed early in training, there are distinct implicit and explicit learning systems. These systems may operate in parallel (e.g., Hayes & Broadbent, 1988; Lewicki, 1986; Lewicki & Hill, 1987; Perruchet, Bigand, & Benoit-Gonin, 1997; Willingham & Goedert-Eschmann, 1999; Willingham, Nissen, & Bullemer, 1989) or synergistically (e.g., Cleeremans, 1993; Dienes, Altmann, & Gao, 1999; Dienes & Fahey, 1995; Mathews et al., 1989; Scott & Dienes, 2010; Sun, 2002). According to Willingham et al. (1989), extensive training may lead to an increase in both explicit and implicit knowledge with neither of the two being a prerequisite for the development of the other. On this view, there are some representations that do not become conscious; implicit knowledge based on these representations should increase over extended training, the increasing quality of the representations simply corresponding to better, more reliable, implicit knowledge. Sun, Merrill, and Peterson (2001) proposed two interacting learning mechanisms, such that initial procedural (implicit) learning facilitates later declarative (explicit) learning. Similarly, Frensch et al. (2003) provide some empirical evidence of their *unexpected-event hypothesis.* On this hypothesis, implicit learning often leads to behavioral changes that, when noticed by participants, may trigger an explicit system and thus result in verbalizable knowledge. Scott and Dienes (2010) likewise proposed that an implicit system can draw attention to parts of stimuli to guide explicit hypothesis testing – implicit knowledge can come first and guide explicit learning. What all these views have in common is that implicit knowledge does not require initial explicit knowledge.

The aim of the present work is to determine whether implicit knowledge may develop at an early stage of concept learning without prior explicit knowledge or whether implicit knowledge emerges only after the development of explicit knowledge. If implicit knowledge is demonstrated at an early stage, our next pursuit is to examine its relationship with explicit knowledge over the course of learning, and decide which of the relevant hypotheses provides the most successful candidate for the interpretation of the present data.

1.2. Concept learning and the implicit/explicit distinction

The present work investigates the time course of implicit and explicit learning using one of the various tasks that researchers have used to study the explicit/implicit distinction, namely a concept learning task. The early theories of concept learning relied only on similarity, ignoring people's prior knowledge about the world or about categories (for a review of these views, see e.g., Komatsu, 1992; Medin, 1989). According to standard similarity-based views of concept learning, a novel item will be classified as a member of a 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. However, the most recently developed view of concepts as well as an increasing number of categorization studies suggest that categorization depends largely on people's background knowledge (e.g., Carey, 1985; Medin, 1989; Murphy, 1993; Murphy & Allopenna, 1994; Murphy & Medin, 1985; Rips, 1989). More specifically, categorization research to date has elicited various effects of prior knowledge on concept learning. For example, Murphy and Allopenna (1994) have shown that categories whose features are interrelated by general knowledge are much easier to learn than categories with the same structure, but without any pre-existing associations among their features. Other studies have shown that background knowledge may lead people to selectively attend to stimulus attributes or observations that are relevant to their prior knowledge, and ignore irrelevant information that would slow down the process of categorization (e.g., Medin, Wattenmaker, & Hampson, 1987; Murphy & Wisniewski, 1989; Pazzani, 1991; Wisniewski, 1995). Another effect of prior knowledge is that it helps people interpret and represent category information (e.g., Lin & Murphy, 1997; Palmeri & Blalock, 2000; Wisniewski & Medin, 1991, 1994; see also Heit, 1997 for a review of additional evidence).

Unlike most implicit learning experiments, the current experiment uses highly meaningful stimuli that activate participants' prior knowledge in order to investigate the effect of this knowledge on implicit and explicit concept learning, and in particular, the time course of this effect. Existing categorization models that incorporate prior knowledge influences (e.g., Heit, 1994; Heit & Bott, 2000; Pazzani, 1991; Rehder & Murphy, 2003) do not address the relationship of prior knowledge with the implicit vs. explicit learning distinction. This is also the case for the majority of categorization research on prior knowledge (see e.g., Ziori & Dienes, 2006, 2008 for an exception). Further, computational models of implicit learning typically do not incorporate general knowledge and their potential influences on implicit learning (but see Dienes & Fahey, 1995 and Sun, 2002). Both the areas of implicit learning and concept learning could benefit from research on the so far neglected and controversial relationship of prior knowledge with the implicit/explicit distinction. Exploring the above relationship may clarify the exact nature of prior knowledge application, whether prior knowledge application favors an implicit or an explicit mode of processing, whether the implicit/explicit nature of the application changes over the course of learning and whether it depends on particular learning conditions. Further, the relationship of prior knowledge with the implicit/explicit distinction could shed more light on the nature of implicit processing. More specifically, this line of research can contribute to the unresolved issue of whether implicit learning may interact with people's theories or is completely independent from any knowledge base that may involve consciously controlled knowledge. According to some researchers, implicit learning is an unselective and passive process of learning, which thus should not be affected by theories (e.g., Hayes & Broadbent, 1988). On the other hand, it has been suggested (e.g., Frick & Lee, 1995; Sun et al., 2001; Ziori & Dienes, 2008) that implicit learning may interact with pre-existing knowledge. We will attempt to give some answers to the above issues by exploring whether the acquisition of implicit and explicit knowledge follows the same time course for meaningless stimuli and stimuli for which subjects had relevant prior knowledge.

Relatedly, the implicit–explicit distinction has been associated with the issue of stimulus salience. According to Hayes and Broadbent (1988), implicit learning is associated with a passive aggregation of frequently co-occurring features, whereas explicit learning is most probable when stimuli are salient. Accordingly, in the present work we used a salient vs. non-salient stimulus manipulation in order to examine the potentially differential effect that the two types of stimuli might have on implicit and explicit learning, as well as the time course of this effect.

2. Overview of the present experiment

The present research aims to investigate how implicit and explicit concept learning develop with continued exposure to category exemplars. As already mentioned, several possibilities seem plausible. For instance, implicit knowledge may be evident only at the beginning of learning. On Cleeremans and Jiménez's (2002) account, for example, explicit knowledge should progressively increase, as better quality representations are formed, but implicit knowledge should not increase; if anything it should decrease over extended training. Similarly, prior knowledge should not increase implicit knowledge over extended training, because over time prior knowledge would progressively increase the quality of representations, allowing them to become explicit. Alternatively, it may be that implicit knowledge increases over time, and can only be formed after relevant explicit knowledge has been formed (cf Anderson, 1983). On this account, prior knowledge might encourage the formation of relevant declarative or explicit knowledge, at an early stage of learning, during which participants would engage themselves in a deliberative and analytical mode of processing causal relationships between features. Through practice, however, participants might abandon conscious processing and progressively rely on an implicit component of prior knowledge (e.g., implicit knowledge of previously experienced exemplars), which would favor the development of implicit knowledge that is inaccessible to conscious awareness.

The present work uses stimuli of Murphy and Allopenna (1994) in order to activate participants' prior knowledge. In this task, participants have to learn two different kinds of category pairs, which have the same structure and features, but different relations among features. In the *Incoherent* condition, in particular, the categories consist of short descriptions (derived from everyday domains) that have no pre-existing connections among them, and cannot elicit useful prior knowledge. In the *Coherent* condition, the categories consist of the same descriptions, which are combined such that they match up with people's common knowledge of familiar domains and are thus expected to activate prior knowledge of these domains. Thus, the comparison between the Coherent and Incoherent conditions allows us to compare concept learning with and without prior knowledge.

According to Murphy and Allopenna (1994), their stimuli were constructed such that they would not indicate a familiar category and, therefore, would enhance an abstraction strategy based on various sources of prior knowledge. However, they found that some participants did identify stimuli as describing a familiar object. Some of these features were very prominent and easily identified. This might enhance explicit learning (cf Hayes & Broadbent, 1988) to such an extent that the detection of implicit learning is impaired. To ensure that the stimuli of our experiment were novel and that the features were not very prominent, some slight changes to the original stimuli of Murphy and Allopenna (1994) were introduced. In particular, some features, namely the very salient ones (e.g., "Made in Africa" vs. "Made in Norway") were replaced with less obvious ones that were not very prominent and, in the Coherent condition, their combination with the other features could not be easily identified with an already known object.

Our work employed a number of factors that may differentially affect implicit vs. explicit knowledge to ensure conclusions with good generality: meaningless vs. meaningful stimuli (cf Ziori & Dienes, 2008); salient vs. non-salient stimuli (cf Berry & Broadbent, 1988; Reber, Kassin, Lewis, & Cantor, 1980); and single vs. dual task conditions (cf contrast Shanks & Channon, 2002; Dienes & Scott, 2005; Jiménez & Méndez, 1999; Roberts & MacLeod, 1995; Waldron & Ashby, 2001).

3. Method

3.1. Participants

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

3.2. Experimental design

The experiment followed a $2 \times 2 \times 2 \times 8$ (prior knowledge [Coherent vs. Incoherent] by task load type [Single vs. Secondary] by stimulus set [salient stimuli vs. non-salient stimuli] by time [block A vs. block B vs. block C vs. block D vs. block E vs. block F vs. block G vs. block H]) mixed-model design.

3.3. Stimuli

Participants learned to distinguish between exemplars of two categories, Categories 1 and 2. Half the participants were presented with the salient categories and the other half with the non-salient ones. The salient categories were the same as those originally used by Murphy and Allopenna (1994), and subsequently applied by Ziori and Dienes (2008) and Heit (2001). Table 1 provides an example of the structure of the categories used in the Coherent and Incoherent conditions (see Appendix A for the remaining salient and all the non-salient coherent categories).

The non-salient stimuli were constructed by replacing some of the old salient features with less prominent ones. For instance, in the coherent category pair that described two different kinds of animals, the less salient feature combination (see Appendix A) did not remind of a particular animal that one could easily name. Piloting on the materials (and in particular, comparing the salient feature combinations of the coherent categories with the non-salient feature combinations of the coherent categories) showed that the stimuli selected as salient were rated as more familiar than those selected as non-salient, .43 vs. .08 on a two point scale, $t(71) = 5.80$, $p < .001$.

Participants presented either with the salient or with the non-salient categories learned only one out of three category pairs that were constructed for each knowledge condition. In particular, the features of the three category pairs were short phrases, such as "Made in Africa" and "Has wheels", which were taken from three domains: vehicles, buildings and animals. So, each participant, independent of the condition they were allocated to, saw only the features of one of the above three domains. The same features were used in both the Coherent and the Incoherent condition. However, the two conditions dif-

Table 1
The structure of one of the three salient category pairs in each knowledge condition. The salient coherent category pair in this table describes the vehicle categories.

Category 1	Incoherent condition	Category 2
Characteristic features	*Random features*	*Characteristic features*
Lives alone		Lives in groups
Made in Africa	Four door, Two door	Made in Norway
Fish kept there as pets	Hibernates, does not hibernate	Birds kept there as pets
Has a barbed tail	Victorian furniture, modern furniture	Has a furry tail
Thick heavy walls		Thin light walls
Convertible		Non-convertible
	Coherent condition	
Made in Africa		Made in Norway
Lightly insulated	Four door, two door	Heavily insulated
Green	Uses gasoline, uses diesel	White
Drives in jungles	Licence plate in front, licence plate in back	Drives on glaciers
Has wheels		Has treads
Convertible		Non-convertible

fered in the relations among features. The features of the coherent categories, in particular, were combined such that they matched up with people's common knowledge about a specific domain. One example of a salient category pair in the Coherent condition 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). An example of a non-salient category pair in the Coherent condition was "Has a dust filter, Seen only in jungles, Uses gasoline, Has wheels, Licence plate in front" (Category 1) and "Has no dust filters, Seen only on glaciers, Uses diesel, Has treads, Licence plate in front" (Category 2). These example illustrate how all features of coherent category pairs were taken from the same domain (that of vehicles). Accordingly, coherent categories were expected to activate prior knowledge that was relevant to a specific domain. The difference between the salient and non-salient coherent category pairs is that the former consisted of some more prominent features and were somewhat easier to name and remind participants of an existing object (e.g. a jeep) than the latter. For example, it would be more difficult to think of a vehicle that can be seen only in jungles and to decide whether a particular vehicle contains a dust filter or not. The features of incoherent category pairs, on the other hand, had no pre-existing connections among them, as they were randomly collected from all three domains. The three incoherent category pairs in each of the two different salience conditions were constructed such that each feature of each domain was used once combined with features from the other two domains. Thus, an example of a salient incoherent category pair would be: "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). In the corresponding non-salient incoherent category pair, the prominent features "Made in Africa" vs. "Made in Norway" were replaced by the less prominent ones "Has a dust filter" vs. "Has no dust filters".

Category pairs in both knowledge conditions in each stimulus set shared the same structure. The features of each pair were derived from the following binary dimensions: six *characteristic* dimensions that always appeared in a specific category and three *random* dimensions that appeared in the two categories with nearly equal frequency. In each stimulus set, 22 exemplars were constructed, each a unique combination of three characteristic features and two random ones.

3.4. Procedure

Each participant learned to distinguish between exemplars of only one out of the six (i.e., three coherent and three incoherent) category pairs in each stimulus set. Participants were randomly assigned to category pairs. Exemplars were presented one at a time on a computer screen and in a random order within a block. Participants had to indicate whether each exemplar belonged to Categories 1 or 2, and give their confidence rating on a scale from 50 (complete guessing) to 100 (complete certainty) within 7 s; otherwise, their response was considered as a missed trial. The order of the features in each exemplar was random.

Prior to each category exemplar, participants allocated to the Dual-task condition saw a string containing six randomly presented digits from 1 to 9, which stayed on the screen for 3 s. Participants had to rehearse this string aloud until they were shown a second six-digit string at the end of each trial (i.e., until after they had provided their classification response and confidence rating and been provided with feedback about their classification accuracy). They were then asked to decide whether the two strings were exactly the same. Half of the strings that followed the category examples were identical to the initial strings, whereas in the other half of these strings, two digits were changed with equal probability in each position of the string. After each decision, feedback about accuracy on the secondary task was provided.

Training stopped after all participants had been presented with eight blocks of 22 category exemplars, all of which provided feedback about participants' accuracy.

3.5. Results

3.5.1. Secondary task performance

Performance on the secondary task was examined to assure that participants allocated to the Dual-task condition retained the memory load while distinguishing between category exemplars. It was found that participants performed the secondary task with a high level of accuracy (94.1%), indicating that they devoted enough attention to this task while learning the concepts.

3.5.2. Categorization performance

Fig. 1a and b presents the time course of accuracy for the four groups presented with the salient stimuli (1a) and the four groups presented with the non-salient stimuli (1b). Participants' accuracy and its direction over the course of training was analyzed using a 4-way ANOVA on the percentage of correct responses, with prior knowledge, task load type, stimulus set (salient stimuli vs. non-salient stimuli) and time (block A vs. block B vs. block C vs. block D vs. block E vs. block F vs. block G vs. block H) as independent variables, with the last one being the only within-subjects variable. As expected, the Coherent group outperformed the Incoherent group, $F(1,88) = 11.97$, $p = .001$ (77% vs. 69%). Moreover, the secondary task interfered with accuracy (84% in the Single-task condition vs. 62%in the Dual-task condition), $F(1,88) = 94.76$, $p < .001$.

Participants presented with the salient stimuli responded more accurately than those presented with the non-salient stimuli, $F(1,88) = 17.79$, $p < .001$ (78% vs. 68%). Further, accuracy increased across the eight blocks, $F(3.98,350.13) = 71.03$, $p < .001$, with Greenhouse–Geisser correction. The time by prior knowledge interaction was not significant, $p = .085$. Thus, even one block of 22 exemplars was enough for the Coherent group to access some useful background knowledge.

The time by task load by stimulus set interaction was significant, $F(3.98,350.13) = 4.17$, $p = .003$. Further analysis revealed that the time by task load interaction was significant only in the non-salient set, $p < .001$, in which the two task load groups differed in all blocks ($ps < .001$) except for in the first block ($p = .281$), and not in the salient set, $p = .221$ (see Fig. 1a and b).

3.5.3. Confidence rates

The development of explicit knowledge in terms of the zero-correlation criterion was examined by analyzing the difference in confidence between correct and incorrect responses with a four-way mixed ANOVA, with prior knowledge, task load, stimulus set, and time (blocks A–D vs. blocks E–H) as independent variables (see Appendix B for the means). (The analysis of metaknowledge across the eight blocks separately resulted in many missing values.) Prior knowledge had no significant ef-

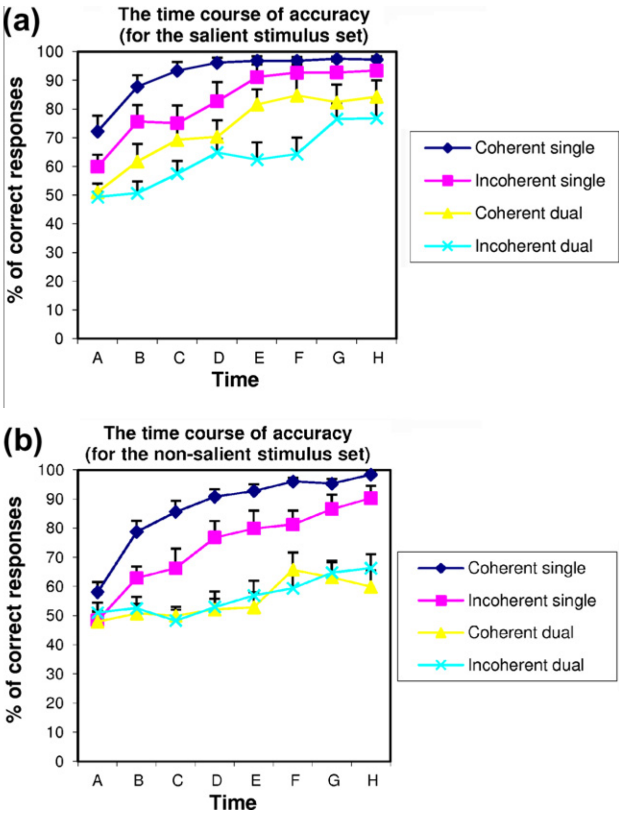

Fig. 1. (a and b) The time course of accuracy for the four groups presented with the salient stimuli (a) and the four groups presented with the non-salient stimuli (b).

fect on explicit knowledge, $p = .080$. (This finding, however, is most probably due to low power because of the missing values; the analysis of total explicit knowledge, ignoring block, showed that the Coherent group acquired more explicit knowledge than the Incoherent group (18.9 vs. 13.8), $F(1,88) = 6.30$, $p = .014$). The Dual-task condition decreased explicit knowledge, $F(1,77) = 40.56$, $p < .001$ (see Fig. 2). Finally, the salient stimuli resulted in more explicit knowledge than the non-salient stimuli, $F(1,77) = 10.90$, $p = .001$.

Explicit knowledge increased significantly in the last four compared to the first four blocks, $F(1,77) = 15.06$, $p < .001$ (see Fig. 2). Explicit knowledge was significantly greater than zero in both the first and the last four blocks, $ps < .001$. Thus, four blocks of exemplars were enough to elicit explicit knowledge, a result that was expected, since each block consisted of 22 exemplars, all of which provided feedback. In order to examine the development of explicit knowledge at a finer grain, we compared explicit knowledge in each of the first four blocks separately. Thus, we conducted another four-way ANOVA with prior knowledge, task load, stimulus set, and time (block A vs. block B vs. block C vs. block D) as independent variables. This analysis showed that explicit knowledge increased with time, $F(2.57,174.53) = 6.19$, $p = .001$, with Greenhouse–Geisser correction. In the first two blocks, metaknowledge was not statistically greater than zero (First block: $M = 0.83$, Second block: $M = 2.15$, $ps > .05$, 95% CIs [−.53,2.18], and [−.07,4.36] respectively, whereas in the next two blocks, the means statistically exceeded zero ($ps < .001$), 95% CIs [2.17,7.34], and [3.69,9.81], respectively.

Participants claimed to be guessing on 19% of trials on average. The analysis of the total percentage of guesses (i.e., responses with a confidence rating of exactly 50) that were correct (ignoring block), which measured the overall amount of implicit knowledge in terms of the guessing criterion, revealed only a significant effect of task load, $F(1,87) = 6.23$, $p = .014$, with participants in the Dual-task condition demonstrating more implicit knowledge than participants in the Single-task condition (54.0% vs. 48.8%). The percent correct while guessing exceeded chance, $p < .001$, only in the Dual-task condition.

A four-way ANOVA on the percentage of guesses that were correct, with prior knowledge, task load, stimulus set, and time (blocks A–D vs. blocks E–H) as independent variables examined whether implicit knowledge increased or decreased over time (see Appendix B for the means). The secondary task increased the percentage of guesses that were correct, $F(1,64) = 19.80$, $p < .001$. Further, the percent correct while guessing decreased with time, $F(1,64) = 16.11$, $p < .001$. The particular percent exceeded chance only in the first four blocks (53.0), $t(71) = 2.48$, $p = .016$, whereas in the last four blocks the corresponding percent (40.2) was significantly lower than chance, $t(71) = -2.61$, $p = .011$.

However, the time by task load by stimulus set interaction was significant, $F(1,64) = 8.42$, $p = .005$ (see Fig. 3a and b). The time by task load interaction was significant only in the salient stimulus set ($p < .001$), and not in the non-salient set ($p = .317$). Thus, implicit knowledge decreased only when participants presented with the salient stimuli were assigned to the Single-task condition, $t(14) = 6.27$, $p < .001$, and not when they were assigned to the Dual-task condition, $p = .756$. As shown in Fig. 3a, the very low percent correct when guessing that these participants demonstrated in the last four blocks constitutes a curious finding, which, therefore, was explored further.

One possibility for below chance performance when guessing is that participants formed their own idiosyncratic implicit rules. If so, participants should respond with a given category to a given exemplar more consistently than chance would predict, and this consistency should increase over sets as the rules were induced. Thus, for each item that received a confidence rating of 50%, the number of times participants responded “1” was calculated in the first four and the last four blocks separately (which could be 0–3 or 4 times). Clearly, 0 and 4 are the most consistent number of responses, since, if participants gave 0 responses of (Category) “1” when they were guessing, this means that they responded consistently with regard to that item throughout the four blocks. Similarly, when they gave four responses of Category “1”, they again responded consistently in the four blocks. On the other hand, 2 was considered the most inconsistent responses, since, in that case, half of the times participants responded “1” and the other half “2” for a given item. Next, the proportions of guesses to which participants responded “1” zero times ($p(0)$), four times ($p(4)$), and two times ($p(2)$) was calculated. The equation $3 \times p(0+4) - p(2)$ [namely, three times the probability of responding most consistently when guessing (i.e., responding “1” zero and four times within the four blocks) minus the probability of responding most inconsistently when guessing (i.e., responding “1” two

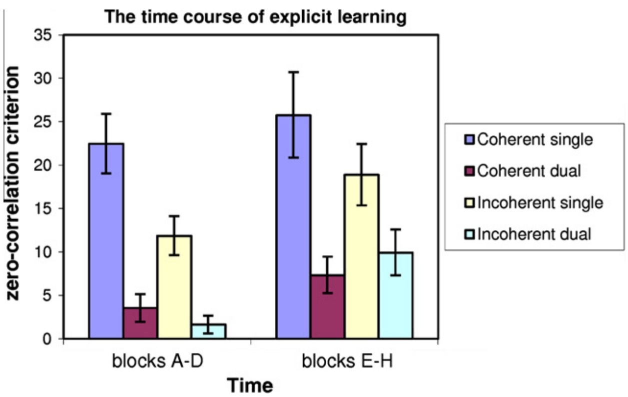

Fig. 2. The mean difference in confidence between correct and incorrect responses in the first and the last four blocks for the four groups.

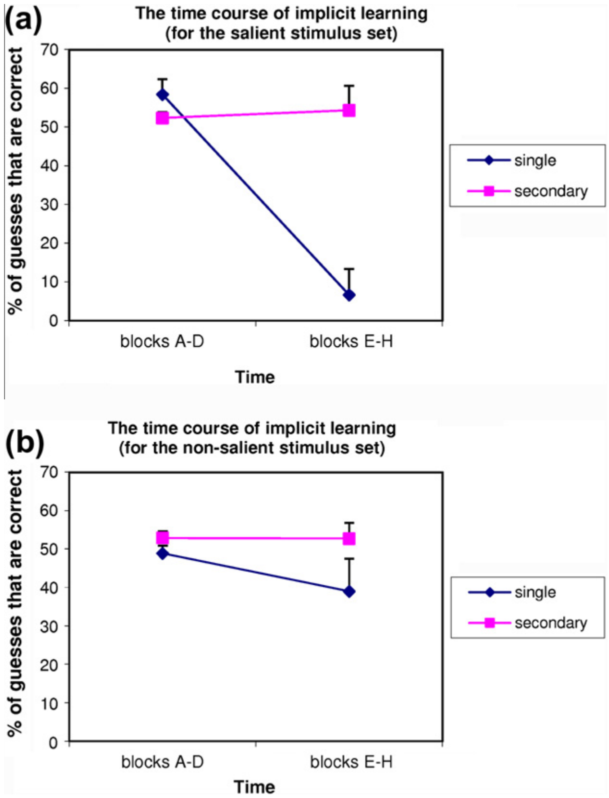

Fig. 3. (a and b) The mean percent correct when guessing for the two task load groups presented with the salient stimuli (a) and the two task load groups presented with the non-salient stimuli (b).

times within the four blocks)], which is derived from the binomial distribution, was applied to estimate the difference between consistent and inconsistent guess responses (this measure would be zero if subjects responded "1" with probability of .5 independently for each exemplar for each block).

An ANOVA on the mean difference between consistent and inconsistent responses when participants were guessing in the first and the last four blocks was used to measure the direction of consistency of responding over the blocks. Participants in the Single-task condition were more consistent than participants in the Dual-task condition (0.53 vs. 0.16), $F(1,27) = 5.18$, $p = .031$. Further, participants were more consistent in the first than in the last four blocks (0.58 vs. 0.08), $F(1,27) = 6.81$, $p = .015$, which rules out the possibility that they formed their own implicit rules in the last four blocks. The only significant interaction was the time by prior knowledge interaction, $F(1,27) = 5.03$, $p = .033$, with consistency in the last four blocks being lower than consistency in the first blocks only in the Coherent condition (0.80 vs. -0.17), $t(14) = 3.84$, $p = .002$. This analysis indicates that participants did not induce more implicit rules over time while they believed they were guessing; if anything, their guess responses were less and less systematic over time. It is possible that knowledge that was originally only implicit became part of the participants' explicit knowledge over time. If the explicit knowledge was largely accurate, then it is the largely inaccurate implicit knowledge that would be left.[1]

In sum, the decrease in percent correct when guessing to below baseline levels did not occur because of increasing inaccurate implicit knowledge. Rather, in conditions that favor accurate explicit knowledge being formed (single task, salient features), those exemplars for which subjects had previously accurate implicit knowledge became explicitly learned. Thus, the implicit knowledge on those trials would have been masked by explicit knowledge, or converted to explicit knowledge. The remaining implicit trials were those for which participants' implicit knowledge classified incorrectly.

4. Discussion

The main goal of the present experiment was to examine the development of the implicit–explicit distinction over the course of concept learning. Which type of knowledge is acquired first, implicit or explicit? Based on skill learning data, Anderson (1983) argues that, at an initial stage of learning, learning is characterized by the acquisition of declarative (explicit) knowledge, which, through practice, becomes "proceduralized" and then proceeds in the absence of any conscious awareness. Thus,

[1] From the point of view of metacognitive measures of implicitness, it should not be relevant whether participants' knowledge is accurate from the experimenter's point of view, but whether participants know they are in different (accurate or inaccurate) knowledge states.

according to this view, explicit knowledge should turn into implicit over the course of learning. As mentioned in the introduction, category learning involves elementary skill aspects, which allows a direct comparison of this type of learning with skill learning. Of course, apart from elementary skill learning, category learning also involves higher-order cognitive abilities. However, this does not render the comparison of skill learning theories and concept learning problematic. On the contrary, production systems, which have a central place in Anderson's skill learning theory, are used to describe procedural knowledge in higher cognitive skills (e.g. problem solving and language production). Thus, skill learning theories, like Anderson's theory, can lend insight into how higher order learning, such as concept learning, may proceed in the absence of conscious awareness.

In contrast to the view that implicit knowledge may develop only after extensive training and following the development of explicit knowledge, Cleeremans and Jiménez's (2002) theory postulates that implicit knowledge is formed first, because initially representations are of low quality; this knowledge can become explicit when the quality of representations improves with learning (cf. Frensch et al., 2003; Scott & Dienes, 2010; Sun et al., 2001).

Explicit knowledge, as measured by the zero-correlation criterion, in particular, increased significantly over time. Even when learning is facilitated by prior knowledge, people may have little or no metaknowledge at an early stage of learning, consistent with Cleeremans and Jiménez's (2002) claim that explicit knowledge requires the development of high quality representations.

In terms of the guessing criterion, implicit knowledge either stayed the same or decreased with learning. This is consistent with theoretical views like Cleeremans and Jiménez (2002) postulate that, as training increases the quality of representations, implicit knowledge may become explicit. The data do not support a theory, by which the implicit knowledge arrives late in training, compiled from explicit knowledge.

A finding of decreasing implicit knowledge is consistent with two theories: Either a single-system theory, like the Cleeremans and Jiménez one, in which implicit knowledge becomes converted to explicit knowledge (and in which the extreme below chance performance is problematic), or a dual-system theory in which increasing explicit knowledge masks the expression of implicit knowledge. Our measure of implicit knowledge is the percentage of correct responses when guessing. If, like Jacoby (1991), we assume dual independent systems, then we can measure the amount of implicit knowledge overall by taking those cases where there is no explicit knowledge (i.e., when participants claim they are guessing) and looking at the proportion of trials that involve implicit knowledge (this is exactly the same logic as the process dissociation procedure). That is precisely what the guessing criterion does. So even if increasing explicit knowledge means the participant expresses implicit knowledge on fewer and fewer trials, the guessing criterion still provides a measure of the total amount of implicit knowledge, assuming independence (i.e., that the amount of implicit knowledge on trials with no explicit knowledge can be used as an estimate of the amount of implicit knowledge on all trials). But how can we then account for the measured amount of implicit knowledge decreasing with training? Surely, an independent implicit system would produce more knowledge with more training.

Implicit knowledge decreased with training for participants shown the salient categories and allocated to the Single-task condition. At face value, this finding would be exactly as expected by the single-system theory, as the above conditions plausibly favor the development of high quality representations; and the result is at face value difficult for the dual-system theory. However, the percentage of guesses that were correct in the Single-task condition presented with salient stimuli was much lower than chance, a result that suggests a consistent pattern rather than a random way of guessing. In other words, participants in that condition were almost always incorrect when they were guessing. We would not have predicted this finding in advance by either theory. One possibility is based on the plausible claim that implicit knowledge is likely to be partially correct rather than completely accurate with respect to the experimenter's view of correct classification. If there are dual independent systems, then, on the one hand, explicit knowledge can have a different content to any existing or pre-existing implicit knowledge. On the other hand, aspects of stimuli that are easy for an explicit system to learn accurately may partly correspond in some stimuli sets to those aspects that are easy for an implicit system to learn accurately. In single-task conditions with salient features, explicit learning may produce content that is more accurate than implicit learning. Thus, those trials that are left unmasked by explicit knowledge will contain a disproportionately high amount of inaccurate implicit knowledge.

Several findings support the use of the zero-correlation and guessing criteria of consciousness by providing converging validity checks. As predicted, the secondary task, which is meant to favor implicit learning, did reduce the amount of explicit knowledge as measured by the zero-correlation criterion. There was increased explicit knowledge for salient rather than non-salient stimuli. The secondary task increased the amount of implicit knowledge, as measured by the guessing criterion. In fact, evidence of implicit learning was found only in the Dual-task and not in the Single-task condition. Thus, the present experiment has confirmed the hypothesis that the dual task favors implicit learning (e.g. Roberts & MacLeod, 1995). Moreover, the metaknowledge criteria results are in line with the verbal reports analyses, which compared accuracy in the last block with the mean validity of the rules that participants reported at the end of the experiment. These analyses, which for space restriction reasons are not included in the present article, have shown that participants' verbal rules could predict their performance in the last block fairly well providing evidence of conscious knowledge at the end of training.

Finally, the current study measured the conscious status of only judgment knowledge, i.e. the knowledge that a test item belonged to a certain category, rather than structural knowledge, i.e. the knowledge needed to make the judgment (cf Dienes, 2008, 2012; Dienes & Scott, 2005). The process by which judgment knowledge becomes conscious when structural knowledge remains unconscious (cf Pasquali, Timmermans, & Cleeremans, 2010; Scott & Dienes, 2008) may be different from the process by which conscious structural knowledge is formed (Scott & Dienes, 2010).

To conclude, the current results more plausibly fit Cleeremans and Jiménez's (2002) view that the emergence of explicit knowledge requires the formation of high quality representations, which arise after extensive training. On this view, implicit knowledge could well decrease over the course of training. The present results are also consistent with an independent systems approach, in which implicit and explicit systems can acquire overlapping yet different knowledge; hence the possibility of below-chance performance for guess responses. How could single and dual system approaches be teased apart? One general argument for dual systems is based on the type of structures best learned by each system. For example, the explicit system seems poorly equipped to learn the structures of natural language. Future research could employ stimuli more uniquely matched to the hypothetical capabilities of just one of the systems. For example, Waldron and Ashby (2001) found that a certain type of stimulus structure (which they call "information integration") could be learned without interference from a secondary task. If an explicit system finds this structure very hard to learn, the development of implicit knowledge, as revealed by subjective measures, could be monitored without masking from explicit knowledge.

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Appendix A

See Table A1.

Table A1
Two of the three salient coherent category pairs and the three non-salient coherent category pairs used in the present research.

Salient coherent category pairs		
Category 1	Animal categories	Category 2
Characteristic features	*Random features*	*Characteristic features*
Has sharp teeth		Has flat teeth
Eats meat		Eats plants
Has a barbed tail	Hibernates, does not hibernate	Has a furry tail
Lives alone	Short snout, Long snout	Lives in groups
Aggressive	Lives in Northwest, Lives in Northeast	Placid
Fast		Slow
	Building categories	
Divers live there		Astronauts live there
Under the water	Has wall-to-wall carpeting,	Floats in the air
Get there by submarine	Has rugs	Get there by plane
Thick heavy walls	Victorian furniture, Modern furniture	Thin light walls
Fish kept there as pets		Birds kept there as pets
Windows can be opened	6-month lease, 12-month lease	Windows can not be opened
	Non-salient coherent category pairs	
Category 1	Vehicle categories	Category 2
Characteristic features	*Random features*	*Characteristic features*
Has wheels		Has treads
Has a dust filter	Four door, two door	Has no dust filters
Lightly insulated	Uses gasoline, uses diesel	Heavily insulated
Seen only in jungles	Licence plate in front,	Seen only on glaciers
Green	Licence plate in back	White
Convertible		Non-convertible
	Animal categories	
Lives alone		Lives in groups
Has sharp claws	Hibernates, does not hibernate	Has flat claws
Eats meat		Eats plants
Active at night	Short snout, long snout	Active in the daytime
	Lives in northwest, Lives in Northeast	Has a furry tail
		Slow
Has a barbed tail		
Fast		
	Building categories	
It is sunless		It is sunlit
Windows cannot be opened	Has wall-to-wall carpeting,	Windows can be opened
	Has rugs	Get there by plane
Get there by submarine	Victorian furniture, Modern furniture	Has thin walls
Has thick walls		Birds kept there as pets
Fish kept there as pets	6-month lease, 12-month lease	Floors are dry
Floors are wet		

Note. The third salient category pair is presented in Table 1. The salient stimuli were identical to the stimuli Murphy and Allopenna (1994, Experiment 2) used.

Table B1
The zero-correlation criterion scores.

Prior knowledge	Task load type	Salience	Blocks A–D			Blocks E–H		
			M	N	SD	M	N	SD
Incoherent	Single	Salient	13.4	9	13.0	21.8	9	17.8
		Non-salient	10.7	12	8.1	16.7	12	15.4
	Secondary	Salient	3.6	12	6.0	11.0	12	13.0
		Non-salient	−0.3	12	12.0	8.9	12	13.1
Coherent	Single	Salient	28.2	9	14.8	35.6	9	17.9
		Non-salient	16.1	8	11.1	14.7	8	17.5
	Secondary	Salient	6.6	11	9.4	10.1	11	11.9
		Non-salient	0.7	12	4.6	4.9	12	7.7
		Total	8.9	85	12.2	14.6	85	16.2
The guessing criterion scores								
Incoherent	Single	Salient	54.4	7	12.4	14.3	7	37.8
		Non-salient	47.1	11	6.9	39.1	11	30.6
	Secondary	Salient	53.0	9	6.6	51.9	9	16.6
		Non-salient	52.3	12	9.6	49.4	12	19.8
Coherent	Single	Salient	61.9	8	17.5	0.0	8	0.0
		Non-salient	52.2	6	10.4	38.8	6	45.5
	Secondary	Salient	51.4	7	5.4	57.4	7	35.0
		Non-salient	53.5	12	7.4	56.0	12	20.7
		Total	53.0	72	10.1	40.2	72	31.8

Appendix B

See Table B1.

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