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Unconscious symmetrical inferences: A role of consciousness in event integration

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Abstract

Explicit and implicit learning have been attributed to different learning processes that create different types of knowledge structures. Consistent with that claim, our study provides evidence that people integrate stimulus events differently when consciously aware versus unaware of the relationship between the events. In a first, acquisition phase participants sorted words into two categories (A and B), which were fully predicted by task-irrelevant primes—the labels of two other, semantically unrelated categories (C and D). In a second, test phase participants performed a lexical decision task, in which all word stimuli stemmed from the previous prime categories (C and D) and the (now nonpredictive) primes were the labels of the previous target categories (A and B). Reliable priming effects in the second phase demonstrated that bidirectional associations between the respective categories had been formed in the acquisition phase (A ↔ C and B ↔ D), but these effects were found only in participants that were *unaware* of the relationship between the categories! We suggest that unconscious, implicit learning of event relationships results in the rather unsophisticated integration (i.e., bidirectional association) of the underlying event representations, whereas explicit learning takes the meaning of the order of the events into account, and thus creates unidirectional associations.

Keywords: Explicit; Implicit learning; S-S conditioning; Memory

Humans often learn explicitly, that is, with the intention to acquire new knowledge about something and an increasing insight into what is learned. However, they also pick up regularities between events in a rather automatic fashion, that is, without a particular learning intention and without being able to report about the knowledge acquired. This observation has led some authors to suggest the existence of two separate learning systems in humans, an explicit system that is accompanied by awareness and an implicit system that operates independently from awareness (e.g., Hayes & Broadbent, 1988; Keele, Ivry, Mayr, Hazeltine, & Heuer, 2003; Lewicki, Czyzewska, & Hoffman, 1987; Reber, 1989).

Although implicit learning has been investigated for quite some time, comprehensive theoretical accounts and models have emerged only recently, and computational modeling has played a central role in deconstructing

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and specifying earlier verbal hypotheses and theories. As Cleeremans, Destrebecqz, and Boyer (1998) have pointed out, there are two broader families of computational models for implicit learning: neural-network models (e.g., Cleeremans, 1993; Cleeremans & McClelland, 1991; Dienes, 1992) and fragment-based models (e.g., Dienes & Fahey, 1995; Logan, 1988; Perruchet & Vinter, 1998; Servan-Schreiber & Anderson, 1987). Both approaches share some important assumptions (Cleeremans et al., 1998): (1) learning involves elementary association or recording processes that are sensitive to statistical structures embodied in stimuli; (2) learning is incremental and continuous; (3) learning is based on the processing of exemplars and produces distributed knowledge; and (4) learning is unsupervised and self-organizing. More recently, Sun (2001; see also Sun, Merrill & Peterson, 2001; Sun, Slusarz, & Terry, 2005) has proposed a hybrid model where the distinction between explicit and implicit learning is captured by the symbolic versus subsymbolic processing mode of the model. Even more recently, Keele et al. (2003) have attributed explicit and implicit learning to the ventral and dorsal visual pathways, respectively.

The distinction has motivated the search for systematic differences between explicit and implicit learning, ideally in the form of double dissociations (see Merikle & Reingold, 1992). Indeed, a number of factors have been identified that affect explicit and implicit learning in different, sometimes opposite ways. For instance, a demanding secondary task, under some circumstances, impairs explicit but facilitates implicit learning (Hayes & Broadbent, 1988; but see Green & Shanks, 1993); performance reflects smaller individual differences and a less pronounced correlation with IQ when people work in an implicit as compared to an explicit mode (Aaronson & Scarborough, 1977; Reber, Walkenfeld, & Herntadt, 1991); and mental disorders (e.g., Alzheimer disease, schizophrenia) affect performance on explicit tasks much more (and often exclusively) than on implicit tasks (Abrams & Reber, 1988). These and other findings have led researchers to characterize implicit, in contrast to explicit, learning as restricted to the acquisition of simple, local event relations[1] (Cohen et al., 1990) and as being uninformed by higher cognitive processes (Keele et al., 2003).

In the present study, we considered the implications of this characterization of implicit versus explicit learning for the acquisition of event predictions and causal judgments—processes that have been claimed to be involved in, or even to be functionally equivalent to different forms of S-S learning (Lewicki, Hill, & Czyzewska, 1994; Lovibond, 1988; Shanks & Dickinson, 1987). As we know since Pavlov's (1927) seminal study, if a given event A is consistently followed by, and thus predicting another event B, humans and other animals pick up and make use of this relationship. Associative accounts in the tradition of Pavlov ascribe this type of learning to the creation and/or strengthening of associations between the neural codes of the two events, S-S associations. In contrast, rule-based, inferential accounts consider animals as intuitive statisticians, who integrate information about the relative probabilities and/or frequencies of events and their succession (Allan, 1993). As pointed out by Shanks and Dickinson (1987), associative and inferential accounts may not provide competing explanations for one type of learning process but, rather, refer to different types of learning. Indeed, if we relate these two accounts to the implicit-explicit distinction,[2] it makes sense to assume that associative

[1] Here and in the following we distinguish between local and (more) global event relations or contexts, which we consider to differ with respect to the temporal window and the type of information or the number of informational subsystems involved (Baars, 1988). For instance, Cohen, Ivry, and Keele (1990) compared the acquisition of sequences consisting entirely of first-order conditionals (e.g., A-E-B-D-C) with sequences consisting of second-order conditionals (e.g., A-B-C-B-A-C). The former type can be learned by a simple associative mechanism that takes only local relations (transitions from one item to the next) into account, because each association will be unique. The latter type of sequence requires information from a broader temporal integration window (a more global context), because predicting an item in the sequence depends on knowing the prior two items. Another example for is the representation of an action outcome, which can be interpreted as one's own achievement only by considering (more global) information about whether one has carried out an action that is likely to have produced the effect.

[2] For presentational purposes we simplify matters here. Backward conditioning in classical conditioning is known to be less effective and has even been thought to be nonexistent for quite a while until Keith-Lucas and Guttman (1975) demonstrated that exposing rats to a single US $\rightarrow$ CS sequence is sufficient to make CS an efficient prime of US. Later research has provided increasing evidence for backward effects (for reviews, see LoLordo & Fairless, 1985; Spetch, Wilkie, & Pinel, 1981). Recent findings suggest that priming effects of backward conditioning (i.e., evidence of bilateral associations) are dominant early in practice but give way to inhibition later on, a finding that has been interpreted to point to an increasing role of context and context integration (Chang, Blaisdell, & Miller, 2003). This idea perfectly fits with our own theoretical position, showing that even associative accounts are well-equipped to deal with multiple types of learning. Hence, in contrasting associative and rule-based accounts we only intend to characterize particular available, popular learning models but do not want to imply that associative models would be unable to model explicit (or context-dependent) learning, or that rule-based models would be unable to model implicit learning, in principle.

accounts describe the implicit, probably automatic creation of links between event representations, whereas inferential accounts refer to cognitive processes that elaborate event relations in a broader context—either triggered by the creation of associations (Shanks & Dickinson, 1987) or concurrently by strengthening them. That is, implicit associative mechanisms and explicit inferential mechanisms may provide alternative, or concurrent, ways to acquire knowledge about event sequences.

Here, we tested a both theoretically and methodologically important implication of this view with respect to the order of events. If event A is consistently followed by B, an *associative* mechanism should strengthen the links between the representations of A and B in the memory system. One would expect this link to be bidirectional and, hence, associate B with A as strongly as it associates A with B (Ash & Ebenholtz, 1962; Gerolin & Matute, 1999; Kahana, 2002; but see footnote 2 for a qualification). If so, learning that A is followed by B should not only render A an effective prime of B but B should also prime A.

This symmetry of priming would not be predicted from an *inferential* account. On the one hand, learning that A (the "cause") is consistently followed by B (the "effect") should induce the expectation that if A is encountered B is likely to appear, that is, A should prime B. However, as A and B are linked by a rule but not directly associated, there is no reason to believe that B would be an effective prime for A (cf. Waldmann & Holyoak, 1992). Applying this logic to our considerations about implicit and explicit learning, we predicted that implicit learning would result in the acquisition of bidirectional associations that transfer from $A \rightarrow B$ to $B \rightarrow A$, whereas explicit learning should not allow for such a transfer of priming effects (see Section 3 for a more detailed treatment of this issue).

In the present study, we assessed the implicit acquisition of bidirectional associations by asking the participants whether they noted the covariation between the label of a category, say BODY, and exemplars of a different unrelated category, say exemplars of "animals" (Experiment 1). Although admittedly a subjective verbal report might not be the best measure of awareness (for critical reviews, see Holender, 1986; Holender & Duscherer, 2004; Shanks & St. John, 1994), the best may to diagnose pure unconscious effects is still matter of heated debate. We consider verbal report useful for our purposes on two grounds. First, our interest is not to assess behavioral effects of subliminally perceived stimuli, the issue on which the debate has concentrated (Hannula, Simons, & Cohen, 2005). In contrast, the present study is concerned with the detection of covariations between arbitrary events, which may (Experiment 2) but need not (Experiment 1) be presented subliminally. Second, using verbal report allows us to relate our findings to other studies that used the same measure. For instance, Lewicki and his colleagues (Lewicki et al., 1987, 1994) have shown that information about covariations between supraliminal events can be acquired through nonconscious indirect inferences—hence, what counts here is the conscious versus unconscious representation of the covariation but not of the covarying events.

To sum up, we were interested in knowledge about the covariation of events that participants cannot articulate and that they are not aware of. In Experiment 1, we compared performance of participants that were able to articulate (aware) with those that were unable to articulate (unaware) the covariation of supraliminal stimuli. In Experiment 2, we used a masking procedure to prevent all participants from being aware of the covariation, thus introducing a stricter criterion for awareness.

1. Experiment 1

The minimal setup to test our hypothesis would have been to use four stimuli (say, A–D), to have two predicted by the other two ($A \rightarrow B$, $C \rightarrow D$), and then to see whether B primes A and D primes C. However, such a manipulation would render the prime–probe relationships so obvious that it would be hard to find a substantial number of nonexplicit learners. We therefore developed a somewhat more complex version of the basic task that made it easier to conceal the predictive relationships and yet can produce priming (see Alonso, 2000). The rationale underlying this version was based on three rather uncontroversial assumptions: (1) activating a word signifying an exemplar of a particular category spreads activation to the label of this category (i.e., activating "dog" primes "ANIMAL"; Glosser, Friedman, Grugan, Lee, & Grossman, 1998); (2) activating a category label spreads activation to the corresponding exemplar words (i.e., activating "BODY" primes "hand"; Neely, 1977); and (3) stimulus representations that are activated in a systematic, predictable sequence tend to become associated (Pavlov, 1927).

Participants carried out two tasks in a row. In a first, acquisition phase they classified target words as belonging to the categories of "animals" and "furniture." Each target was preceded by a task-irrelevant prime, the category label BODY or PLANT. These labels were perfectly predictive of the correct target category, that is, BODY preceded all animal words and PLANT preceded all furniture words (see Fig. 1). Based on assumption (1) we assumed that processing an animal or furniture word would spread activation to the corresponding category label (ANIMAL or FURNITURE), as sketched in Fig. 2. If so, the prime-induced activation of the category label BODY, say, would precede, and thus predict, the activation of both the representation of the word "dog" and the word "ANIMAL." According to assumption (3) this predictive relationship ($A \rightarrow b$ and $A \rightarrow B$) should induce associations between BODY and dog and between BODY and ANIMAL.

In a second, test phase we tested whether the novel, just acquired link between the categories was bidirectional ($A \leftrightarrow B$). Here, participants performed a lexical decision task, in which all the word stimuli stemmed from the categories BODY(-PARTS) and PLANTS, that is, from the categories the labels of which served as predictive primes in the acquisition phase. Conversely, the category labels from the previously predicted categories (ANIMAL and FURNITURE) were now used as (nonpredictive!) primes. If the acquisition phase indeed induced bidirectional associations ($A \leftrightarrow B$), we would expect that processing the category label ANIMAL, say, would prime the category label BODY (see Fig. 2). In addition to or instead of that, it is possible that processing ANIMAL primes the semantically related word "dog" (assumption (2)), which in the case of bidirectional associations primes BODY. (Note that our reasoning does not rely on which of these pathways are actually effective.) In any case, according to assumption (2) activating the category label BODY (via ANIMAL, via ANIMAL-dog, or both) would then prime corresponding exemplar words, such as "hand." In short, if the acquisition phase produced bidirectional associations between (the codes belonging to) BODY and ANIMAL and between PLANT and FURNITURE, the category label ANIMAL should now prime (members of) the category BODY while the label FURNITURE should now prime (members of) the category PLANTS. Importantly, we expected that this episodic relatedness effect should be found only with implicit learning, that is, in participants who were unaware of the prime–target relationship in the acquisition phase. Finally, we checked for contributions from prime-related elaborative or expectation processes by varying the

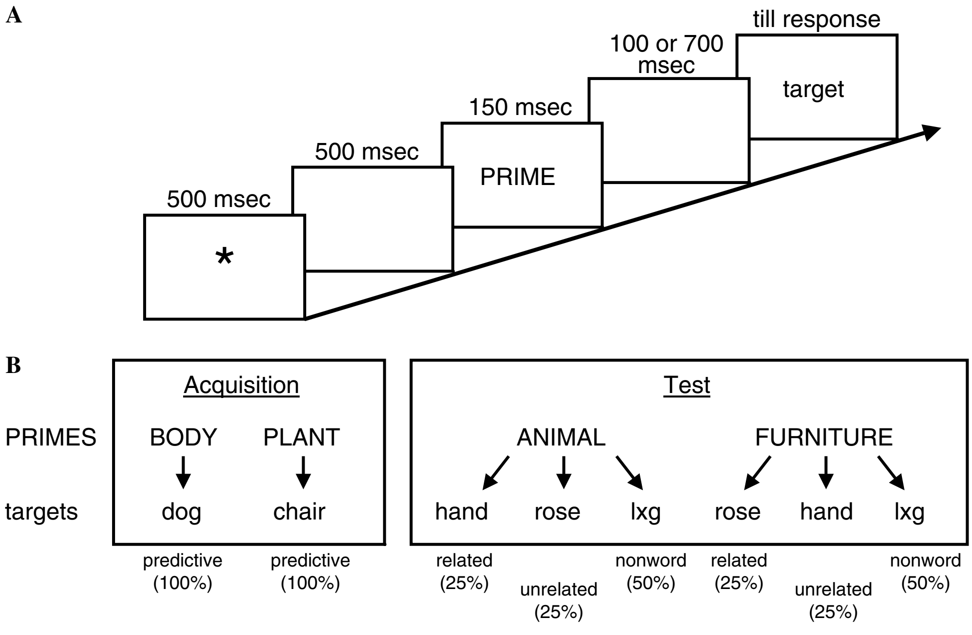

Fig. 1. (A) Succession and timing of events in Experiment 1. (B) Design and conditions in Experiment 1. In the acquisition phase, category labels predicted the category of target words (animals and furniture, dog and chair are examples). In the test phase, category labels were not predictive; each of the two labels were followed by words from the categories body parts and plants or by nonwords in 25, 25, and 50% of the trials, respectively.

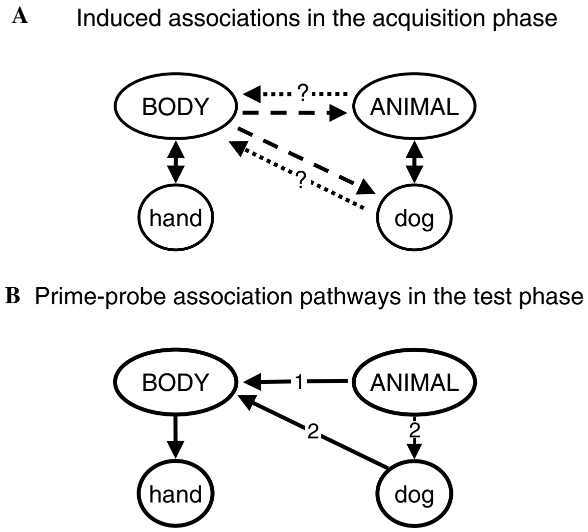

Fig. 2. Overview of the assumed associations in the acquisition phase and the test phase, using the example of the prime word "BODY" and the target word "dog" (in the acquisition phase). (A) Due to the predictive relationship between "BODY" and "dog" in the acquisition phase, the representations of these words should become associated in the forward direction (hatched lines) and, perhaps, in the backward direction (dotted lines). To the degree that the processing of "dog" also activates "ANIMAL," the two category labels may also become associated. (B) If the acquisition phase induced bidirectional associations, processing the category label "ANIMAL" in the test phase should spread activation to the category label "BODY," either directly or via the activation of "dog," which again should spread activation, and thus prime the processing of, the word "hand."

temporal interval between prime and target in the test phase (the Stimulus Onset Asynchrony or SOA)—the idea being that such processes would have more time to unfold during a longer interval (Neely, 1977).

1.1. Method

1.1.1. Participants

One hundred and sixty-eight male and female undergraduates at the University of Almería participated in partial fulfillment of a course requirement. They all reported normal or corrected-to-normal vision. Eighty were assigned to the long-SOA group and 88 to the short-SOA group.

1.1.2. Stimuli and materials

IBM-compatible PCs were used to present the stimuli and to collect the data. Stimuli were Spanish 4- to -7-letter words from 4 categories, Animals (5.13 letters on average), Furniture (5.75 letters on average), Body parts (5.25 letters on average); and Plants (5.75 letters on average) (see Appendix A). All exemplars were chosen for the highest possible frequency in their category, according to the norms of Soto, Sebastián, García, and Del Amo (1982). Apart from the fixation asterisk, 34 word stimuli (all in Spanish) were used in the *acquisition phase*. The category labels BODY and PLANT served as primes (presented in uppercase) and 16 exemplar words from each of the categories "animal" and "furniture" as targets (presented in lowercase). In the *test phase*, 64 stimuli were used: The category labels ANIMAL and FURNITURE served as primes; 16 exemplar words from each of the categories "body part" and "plant" were employed as targets; and 32 additional pseudowords were constructed from the target set by changing one letter per word. All stimuli were presented in white at the center of the black screen. From a viewing distance of 60 cm, each letter measured about $.38 \times .48$ deg.

1.1.3. Design and procedure

The experiment consisted of two phases that differed with respect to the word material and the task. In both phases, a fixation mark appeared for 500 ms, followed by a 500-ms blank. Then the prime appeared (always uppercase) for 150 ms, followed by an interval of 100 ms (in the short SOA group) or 700 ms (in the long-SOA group). Then the (lowercase) target appeared until the participant made a speeded choice response by pressing one of two keys of the computer keyboard (see Fig. 1). In the acquisition phase, participants decided whether the target belonged to the category "animal" or "furniture." In the test phase, they decided whether the target was a word or a nonword.

The acquisition phase consisted of three blocks. In each block there were 64 randomly ordered trials in which the prime BODY was always followed by an exemplar from the category "animal," and the prime PLANT was always followed by an exemplar from the category "furniture." Both kinds of trials repeated twice per block so that participants saw each CATEGORY-exemplar pair six times in total during this phase (see Fig. 1). Participants were told to pay attention to all stimuli appearing on the screen but were not informed about the relationship between primes and targets.

After the acquisition phase, participants worked through 128 test trials, two 64-trial blocks composed by combining the two possible primes (now the category labels from the target words in the acquisition phase: ANIMAL and FURNITURE), with 16 exemplars from one of the prime category label in the acquisition phase (body-part words), 16 exemplars from the other prime category label in the acquisition phase (plant words), and 32 pseudowords. Primes were not predictive, so that each of the two primes was followed by 16 body-part words, 16 plant words, and 32 nonwords in total (see Fig. 1B). Accordingly, there were 32 "related" trials that heeded the relation between categories from the acquisition phase (ANIMAL $\rightarrow$ $\langle$body part$\rangle$ and FURNITURE $\rightarrow$ $\langle$plant$\rangle$) and 32 "unrelated" trials that did not (ANIMAL $\rightarrow$ $\langle$plant$\rangle$ and FURNITURE $\rightarrow$ $\langle$body part$\rangle$).

1.1.4. Learning mode

Upon completion of the experiment, each participant was asked whether he/she had observed some relationship between primes and targets in the acquisition phase. Those that reported having detected the relationship were asked to reproduce the mapping to confirm they knew the correct rules. All participant of this group knew the rules and were therefore considered "aware." Those that were unable to report about any relationship between primes and targets were considered "unaware."

1.1.5. Control study

Before conducting Experiment 1 we ran a control study to rule out any confounding pre-experimental relations between the stimuli used in the test phase. Forty additional participants from the same pool worked through 128 test trials composed exactly as in the long-SOA group of Experiment 1 (with the combinations ANIMAL $\rightarrow$ $\langle$body part$\rangle$ and FURNITURE $\rightarrow$ $\langle$plant$\rangle$ treated as "related" and the combinations ANIMAL $\rightarrow$ $\langle$plant$\rangle$ and FURNITURE $\rightarrow$ $\langle$body part$\rangle$ as "unrelated"), preceded by 32 randomly chosen practice trials. Table 2 shows the results for the word decisions: they compare well with those from Experiment 1 in general and, most importantly, yielded no evidence of any "relatedness" effect in RTs or errors, F's$(1,39) < 1$.

1.2. Results

Eighty-four participants (44 from the short and 40 from the long-SOA, respectively) reported having been aware of the predictive prime–target relationship in the acquisition phase, whereas the remaining 84 (44 from the short and 40 from the long-SOA, respectively) did not.

1.2.1. Acquisition phase

After classifying participants as aware or unaware of the prime–target relationship, the RT and error rate data from the acquisition phase, shown in Table 1, were analyzed by means of a 2×3 mixed analysis of variance (ANOVA) with "awareness" as between-participants factor and "block" of trials as the within-participants factor. Reaction times results showed significant main effects of awareness, $F(1,166) = 11.16$, $MSE = 41720.41$, $p < .001$, and block, $F(2,332) = 426.10$, $MSE = 2840.84$, $p < .001$. Aware participants were faster than unaware participants (364 vs. 425 ms) and RTs decreased with practice. Most importantly, the awareness $\times$ block interaction was significant, $F(2,332) = 6.54$, $MSE = 2840.84$, $p < .01$. Even though both groups of participants benefited from practice (aware participants: $F(2,166) = 208.85$, $MSE = 3624.49$, $p < .001$; unaware participants: $F(2,166) = 229.48$, $MSE = 2057.19$, $p < .001$), the practice effect was more

Table 1
Means of median reaction times (in milliseconds), standard deviations, and error rates (%), as a function of awareness and block of trials

Awareness	Block 1			Block 2			Block 3		
	RT	SD	%	RT	SD	%	RT	SD	%
Aware	468	135	4.1	343	121	1.9	281	99	2.0
Unaware	504	146	4.3	415	129	3.1	355	118	2.3

Acquisition phase of Experiment 1.

pronounced in aware participants than in unaware participants. Blockwise ANOVAs revealed that the two groups did not differ in block 1 (36 ms), $F(1,166) = 2.83$, $MSE = 19828.46$, $p > .05$ but aware participants were faster than unaware participants in blocks 2 (72 ms), $F(1,166) = 13.90$, $MSE = 15624.07$, $p < .01$, and 3 (74 ms), $F(1,166) = 19.22$, $MSE = 11949.56$, $p < .01$.

The error rate analysis only showed a main effect of block, $F(2,332) = 18.11$, $MSE = 11338$, $p < .001$, also indicating better performance as a function of practice. The main effect of awareness and the awareness × block interaction approached but did not reach statistical significance, $F(1,166) = 1.78$, $MSE = 20113$, $p > .05$, and $F(2,332) = 1.07$, $MSE = 11338$, $p > .10$, respectively.

These results suggest that participants who became aware of the predictive covariation between prime words and target words were able to use that knowledge for improving their categorization performance.

1.2.2. Test phase

Correct median RTs and error rates on word decisions from the second test block were analyzed as a function of the within-participant factor "relatedness" and the between-participant factors "SOA" and "awareness," see Table 2 for means. The RTs yielded a main effect of SOA, $F(1,164) = 15.44$, $MSE = 24.32$, $p < .005$, reflecting faster RTs with longer SOA, whereas the main effects of relatedness and awareness were not significant, $F(1,164) = 2.48$, $p > .10$, and $F < 1$, respectively. The interactions involving SOA as a factor were not significant (relatedness × SOA, and relatedness × awareness × SOA, Fs < 1; and awareness × SOA, $F(1,164) = 1.09$, $p > .10$). However, the interaction between relatedness and awareness was significant, $F(1,164) = 8.67$, $MSE = 908.16$, $p < .005$. As Table 2 shows, aware participants did not produce a reliable relatedness effect, $F < 1$, whereas unaware participants were about 14 ms faster with related than unrelated primes, $F(1,83) = 12.56$, $MSE = 741.16$, $p < .01$. The error rates showed that only the awareness × SOA interaction was significant, $F(1,164) = 4.24$, $MSE = 47.13$, $p < .05$. As shown in Table 2, the interaction was due to a significant reduction in error rate for aware participants at the long SOA.

Even though in some related conditions, RTs were slightly longer and error percentage smaller than in the correspondent unrelated conditions, this pattern is unlikely to reflect a speed-accuracy trade-off: as shown in Table 2, the pattern was obtained only in the conditions where priming was not significant (aware participants in the two SOAs).

Table 2
Means of median reaction times (in milliseconds), standard deviations, and error rates (%) as a function of SOA, awareness, and prime–target relatedness in Experiments 1 and 2

SOA	Awareness	Related			Unrelated			Effect
		RT	SD	%	RT	SD	%	
Control study								
Long	n/a	648	96	6.8	643	104	7.0	−5
Experiment 1								
Short	Aware	677	85	7.0	671	84	7.9	−6
	Unaware	693	113	6.5	708	118	7.7	15
Long	Aware	632	97	4.5	629	93	5.0	−3
	Unaware	618	97	7.4	631	106	7.5	13
Experiment 2								
Long	Unaware	628	77	7.1	654	95	6.7	26

The size of the relatedness effect is also presented ($RT_{unrelated} - RT_{related}$).

1.3. Discussion

The experiment yielded three important findings. First, the presence of a relatedness effect confirms that stimulus–stimulus associations can be bidirectional, an observation that is consistent with previous findings in rats (e.g., Matzel, Held, & Miller, 1988) and humans (Gerolin & Matute, 1999). Second, and most important for our purposes, bidirectional associations seem to be formed in an implicit learning mode only, that is, if people have no idea about any predictive relationship between the events involved. Third, consistent with the second observation, there was no evidence that elaborative processes (as measured by SOA-related effects) contribute to the effect of relatedness.

2. Experiment 2

Experiment 2 was designed to provide converging evidence that an implicit learning mode allows for the creation of bidirectional associations. Rather than relying on a "natural" manipulation of learning modes we this time took measures to actively prevent participants from consciously processing the prime in the acquisition phase. To do so, we replicated the long-SOA condition of Experiment 1 but pattern-masked the prime to a degree that participants were unable to detect its presence. According to our considerations, this should yield an outcome comparable to the unaware group in Experiment 1.

2.1. Method

Twenty-five new students participated. Stimuli, procedure, design, and task were as in the long-SOA condition of Experiment 1, with two exceptions. First, in the acquisition phase, primes appeared for 30 ms only and were followed by a 120-ms pattern mask composed of three rows of random letters covering the area where the prime had previously appeared. Previous studies carried out in our laboratory have shown the utility of this procedure to obtain processing under conditions near to the objective threshold of consciousness (cf. Fuentes, Carmona, Agís, & Catena, 1994; Sánchez, 1988). Second, upon completion of the test phase, participants were asked whether they had seen any stimulus before the mask—but none did.

2.2. Results and discussion

The median RTs produced a reliable effect of relatedness, $F(1,24) = 5.25$, $MSE = 1592.27$, $p < .05$, whereas the error rates did not, $F < 1$. Thus, as predicted, the outcome was as in the unaware group of Experiment 1 (see Table 2). The relatedness was even larger than in Experiment 1 for unaware participants (26 vs. 14 ms), although this numerical increase was not statistically significant, $F(1,107) = 1.24$, $p > .10$.

3. General discussion

The aim of our study was to investigate whether the association between a predictive prime and a predicted target stimulus is bidirectional and, if so, whether this bidirectionality depends on the learning mode. Indeed, both experiments provide evidence that prime–target associations are bidirectional but only if they are acquired under an implicit learning mode. We suggest that this dissociation reflects the amount of global information considered under the learning modes.

Under an implicit mode people pick up correlations between events rather automatically and create associations between the representations of these events. These associations are local and do not take the nonlocal context into account (Tubau, Hommel, & López-Moliner, 2005), such as the roles of primes and targets as predicting and predicted events, and the meaning of their relation(s). As a consequence, the emerging associations may or may not represent external state of affairs and their meaning in an appropriate fashion so that, among other things, causes become associated with their effects just the same way as the effects become associated with their causes. That is, implicitly created associations in memory may not maintain the true temporal order of the events they connect, which makes priming between the representations of the associated events symmetric.

In contrast, under an explicit mode, people learn about the relations between particular events in a particular task context. As a consequence, associations between causes and their effects are asymmetric, so that causes prime effects but effects do not prime causes.

Our findings provide further support for a distinction between implicit and explicit learning and claims that different functional and probably even neural systems underlie these learning modes (Keele et al., 2003; Schacter, 1995). Implicit learning exhibits properties that points to an evolutionary old and efficient (Reber, 1989) system that we are likely to share with other animals, whereas explicit learning makes use of and integrates all the information available from the environment, internal knowledge, and inferential processes. Our observations also support the idea that associative and inferential accounts of causal judgment may not represent competing approaches (Waldmann & Holyoak, 1992) but, rather, refer to different modes of acquiring knowledge about event sequences (Shanks & Dickinson, 1987).

We conclude that people may associate causes and effects in a rather unsophisticated manner before, or concurrently with, penetrating the causal meaning of the sequence of events. We see at least two possibilities of how implicit and explicit learning might have produced our findings. One possibility is thus that associative, local learning comes first and is only followed by (perhaps even triggers) a learning mode that is more sensitive to causal inferences. If so, our implicit participants were caught in an earlier learning phase than explicit participants. A second possibility that is consistent with most dual-process theories is that both types of learning took place in parallel. The challenge then is to explain why our findings do not show evidence of contributions from both types of learning, that is, why the generation of explicit knowledge would eliminate any effect of implicit knowledge, giving the impression of the former being less transferable than the latter. Again we see two possibilities. One is that the products of both types of learning may enter a competition in which explicit knowledge is assigned greater weight (perhaps to compensate for the "known" weaknesses of implicit learning); so that the associations representing the implicit knowledge would be suppressed. Another possibility is that the availability of explicit knowledge allows for a different kind of coding the relevant stimulus events. For instance, Tubau et al. (2005) showed that inducing an explicit learning mode tempts participants to code spatial stimuli and responses verbally rather than spatially. In the present study, people may have created "implicit" associations between the visual codes of words and explicit participants were able to prevent these associations from impacting their behavior by switching to a verbal or symbolic mode.

Taken altogether, we conclude that consciousness is connected with and thus indicates a mode of event integration that may not prevent the acquisition of local event associations but effectively excludes them from impacting action control.

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Appendix A

ANIMAL	FURNITURE	BODY	PLANT
Words	*Words*	*Words*	*Words*
perro (dog)	mesa (table)	cabeza (head)	geranio (geranium)
gato (cat)	silla (chair)	boca (mouth)	jazmín (jasmine)
león (lion)	cama (bed)	tronco (trunk)	rosal (rose bush)
tigre (tiger)	sillón (armchair)	dedo (finger)	helecho (bracken)
caballo (horse)	armario (wardrobe)	cuello (neck)	rosa (rose)
gallina (hen)	sofá (sofa)	tórax (thorax)	clavel (carnation)
vaca (cow)	lámpara (lamp)	abdomen (abdomen)	pino (pine)
pantera (panter)	mesilla (bedside table)	brazo (arm)	amapola (poppy)
jirafa (giraffe)	cómoda (bureau)	pies (feet)	abeto (fir)

(*continued on next page*)

Appendix A (*continued*)

ANIMAL	FURNITURE	BODY	PLANT
pájaro (sparrow)	cuadro (frame)	nariz (nose)	palmera (palm)
conejo (rabbit)	espejo (mirror)	oreja (ear)	cactus (cactus)
ratón (mouse)	estante (shelf)	pecho (chest)	ficus (ficus)
toro (bull)	butaca (armchair)	corazón (heart)	azucena (lily)
lobo (wolf)	consola (console table)	piernas (legs)	árbol (tree)
mono (monkey)	cocina (cooker)	mano (hand)	flores (flowers)
pato (duck)	tocador (dressing table)	ojos (eye)	nardo (nard)
		Nonwords	*Nonwords*
		capeza	geramio
		buca	jasmín
		troncu	rusal
		dedu	helechu
		coello	rose
		tórac	cravel
		abdumen	pinu
		brazu	amapula
		piex	abetu
		naris	balmera
		ureja	cactuz
		pechu	ficos
		corazún	azocena
		piermas	árpol
		manu	flures
		ojus	nerdo

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