THE EFFECT OF EXPLICIT KNOWLEDGE ON SEQUENCE LEARNING: A GRADED ACCOUNT

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In this paper, we study the effect of conscious knowledge on implicit sequence learning. To do so, in three sequence learning experiments, we manipulated (1) the extent to which instructions were intentional vs. incidental—intentional participants were informed of the existence of sequential regularities, and (2) the amount of explicit knowledge given to participants about the stimulus material. Results indicated that explicit knowledge improves sequence learning, as indexed by an increase in reaction times when the training sequence is unexpectedly replaced by another one. To enable us to differentiate between implicit and explicit learning, we applied the process dissociation procedure in a subsequent free generation task. Results indicated that both reaction time and generation results were influenced by different levels of explicit knowledge. However, we failed to find any evidence for an automatic influence on generation performance. We also report on simulation studies using the simple recurrent network, and show that the model can account for the effects of explicit knowledge on both reaction time and generation performance. Because the model uses a single pathway to process information, these simulation results are suggestive that dissociations between implicit and explicit learning might result from continuous, gradual changes in a single dimension rather than from the involvement of different brain networks.

Introduction

In many everyday life situations, our ability to master a complex and changing environment improves with no concurrent enhancement in our ability to accurately describe the relevant regularities. This particular type of adaptation - which expresses itself in many domains, ranging from motor performance to the processing of linguistic material - is generally attributed to the operation of an implicit mode of learning that is further assumed to be independent of explicit, hypothesis-driven learning processes. In this paper, we aim to explore the relationships between implicit and explicit learning, and, more specifically, to assess to what extent *implicit* learning occurs when

participants know about the rules governing the environment they are confronted with.

Implicit learning can be defined as the acquisition of new information without intention to do so, and in such a way that the resulting knowledge is difficult to express (Berry & Dienes, 1993; Cleeremans, Destrebecqz, & Boyer, 1998). While different experimental paradigms have been used to study implicit learning, some authors have pointed out that sequence learning is particularly well suited to do so because it provides us with truly incidental learning conditions (Cleeremans, 1993b; Cleeremans & Jiménez, 1998). In sequence learning studies, participants are faced with a serial reaction time (SRT) task in which they simply have to indicate as fast and as accurately as possible the location of a stimulus presented on a computer screen. Unknown to them, the sequence of stimuli involves some regularity. Performance measures, such as faster reaction times for regular than for random trials, clearly indicate that participants learn the sequence even if they often fail to exhibit precise knowledge of the repeating pattern. However, the ability to learn without awareness has been the object of numerous controversies, ranging from quarrels about how one should define consciousness to methodological debates about to best measure and contrast implicit and explicit learning (Perruchet & Amorim, 1992; Shanks & St. John, 1994).

As a result of these conceptual challenges, some authors have suggested that we should focus on the *processes* engaged in implicit learning rather than on the conscious or unconscious nature of the acquired *knowledge* (Frensch, Lin, & Buchner, 1998). In line with this idea, it has been proposed that a fruitful strategy through which to contrast implicit and explicit learning consists of comparing performance between intentional participants, (who are instructed to attempt to discover the regularities present into the sequence), and incidental participants (who are given neutral instructions that do not refer to a systematic pattern). Using this procedure, previous studies have indicated that intentional instructions improve sequence learning (Curran, 1997; Curran & Keele, 1993; Frensch & Miner, 1994). Other reports, however, have shown that this facilitation disappears when the sequence involves probabilistic regularities (Jiménez, Méndez, & Cleeremans, 1996); therefore suggesting that intention to learn interacts with the complexity of the material to be learned.

Other functional studies have further contributed to characterize implicit sequence learning as a robust and powerful process that is relatively independent of attentional resources, stimulus complexity or task demands (Cleeremans, 1997; Hsiao & Reber, 1998; Jiménez & Méndez, 1999, 2001; Stadler, 1995). As recently pointed out by (Willingham & Goedert-Eschmann, 1999), however, only but a few studies have focused on the relationship between implicit and explicit learning.

The goal of this study is to further explore the nature of the relationship between implicit and explicit learning. We conducted a series of sequence learning experiments in which (1) we compared incidental and intentional instructions, and in which (2) we manipulated how much explicit knowledge was given to participants prior to their performing the SRT task. In both cases, we measured the effects of the experimental manipulation on both implicit and explicit sequence learning. To obtain the relative contribution of implicit and explicit learning, the process dissociation procedure (Jacoby, 1991; see below) was used in two of our three experiments.

The nature of the relationship between implicit and explicit learning is a rather complex issue because different types of relationships might be consistent with the data. In particular, implicit and explicit learning might either depend on distinct, independent processing systems, or might instead simply reflect different aspects of a single set of learning mechanisms. When assumed to depend on dissociable systems, implicit and explicit learning might further operate either in parallel, or instead stand in a mutually exclusive relationship (see Figure 1). To further complicate matters, these different possibilities might prove to be equivalent under some conditions, thus making it difficult to differentiate between them based on behavioural data alone.

As a case in point, consider the recent study by Willingham and Goedert-Eschmann, who trained two groups of intentional and incidental participants in a SRT task using a 12-element repeating sequence. The final practice block involved both random and sequenced trials. For half of the participants in both incidental and intentional groups these sequenced trials corresponded either to the training sequence or to a different 12-element sequence. To measure implicit learning, the authors computed a "learning score" by subtracting the mean reaction time elicited by sequenced trials from the mean reaction time elicited by random trials in the final block of practice. Learning scores were larger for participants who had been presented with the same sequence throughout training but did not differ between incidental and intentional participants. Intentional instructions had no effect on implicit learning scores, but intentional participants performed better than incidental participants in an explicit free recall test. Willingham and Goedert-Eschmann therefore concluded that implicit and explicit sequence learning occur in parallel.

Importantly, these results further imply that implicit and explicit learning processes are subtended by different neural systems (Willingham, 1998). This conclusion is supported by brain imaging studies showing that very different brain networks are activated by implicit and explicit modes of learning (Grafton, Hazeltine, & Ivry, 1995; Rauch et al., 1995). Crucially, however, these studies have also suggested that implicit and explicit learning systems do not operate in parallel, but that they are instead mutually exclusive.
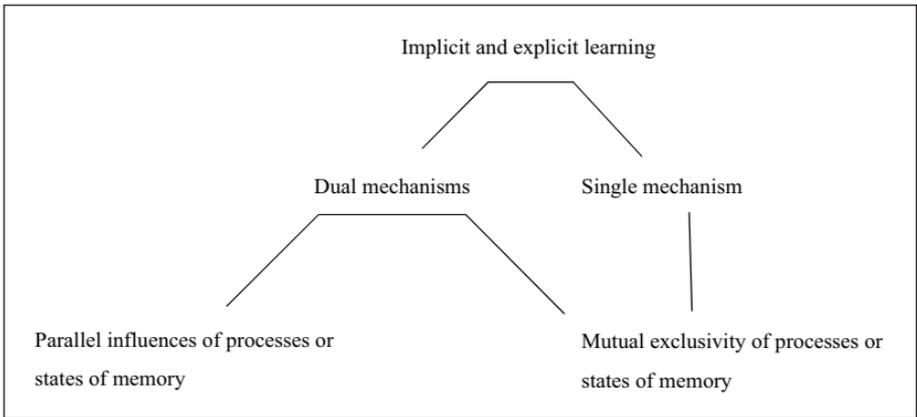
Figure 1. This figure illustrates that implicit and explicit forms of learning can be based either on a single or on two different mechanisms. In this latter case, both mechanisms can stand in a mutually exclusive relationship: implicit and explicit knowledge do not reflect similar aspects of the environment, or they can influence performance in parallel: a specific piece of knowledge has been acquired implicitly and explicitly at the same time and influence performance simultaneously. By contrast, in a single process view, implicit and explicit learning reflect different aspects of a single set of learning mechanisms. In this framework, accessibility to consciousness depends on different aspects of the acquired knowledge, such as the distinctiveness, stability in time, or the quality of the corresponding representations. Conscious and unconscious influences are therefore mutually exclusive as they stem from different components of a single knowledge base about the environment.

Indeed, the brain regions associated with implicit and explicit learning tended to be activated separately, suggesting that implicit learning processes cease to contribute to performance as soon as explicit knowledge is involved.

Other authors have instead suggested, based on simulation studies, that the dissociation between implicit and explicit processing could be captured within a unique system. According to this view, accessibility to consciousness depends on different aspects of the acquired knowledge, such as the distinctiveness or stability in time of the corresponding representations (Mathis & Mozer, 1996; O'Brien & Opie, 1999). Likewise, it has been recently suggested that the differences between implicit and explicit learning might be best characterized as resulting from continuous, gradual changes in a single dimension involving "quality of representation" (Cleeremans & Jiménez,

2002). Thus, stable, strong, and distinctive representations will tend to be associated with different behavioural and phenomenal correlates than weaker representations, such as, for instance, improved availability to conscious control and to meta-knowledge. Kinder and Shanks (2003) made a similar claim in the field of neuropsychological dissociations. These authors have shown that the memory impairments associated with amnesia can be accounted for within a single-system connectionist model of learning in which amnesia is simply simulated by a reduced learning rate. According to Kinder and Shanks different memory systems are thus not required to account for dissociations between normal and amnesic subjects.

To further explore the relationship between implicit and explicit learning, we examine in a series of experiments whether increasing levels of explicit knowledge leave the implicit influences measure (i.e. the exclusion scores, see below) unaffected —suggesting that implicit and explicit learning are independent from each other), or whether implicit influences during generation tend to decrease when participants are given more explicit knowledge about the sequence—suggesting that implicit and explicit learning might be mutually exclusive. To assess the relative contribution of implicit and explicit learning, we applied the process dissociation procedure (Jacoby, 1991) to a subsequent free generation task.

The process dissociation procedure, as applied to sequence learning tasks (see Destrebecqz & Cleeremans, 2001), is based on comparing performance in two generation tasks—inclusion and exclusion—that differ only by the instructions given to participants. In the inclusion task, participants are told to try to reproduce the training sequence. Performance in this task can depend either on explicit recollection or on guessing based on intuition or familiarity. Hence, both implicit and explicit knowledge can contribute to inclusion performance. By contrast, in the exclusion task, participants are told to produce a sequence of stimuli that differs as much as possible from the training sequence. Implicit and explicit influences are thus now set in opposition, for to successfully avoid reproducing the sequence, one has to consciously retrieve its regularities so as to be able to produce some other sequential transitions. Of course, one can also exclude based on a mere feeling of familiarity, which may not be associated with explicit recollection of the sequence. In other words, one may estimate that a given response would reproduce the training sequence without remembering that response explicitly, and, based on this (explicit) feeling of familiarity, conservatively decide to generate a different transition. This is precisely why applying the process dissociation procedure to a free generation task makes it possible to dissociate conscious and unconscious knowledge acquisition: If participants keep generating the training sequence against exclusion instructions, one can safely assume that such performance only reflects the automatic influence of

unconscious knowledge[1] (for a discussion on this issue, see also Richardson-Klavehn, Gardiner, & Java, 1996).

Experiment 1

The goal of this experiment was to measure the influence of orientation to learn on the indirect measure of sequence learning, i.e., the cost in reaction time that is incurred when the repeating sequence is unexpectedly replaced by another one.

Method

The experiment consisted of a four choice reaction time task involving 7 blocks of 96 trials, for a total of 672 trials. The reduced number of trials was used in order to limit the acquisition of explicit knowledge by incidental participants. On each trial, a black dot appeared at one of four possible locations on a computer screen. For each trial, participants were to press as fast and as accurately as possible on the key that corresponded to the location at which the target had appeared. The mapping between keys and stimulus locations was fully compatible. Errors were signalled through the emission of a short beep, but did not need to be corrected. Instructions stressed the importance of fast reaction times and indicated that a small amount of errors was tolerated. The response-stimulus interval was set to 120 ms. Participants practiced the task for 60 random trials before the first block.

Sequences of successive target locations were determined based on the repetition of a 12-element sequence that consisted of four different elements (hereafter *a*, *b*, *c*, and *d*). The same sequence was repeated over the first 6 blocks. Each block started with a different initial element. Block 7 consisted of eight repetitions of a different sequence (see below). A significant increase in reaction time was expected during block 7 if participants had learned the regularities of the training sequence.

The experiment involved two conditions. In the incidental condition, participants were not informed of the fact that the sequence of targets was reg-

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[1] Other measurement models have been proposed in order to obtain quantitative estimates of implicit and explicit influences on performance with the process dissociation procedure. These models reflect the different hypothetical possible relationships between both influences. However, this question is very controversial and, in order to circumvent this issue, we based our adaptation of the PDP on the comparison between inclusion and exclusion performance only (see also Neal & Hesketh, 1997).

ular. In the intentional condition, participants were told that the sequence of stimuli was not random, and were asked to try to identify those regularities so as to improve their performance in the SRT task. We hypothesized that if an intentional orientation to learn improves sequence learning, the increase in reaction time in the transfer block should be more important in the intentional than in the incidental condition.

Subjects

Forty participants aged 18-26 years, all undergraduate students at the Université Libre de Bruxelles, were randomly assigned to one of the two experimental condition and paid €6.

Material

The experiment was run on a Macintosh computer. The display consisted of four dots arranged in a horizontal line on the computer's screen and separated by intervals of 3 cm. Each screen position corresponded to a key on the computer's keyboard. The spatial configuration of the keys was fully compatible with the screen positions. The stimulus was a small black circle 0.35 cm in diameter that appeared on a white background, centred 1 cm above one of the four dots.

Sequential Material

Participants were presented with the following training sequence: *a b c d a c b a d b d c*. The structure of the transfer sequence presented during the seventh block was *d b c a d c b d a b a c*. A 4✕4 Latin square design was used to balance the correspondence between the letters and the four screen locations. In both conditions, one of the four different 12-element training sequences and the corresponding transfer sequence (see Table 1) was randomly attributed to each participant. The sequences consisted entirely of so-called "second order conditional" transitions or SOCs (Reed & Johnson, 1994). With SOC sequences, two elements of temporal context are always necessary to predict the location of the next stimulus. In other words, each element can be preceded or followed by any of the three other elements. Both training and transfer sequences were balanced for stimulus locations and transition frequency, but differed in terms of the subsequences of three elements that they contained. For instance, the transition '34' was followed by

Table 1. *Training And Transfer Sequences*

	Training	Transfer
Sequence A	1 4 2 3 1 2 4 1 3 4 3 2	1 4 1 2 3 4 2 1 3 2 4 3
Sequence B	2 1 3 4 2 3 1 2 4 1 4 3	2 1 2 3 4 1 3 2 4 3 1 4
Sequence C	3 2 4 1 3 4 2 3 1 2 1 4	3 2 3 4 1 2 4 3 1 4 2 1
Sequence D	4 3 1 2 4 1 3 4 2 3 2 1	4 3 4 1 2 3 1 4 2 1 3 2

location 3 in the training sequence A and by location 2 in the transfer sequence A.

Results and Discussion

Errors in the SRT task did not exceed 4% of the trials in both conditions and were excluded from data analysis. Figure 2 shows the average reaction time obtained over the entire experiment, plotted separately for the two conditions. Inspection of the figure suggests that intentional participants perform better than incidental participants. An analysis of variance (ANOVA) on the first six blocks of the SRT task with Practice [6 levels] as a within-subject variable and Condition [two levels] as a between-subjects variable revealed a significant Practice $\times$ Condition interaction [$F (14, 308) = 2.751$, $p < 0.001$, Mse = 1110.455]. The simple effect of Condition was only marginally significant [$F (1,38) = 3.154$, $p = .08$, Mse = 118228.969]. There was no reliable effect of Practice[2].

The increase in reaction time during Block 7 suggests that participants have learned the sequence in both conditions. Another ANOVA with Block [2 levels, Blocks 6 and 7] as a within-subjects variable and Condition [two levels] as a between-subjects variable revealed a significant effect of Block [$F (1,38) = 82.346$, $p < .0001$, Mse = 90749.267] and a significant Block $\times$ Condition interaction [$F (1,38) = 9.404$, $p < .005$, Mse = 10363.251]. The effect of Condition did not reach significance.

This analysis shows that the reaction time cost incurred by the transfer block is more important in the intentional than in the incidental condition. This result suggests that sequence learning is improved in the former condition, and is in line with previously reported results with other types of sequential regularities (Curran & Keele, 1993; Curran, 1997).

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[2] A non-significant effect of practice has previously been reported in the literature for limited amounts of training (Perruchet, Bigand, & Benoit-Gonnin, 1997), and does not necessarily reflect the absence of sequence learning, as indicated by the transfer effect during Block 7 in Experiment 1.
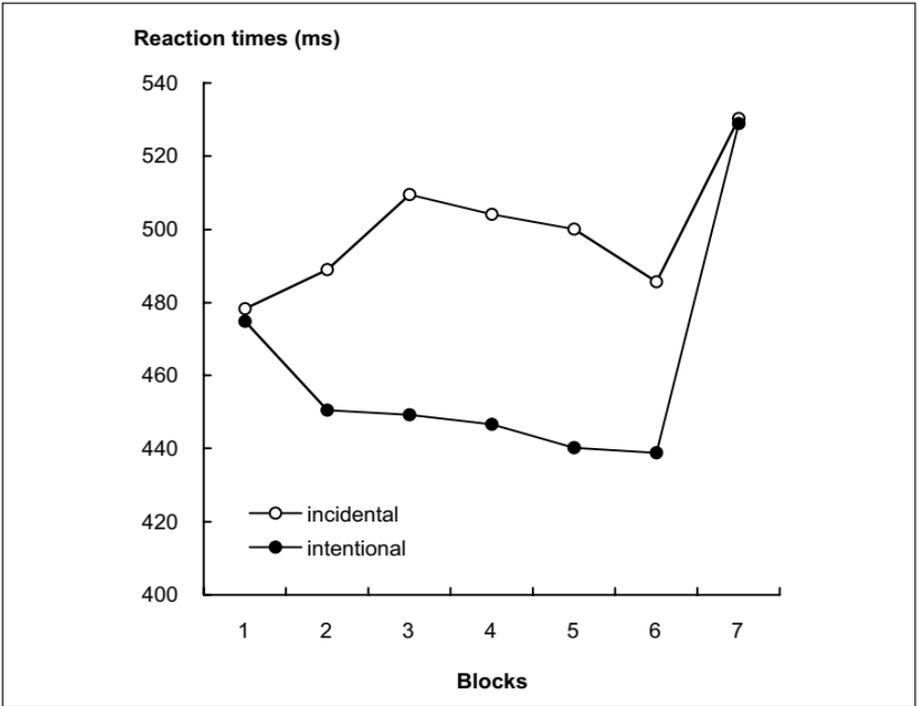
Figure 2. Mean reaction times for each training block, plotted separately for incidental and intentional participants.

To further analyze the transfer effect, we measured the individual transfer effect associated with each of the twelve SOC transitions (Reed & Johnson, 1994; Shanks & Johnstone, 1998). To perform this analysis, we simply subtracted the mean reaction time associated with the third element of a given triplet of the training sequence in the sixth block (e.g., bd-*c*) from the reaction time associated with the third element of the same transition in the transfer sequence (e.g., bd-*a*). We performed *T* tests to assess which SOC transitions were associated with a significant transfer effect, and hence with significant sequence learning.

Figure 3 shows the transfer effects measured for the twelve SOC transitions, represented on the horizontal axis according to the abstract structure of the training sequence. Significant transfer effects are indicated with an asterisk. The figure indicates that, in both conditions, participants only learn a subset of the sequential transitions. The transfer effect is significant, or marginally significant, for three (incidental condition) and for eight (intentional condition) of the twelve sequential transitions, suggesting that sequence learning was improved in the latter condition. However, the figure makes it
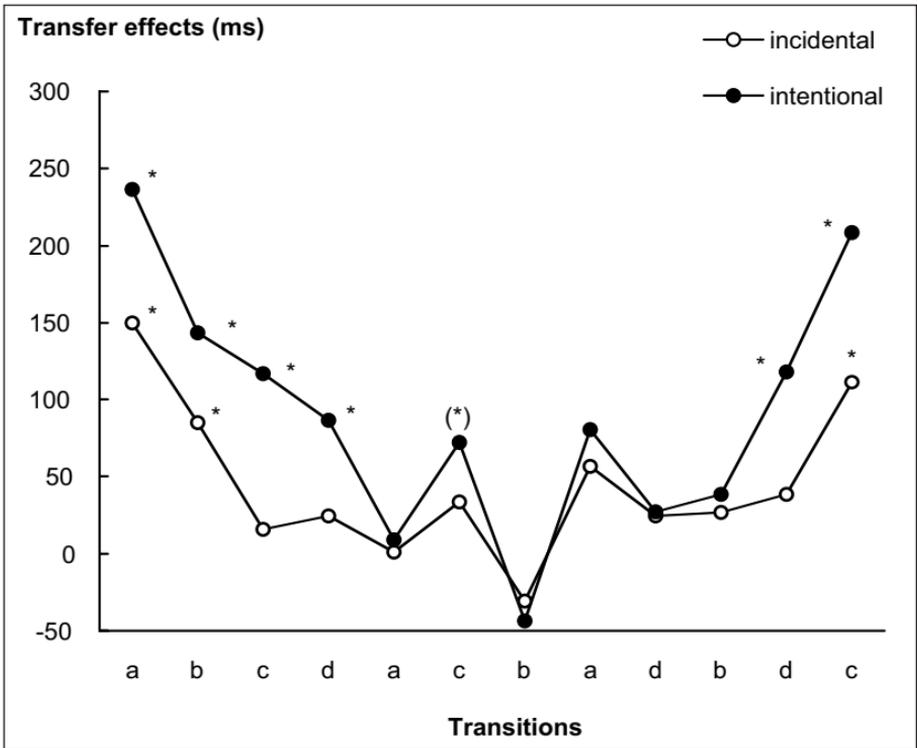
Figure 3. Mean transfer effects for the twelve locations of the training sequence plotted separately for the incidental and intentional conditions. Each data point corresponds to the reaction time difference between the transfer and the training sequence for a specific transition. For instance the rightmost data point corresponds to the mean reaction time associated with stimulus *a* that follows the transition *bd-* in the seventh block minus the mean reaction time associated with the location *c* that follows the same transition *bd-* in the sixth block of training. *Note*. * indicates a significant increase in reaction time (p < .05), (*) a marginally significant difference (p < .06)

clear that intentional instructions did not influence sequence learning quali- tatively, as indicated by the similarity of the transfer curves. These impres- sions were confirmed by an ANOVA conducted on reaction time differences between blocks 6 and 7, with Transitions (12 levels) as a within-subject fac- tor and Condition (2 levels) as a between-subjects factor. This analysis revealed a significant effect of Condition [F (1,38) = 10.684, p< .005, Mse = 258378.865], and of Transitions [F (11,418) = 8.641, p < .0001, Mse = 163104.484]. The Condition × Transitions interaction was not signif- icant.

To summarize, the results of this experiment show that participants were able to learn sequential regularities as complex as second order contingencies despite the relatively short amount of practice (48 repetitions of the training sequence). Further, while intentional instructions improved performance, they did not influence sequence learning qualitatively, as suggested by the detailed analysis of the transfer effect for the twelve transitions. In short, participants in both conditions learn something about the stimulus material, and intentional participants simply appear to learn more about it than incidental participants do. In Experiment 2, we explore to what extent the difference between incidental and intentional learning instructions can be attributed to an increase of explicit knowledge acquisition.

Experiment 2

To make it possible to differentiate between implicit and explicit sequence learning, Experiment 2 participants performed a free generation task under inclusion and exclusion instructions after training on the main SRT task. As for Experiment 1, half of the participants performed the choice reaction time task under incidental instructions and the other half under intentional instructions. Based on the results of experiment 1, we hypothesized that participants in both conditions would learn the sequence and be able to reproduce it under inclusion instructions. We also hypothesized that participants in the incidental condition (under the assumption that learning is completely implicit in this condition), would lack control over their knowledge and hence fail to be able to avoid producing the regularities of the training sequence when performing the generation task under exclusion instructions. This should not be the case in the intentional condition (under the assumption that learning includes explicit components in this condition), and we therefore expected these participants to be better able to avoid reproducing the training sequence when performing the generation task under exclusion instructions.

Method

The experiment was divided in two phases. The first phase consisted of a four choice reaction time task identical to Experiment 1, except that there was no transfer block. Participants performed the task for six blocks of 96 trials. Each block consisted of eight repetitions of the same 12-element SOC sequence. As for Experiment 1, half of the participants were given intentional instructions prior to the SRT task and the other half performed the task under incidental instructions.

After the SRT task, participants were informed that the dots had followed a repeating pattern. They were then presented with a single stimulus that appeared in a random location, and asked to freely generate a series of 96 trials that "resembled the training sequence as much as possible". They were told to rely on intuition when feeling unable to recollect the location of the next stimulus. After this generation task—performed under inclusion instructions—subjects were asked to generate another sequence of 96 trials, this time under exclusion instructions. They were told they now had to try to *avoid* reproducing the sequential regularities of the training sequences. In both generation tasks, subjects were also told not to repeat responses. The stimulus moved whenever subjects had pressed one of the keys, and appeared at the corresponding location after a delay of 120 ms.

Subjects

Twenty-four participants aged 18-26 years, all undergraduate students at the Université Libre de Bruxelles, were randomly assigned to one of two experimental condition and paid € 6.

Results and Discussion

SRT task. In both conditions, errors were below 3% of the trials and were excluded from data analysis. Figure 4 (left panel) shows the average reaction times obtained over the six blocks of practice plotted separately for the two conditions. As for Experiment 1, reaction times appear to be faster and to decrease more with practice in the intentional than in the incidental condition. These impressions were confirmed by an analysis of variance (ANOVA) conducted on reaction times with Practice [6 levels] as a within-subject variable and Condition [two levels] as a between-subjects variable. This analysis revealed a significant effect of Condition [$F_{(1,22)} = 33.525$, $p < .001$, Mse = 290315.336] and a significant Practice $\times$ Condition interaction [$F_{(5,110)} = 3.124$, $p < .05$, Mse = 2662.893]. The main effect of Practice did not reach significance[2]. These results are in line with those of Experiment 1 and suggest that intentional instructions improve sequence learning in the same way in Experiment 2.

Generation task. As each SOC transition involves three consecutive elements, we computed the number of generated chunks of three elements that were part of the training sequence in both inclusion and exclusion tasks to measure generation performance. As the generated sequences were 96 trials long, the maximum number of correct chunks is 94. To obtain inclusion and exclusion scores for each participant, we therefore divided the corresponding

number of correct chunks by 94.

Figure 4 (right panel) shows average inclusion and exclusion scores for both conditions. An ANOVA with Condition (incidental vs. intentional) as a between-subjects variable and Instructions (inclusion vs. exclusion) as a within-subject variable revealed a significant effect of Instructions [$F_{(1,22)} = 14.553$, Mse = 0.239, $p < .001$]. Neither the main effect of Condition nor the Condition × Instructions interaction reached significance.

As participants were told not to produce repetitions, chance level can be set at 0.33. Two-tailed *t* tests were used to compare generation scores to chance level. Inclusion scores are above chance level in both conditions [mean=0.52, SE=0.04, $t_{(11)}$=4.79, p< 0.001 and mean=0.52, SE=0.05, $t_{(11)}$=3.89, p<0.01 for the incidental and the intentional condition respectively]. Exclusion scores did not differ from chance level in the incidental condition [mean=0.35, SE=0.04, $t_{(11)}$=0.61] but were reliably above chance in the intentional condition [mean=0.41, SE=0.03, $t_{(11)}$ = 3.01, $p < 0.05$]. At first sight, these results seem to suggest that generation performance depends partly on unconscious influences in the intentional but not in the incidental condition in which learning appears to be essentially explicit. However, there are good reasons to believe that the use of 33% as baseline might overestimate sequence learning (Reed & Johnson, 1994). For example, participants may learn that the training sequence contains only one reversal (3-4-3, 4-1-4,1-2-1 or 2-3-2) and, based on this information, avoid or increase reversal responses in the inclusion or exclusion task respectively. In that case, chance level would be different from 33% even if participants did not acquire SOC knowledge as such (Shanks & Johnstone, 1999).
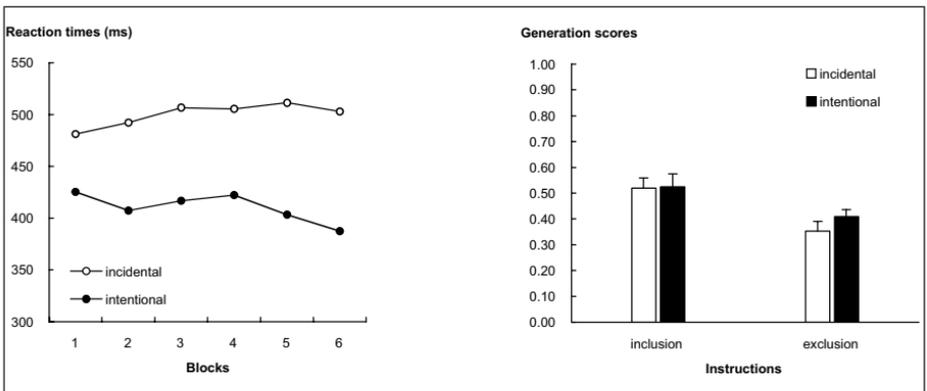

Figure 4. Mean reaction times for each training block, plotted separately for incidental and intentional participants (left panel). Mean inclusion and exclusion scores for incidental and intentional participants (right panel).

Therefore, to further analyze generation performance, we also computed, for each participant, the number of generated triplets that corresponded to the transfer sequence. Indeed, recall that training and transfer sequences differed in terms of their SOC transitions but were balanced for all other sequential regularities. If participants learn the SOC transitions of the training sequence, they should produce these triplets more frequently than those of the transfer sequence in the inclusion task. This is the pattern of results that we observed in both incidental [paired t (11) = 3.90, p < .01] and intentional [paired t (11) = 2.43, p < .05] conditions. Moreover, if sequential knowledge has been acquired *explicitly* during the SRT task, participants should be able to control their behaviour and be able to avoid producing more triplets from the training sequence than from the transfer sequence in the exclusion task. We also observed this result in both incidental [paired t (11) = 0.97, p > .3] and intentional conditions [paired t (11) = 1.44, p > .1].

To summarize, according to this analysis, sequence learning appears to be explicit in both conditions. Indeed, participants were simultaneously (1) able to project their knowledge in the inclusion task, and (2) able to avoid reproducing the training sequence when so instructed in the exclusion task. These results stand in contrast with the idea that sequence learning depends on unconscious knowledge acquisition under incidental instructions, and instead suggest that sequence learning occurs explicitly. Previous studies, however, have shown that sequence learning can occur implicitly when participants are prevented by the training conditions to become aware of the systematic pattern. This might be the case, for instance when a secondary task is performed during the SRT task (Goschke, 1997, 1998), when the pace of the SRT task is too sustained to allow participants to anticipate the apparition of the next element (Destrebecqz & Cleeremans, 2001), or when using complex probabilistic sequential regularities (Jiménez et al., 1996).

As previously reported in the literature (Buchner, Steffens, Erdfelder, & Rothkegel, 1997; Curran, 1997; Curran & Keele, 1993; Frensch & Miner, 1994), intentional participants responded faster in the SRT task. Generation results, however, do not indicate that this reaction time difference can be attributed to an increase of explicit learning in the intentional condition. Rather, in both conditions, participants acquired explicit knowledge as complex as SOC transitions after only 48 sequence presentations and obtained comparable generation scores. This result contrasts with previous reports indicating improved performance under intentional instructions in continuous generation (Frensch & Miner, 1994) or recognition tasks (Buchner et al., 1997; Curran, 1997). A possible explanation might be that the generation task, in contrast with the SRT task, is not sufficiently sensitive to reveal qualitative dissociations between intentional and incidental conditions. To increase the contrast between training conditions, we explored, in

Experiment 3, the effect of different levels of explicit knowledge on direct and indirect measures of sequence learning.

Experiment 3

In this experiment, participants were informed about the exact sequential regularities of the material prior to the SRT task. We compared participants' performance in two conditions: In the "limited knowledge" (henceforth, LK) condition, participants were asked to study the sequence during a limited time. In the "full knowledge" (henceforth, FK) condition, they had to learn the sequence until they knew it perfectly. Sequence learning was measured through the cost in reaction time during a transfer block of the SRT task, and through generation performance under inclusion and exclusion instructions. We expected that direct and indirect measures of sequence learning would be improved for participants who had perfect knowledge of the sequence.

Method

Participants were first given SRT task instructions and performed 60 random practice trials. They were then presented with the 12-element sequence depicted on a sheet of paper. Each of the 12 stimuli was indicated by a black dot occupying one of four locations. In the LK condition, participants were allowed to observe and learn the sequence for 2 minutes. In the FK condition, participants had to learn the sequence perfectly: They had to be able to describe the sequence without any error before being introduced to the SRT task.

Participants subsequently performed seven blocks of a four-choice reaction time task. Each of the first six blocks corresponded to eight repetitions of a 12-element sequence. A different sequence was used in the seventh block. The details of the procedure and the sequential material were identical to Experiments 1 and 2. After the SRT task, participants were introduced to the inclusion and exclusion tasks. The procedure was identical to Experiment 2 [3].

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[3] Contrary to Experiments 1 & 2, we measure sequence learning indirectly (through a transfer block in the SRT task) and directly (through generation performance) in a within-subject design. Indeed, given the pre-training in Experiment 3, there was no doubt that participants knew the training sequence by the end of the SRT task and we were therefore less concerned by a potential contamination of generation performance due to the presentation of the transfer sequence in the last block of the SRT task.

Subjects

Thirty participants aged 18-26 years, all undergraduate students at the Université Libre de Bruxelles took part to this experiment and were paid € 6. Fifteen were assigned to the LK condition and fifteen to the FK condition.

Results and Discussion

SRT task. In both conditions, errors were below 3% of the trials and were excluded from data analysis. Figure 5 shows the average reaction times obtained over the seven blocks of practice plotted separately for the two conditions. To analyze reaction time data, we first performed an analysis of variance (ANOVA) with Condition as a between-subjects factor [2 levels] and Practice [6 levels, blocks 1-6] as a within subject factor. This analysis revealed a significant effect of the factors Condition [$F_{(1,28)} = 10.033$, Mse = 368798.248, $p < .005$] and Practice [$F_{(5,140)} = 5.436$, Mse = 1629.459, $p < .0001$]. The Practice $\times$ Condition interaction was not significant ($F < 0.5$).
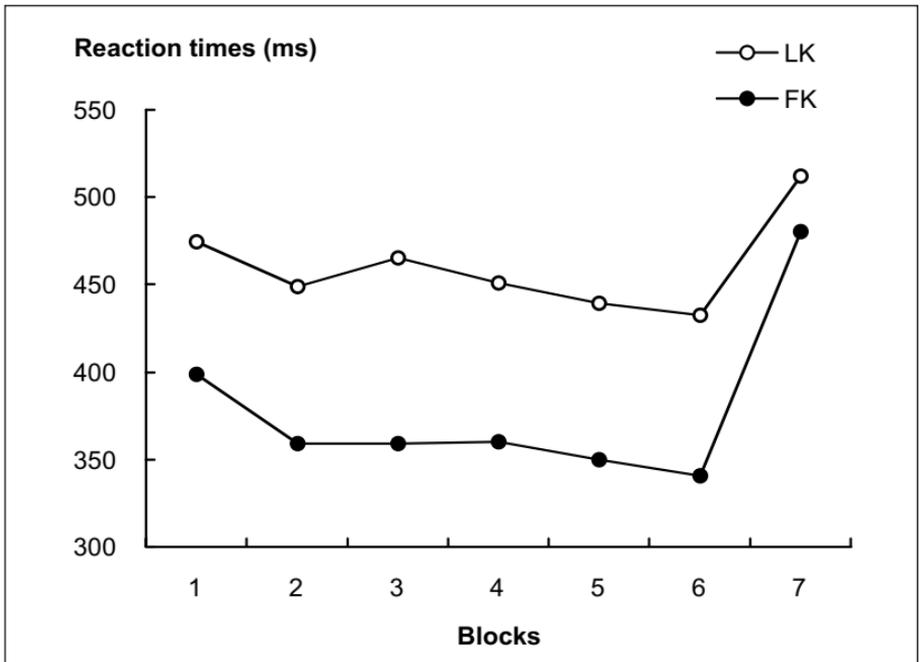

Figure 5. Mean reaction times for each training block, plotted separately for the LK and FK conditions.

To analyze transfer, we performed another ANOVA with Blocks as a within subject factor [2 levels, the sixth and seventh blocks] and Condition as a between subjects factor [2 levels]. This analysis showed a significant effect of Blocks [$F(1,28) = 33.821$, Mse = 5327.925, $p < .0001$] and of Condition [$F(1,28) = 5.395$, Mse = 10640.333, $p < .05$]. The Blocks $\times$ Condition interaction failed to reach significance ($F < 2.6$).

The significant transfer effect is not surprising given that participants knew the sequence before the SRT task. Faster reaction times in the FK condition suggest that perfect explicit knowledge improves performance. Transfer, however, was not significantly larger in the FK condition.

As for Experiment 1, we also performed *T* tests to analyze transfer for each of the twelve SOC transitions. This analysis showed that the increase in reaction time is significant or marginally significant for nine of the twelve transitions in the LK and in the FK conditions (see Figure 6). An analysis of variance (ANOVA) conducted on transfer effects measured for the twelve transitions with Transitions (12 levels) as a within subject factor and Condition (2 levels) as a between subjects factor revealed a significant effect
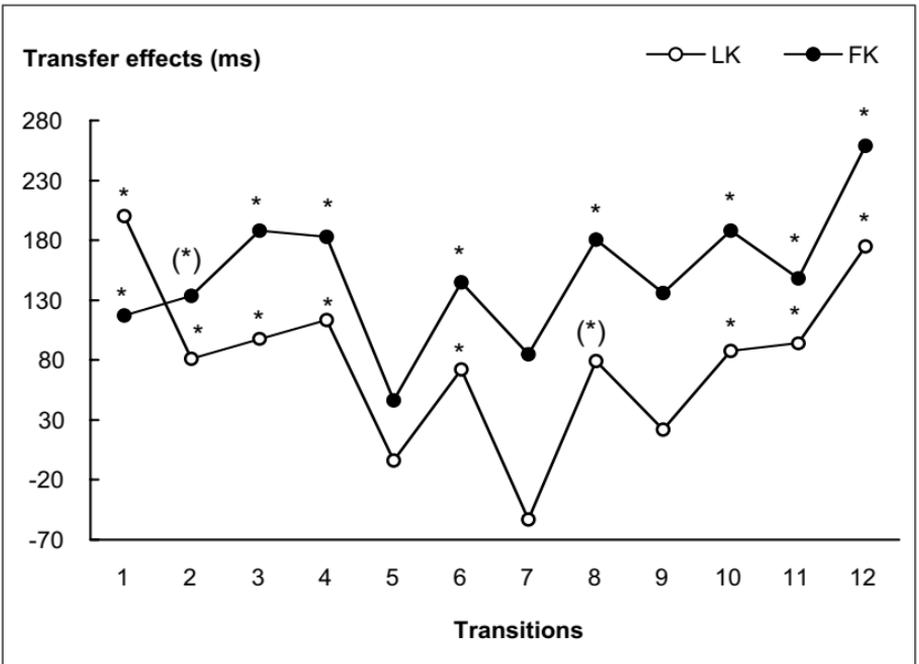

Figure 6. Mean transfer effects for the twelve locations of the training sequence plotted separately for the LK and FK conditions. *Note.* * indicates a significant increase in reaction time ($p < .05$), (*) a marginally significant difference ($p < .07$)

of Transition [F (11,308) = 4.031, Mse = 95518.711, p < .0001] and a marginally significant effect of Condition [F (1,28) = 3.266, Mse = 446965.442, p = .08]. This analysis confirms that transfer differs for the different transitions but is qualitatively equivalent for the two conditions.

Generation task. Figure 7 shows inclusion and exclusion scores for the FK and LK conditions. We conducted an ANOVA on inclusion and exclusion scores (computed as for Experiment 2) with Condition [2 levels] as a between-subjects factor and Instructions [2 levels] as a within-subject factor. This analysis revealed a significant effect of Instructions [F (1,28) = 93.009, Mse = 1.897, p < .0001] and Condition [F (1,28) = 15.874, Mse = 0.151, p < .0005]. The Condition $\times$ Instructions interaction also reached significance [F (1,28) = 21.668, Mse = 0.442, p < .0001]. Planned comparisons further indicated that inclusion scores exceed exclusion scores in both the LK [F (1,14) = 10.983, Mse = 0.254, p < .01] and the FK conditions [F (1,14) = 117.951, Mse = 2.086, p < .0001]. In the inclusion task, FK participants produced more regularities (mean = 0.860, SE= 0.030) from the training sequence than LK participants did (mean = 0.589, SE= 0.043)

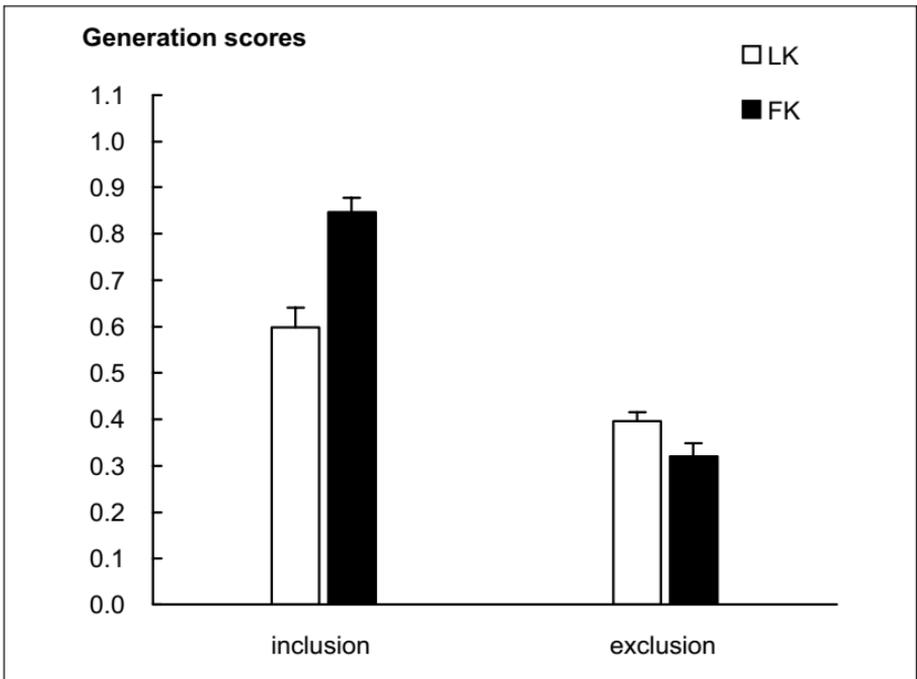*Figure 7.* Mean inclusion and exclusion scores computed in the LK and FK conditions.

[F $(1,28)$ = 26.127, Mse = 0.555, p < .0001]. The opposite pattern was observed under exclusion instructions, with LK participants producing more chunks from the training material (mean = 0.405, SE=0.019) than FK participants did (mean = 0.333, SE=0.028) [F $(1,28)$ = 4.399, Mse = 0.038, p < .05]. Overall, these results indicate that inclusion and exclusion performance tend to reflect differences in explicit knowledge between LK and FK conditions: Participants exert more control on their sequential knowledge in the FK than in the LK condition.

We also compared inclusion and exclusion scores to chance level (0.33). Inclusion scores are above chance level in both conditions [t (14)=5.95, p< 0.001 and t (14)=17.83, p<0.001 for the LK and FK condition respectively]. Exclusion scores did not differ from chance level in the FK condition [t (14)=0.12] but were reliably above chance in the LK condition [t (14) = 3.86, p < 0.01]. However, neither in the LK [paired t (14) = 0.6, p > .55] nor in the FK condition [paired t (14) = -0.973, p > .35] did participants tend to more frequently produce the regularities of the training sequence than those of the transfer sequence in the exclusion task. These results indicate that, just as for Experiment 2, generation performance does not depend on unconscious knowledge influence.

To summarize, in all four conditions of these experiments (incidental, intentional, LK, and FK), participants appear to have learned the sequence explicitly. They were indeed able to control the expression of their knowledge and to conform to the instructions of the generation task. The results of these experiments also suggest that increased level of explicit knowledge improve sequence learning. Intentional participants were faster than incidental participants and showed increased transfer. FK participants responded faster than LK participants, and also produced more training triplets in inclusion, and fewer training triplets in exclusion than LK participants. Regardless of their level of explicit knowledge, participants did not tend to reproduce the regularities of the training sequence under exclusion instructions. In the next section, we present simulation results showing how the results summarized above can be accounted for within a single processing pathway.

Simulations

What might be the cognitive processes subtending sequence learning in our study? While a few novel computational models have been recently proposed to account for human performance in this task (Dominey, 1998; Sun, Merrill, & Peterson, 2001; Wallach & Lebiere, 2003), in this paper, we focus on the Simple Recurrent Network (SRN) first proposed by (Elman, 1990) and subsequently adapted by (Cleeremans & McClelland, 1991) to sequence

learning. This model has been widely used to simulate human performance in SRT tasks (Cleeremans, 1993) and in other implicit learning paradigms, such as artificial grammar learning (Dienes, Altmann, & Gao, 1999; Kinder, 2000). The SRN is a connectionist network that is trained through back-propagation to *predict* the next element of a sequence based on the current element and on a representation of the temporal context that the model has elaborated itself through training.

To achieve this task, the network is endowed with a pool of context units, which, on each trial, hold a copy of the pattern of activation that existed over the network's hidden units during the previous time step (see Figure 8). During training, the SRN progressively improves its prediction performance by developing sequential representations that take into account an increasing number of context elements. To simulate reaction times, Cleeremans and McClelland (1991) assumed that the activation of the output unit corresponding to the next element is related to the level of preparation to the next stimulus in human participants. Strong prediction responses thus correspond to higher activation of the corresponding output unit, and to shorter reaction times. Based on this simple assumption, the associative learning processes implemented in the SRN have been shown to provide an adequate account of human performance in many sequence learning experiments.

As we recognize elsewhere (Destrebecqz & Cleeremans, 2003), however, the SRN suffers from important shortcomings. The fact that the SRN exclu-
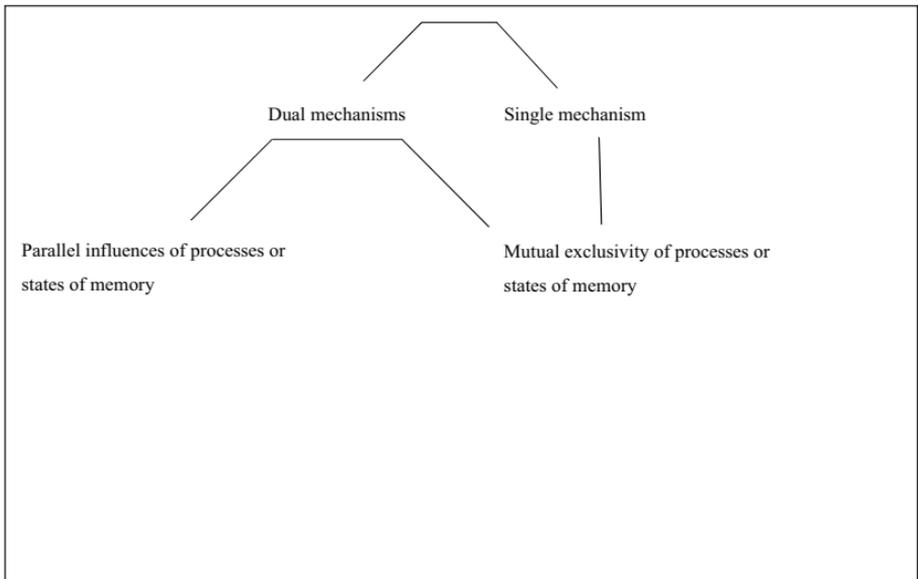

Figure 8. The Simple Recurrent Network (SRN).

sively produces prediction responses is indeed inconsistent with practice of the choice reaction time task, in which participants have simply to locate the current target (we do not discuss this problem here, but see Destrebecqz & Cleeremans, 2003). Moreover, it also makes it impossible for the SRN to account for the difference between identification (performed in the SRT task) and prediction (as in the generation task)—a limitation that makes it, in principle, impossible for the SRN to simulate both SRT performance and generation performance in our experiments.

To make it possible for the SRN to capture generation results, we simply interpreted the pattern of activations of the output units as a series of potential successors in the production of a sequence of stimuli rather than as preparation to the next element in a SRT task (Christiansen & Chater, 1999). We used the usual procedure to simulate the SRT task, and the model was trained on the same material as participants. Afterwards, learning was blocked in the network to simulate generation performance. Indeed, no feedback was given during this task. As for participants, the simulation of the generation task begins by the presentation of a randomly chosen stimulus to the network. One of the prediction responses the network produces is then selected based on activation at the output level. This response is then presented as the next stimulus to the SRN by setting the activation of the corresponding input unit to 1.0 and the activation of the other input units to zero. The same procedure is used for every trial in both inclusion and exclusion, but the response selection procedure differs between both tasks. In inclusion, the next stimulus corresponds to the most activated output unit at the previous trial. In exclusion, that particular response is excluded from the pool of potential successors, and the next stimulus is chosen randomly between the other possible responses. To remain consistent with the instructions given to participants, repetitions of the same stimulus were also excluded as potential responses in both tasks. With these assumptions in place, we will now describe simulation studies that explore the influence of prior sequential knowledge on reaction time and generation performance.

Simulation Method

Simulations of Experiments 1 and 2 will be presented jointly. Indeed, we considered that the four conditions included in these two experiments represent four levels of prior explicit knowledge: Incidental participants of Experiment 1 did not know anything about the sequence before the SRT task; intentional participants from the same experiment knew that the sequence was regular but they were not presented with it before the task; participants in the LK condition were presented with the sequence for a limited time, and

participants in the FK condition knew it perfectly before the task. Given that there is no simple way of accounting for intentional orientation to learn, we only simulated the incidental, LK, and FK conditions. Each network had four input units and four output units, each corresponding to one of the four target locations. The hidden and context layers consisted of 15 units. The model was trained on the same material and, apart from the pre-training involved in simulating the LK and FK conditions, for the same number of trials as human participants (see Appendix for the detailed parameters used in these simulations).

Results and Discussion

During training, the activation of the output unit corresponding to the next stimulus was transformed into Luce ratios (Luce, 1963) and then subtracted from 1.0 to make increases in response strength consistent with reductions in reaction time. To facilitate comparisons, the networks' responses and human reaction times were transformed into z-scores with respect to their respective entire distributions.

Figure 9 shows human and simulated reaction times for the three conditions. The model appears to be able to qualitatively approximate human performance. Indeed, increased levels of prior knowledge results in improved
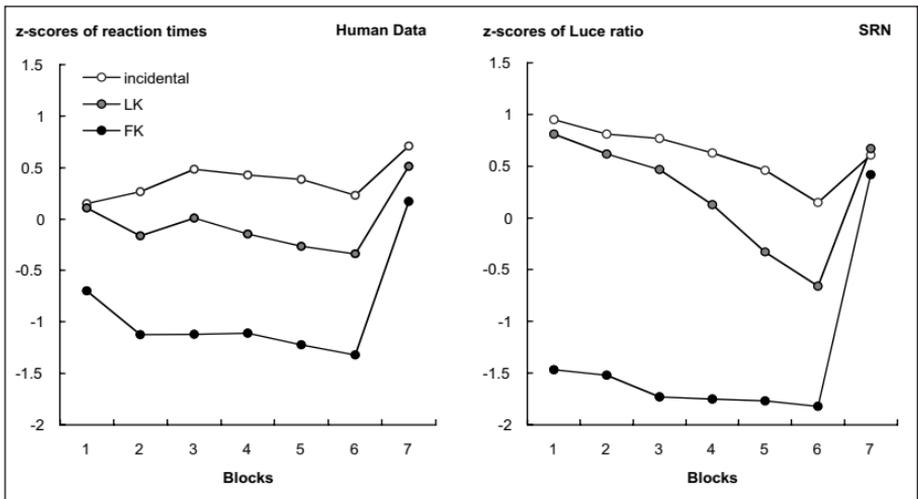

Figure 9. Human and simulated reaction times for the incidental, LK, and FK conditions. All data have been separately transformed into z-scores based on the data obtained for each source over the three conditions

performance. Further, transfer to a different sequence during the seventh block exerts a detrimental effect on performance. Simulated reaction times decreased more with practice than in human participants and the transfer effect is more pronounced in the simulated FK condition but these observations might be attributed to motor performance effects rather than to differences in learning. Even with our very simple assumptions, it is worth pointing out that, over the entire data set, the model accounts for about 85% of the variance in SRT data ($R^2 = .87$).

To further study the effect of the training regimen on learning, we computed the sum of the absolute values of the connection weights after the SRT task was completed. Because connections weights grow (positively or negatively) in magnitude during training, the sum of the weights between any two pools of units provide a measure of the influence exerted by the sending units on the receiving units. Comparing the global magnitude of the weights between different pools of units in different conditions can then provide us with an estimation of the relative importance of different sources of information (Cleeremans, 1997).

Figure 10 shows that the main effect of the pre-training in the LK and FK conditions is an increase in the magnitude of the connection weights between
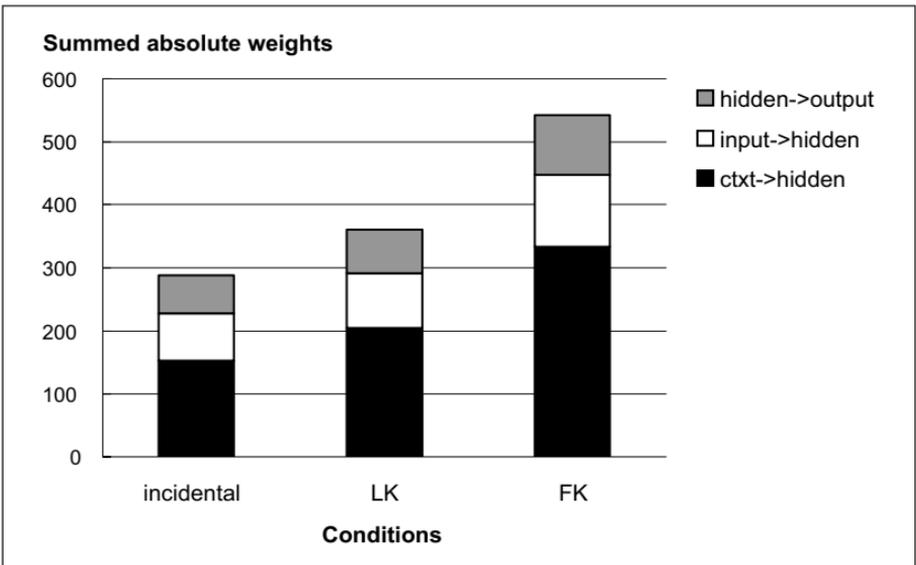

Figure 10. Summed absolute weights on connections of the SRN, represented separately for the three simulated conditions and for connections coming from the sequential context and the current stimulus to the hidden units, and from the hidden units to the output units.

the context and hidden units. This observation suggests that the networks developed stronger representations of the temporal context in these latter conditions than in the incidental condition.

The differences in training regimen also influenced generation performance. Figure 11 shows a comparison between human (left panel) and simulated generation results[4] (right panel). The simulation results match qualitatively human performance: Inclusion scores tend to increase with the amount of pre-training and are systematically above exclusion scores. Exclusion performance differs more between the network and the participants. We observed that participants generated fewer training triplets in the FK than in the LK condition, whereas this is obviously not the case for the SRN. Over all conditions, the model produced a relatively constant and lower number of training triplets than participants in exclusion. Over the entire data set, however, the model accounts for about 95% of the variance in generation data ($R^2 = .96$).

Even though these simulations are far from perfect, they suggest that a single process model of sequence learning such as the SRN can account for
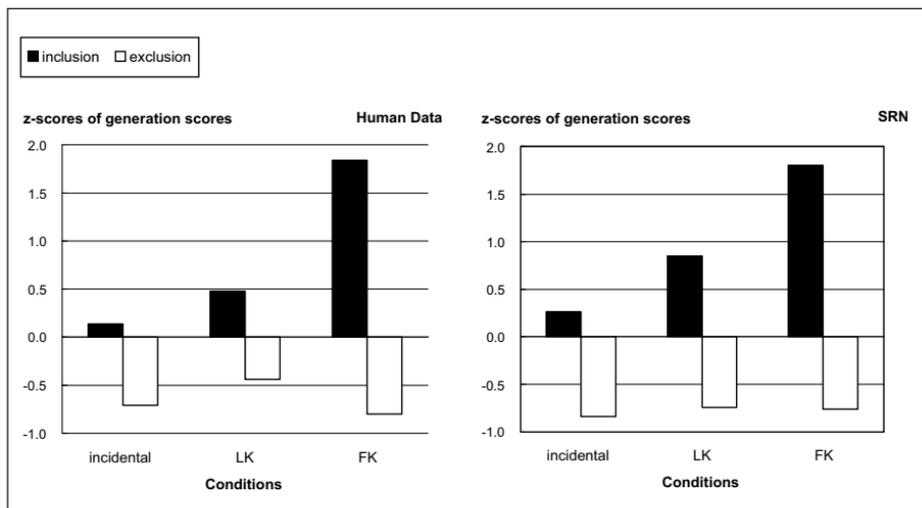

Figure 11. Human and simulated generation scores for the incidental, LK, and FK conditions. All data have been separately transformed into z-scores based on the data obtained for each source over the four conditions.

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[4] In contrast with Experiments 1 and 2, the same networks were used to simulate both the SRT and generation tasks.

inclusion *and* exclusion performance, and for the main aspects of reaction time performance in our experiments. The pre-training procedure we used to simulate the increasing amounts of explicit knowledge hold by the participants made it possible for the model to improve its performance in the SRT task and to produce more correct transitions in the inclusion task. The model was also able not to reproduce the training sequence in exclusion. On this latter point, it behaves in the same way as participants, although its performance seems to be better overall. Network performance is attributable to the development of stronger sequential representations.

Other mechanisms, however, are probably able to account for our results. (Cleeremans, 1993a) showed, for instance, how a dual architecture involving a SRN and an encoder that learned single associations between two successive stimuli could account for the difference between incidental and explicitly oriented learning in the Curran and Keele's study (1993). In this previous work, pre-training was simulated through processing within the encoder exclusively, while both the SRN and the encoder influenced processing during the SRT task. This procedure has the advantage of distinguishing two different processes for the pre-training and for learning during the SRT task—which is probably also the case for participants. Although our pre-training procedure shows in this respect a simplification, our simulation work nevertheless indicates that a single process can account for the direct and indirect measures of sequence learning that we observed experimentally. Other approaches involving separable processing systems to account for implicit and explicit learning processes have also been shown to be able to simulate learning differences between incidental and explicit instructions (Sun, 2001). The simulations presented in this paper suggest in contrast that a single process account is sufficient to understand the data (see also Kinder & Shanks, 2003 for a similar claim).

General discussion

Using the process dissociation procedure, we did not find in any of the four training conditions considered in this study a reliable automatic influence in a generation task—a result that would have suggested unconscious knowledge acquisition. On the contrary, participants were systematically able to reproduce, at least partly, the training sequence in the inclusion task and to avoid reproducing these sequential transitions under exclusion instructions, therefore suggesting that learning was in fact essentially explicit. This result has been observed when participants were initially informed about the repeating sequence but also when this was not the case, suggesting that sequence learning was mostly explicit even under incidental instructions.

These results are consistent with previous reports claiming that sequence learning is in fact based on the acquisition of conscious knowledge (Perruchet & Amorim, 1992; Shanks & Johnstone, 1998, 1999). In the following discussion, we would like to reflect on the implications of our experimental 0and simulation results concerning the relationship and the neural modularity of implicit and explicit learning modes.

According to Willingham and Goedert-Eschmann, implicit and explicit learning do occur in parallel. The discrepancy between their position and our results is most likely rooted in the methodology we used to measure implicit learning. In the Willingham and Goedert-Eschmann's study, the transfer effect was used to measure implicit learning while a free recall task was used to measure explicit learning. Intentional participants achieved better performance in the recall test but obtained the same transfer effect than incidental participants. The authors therefore concluded that intentional instructions increased explicit learning but leaved implicit learning unaffected. According to the authors, the transfer effect constitutes a pure-measure of implicit learning because subjects were unaware of the fact that the sequence was present at transfer. In this methodological framework, tasks and processes are thus closely associated. Several reports indicate, however, that no task can be considered as process-pure (Jacoby, 1991; Reingold & Merikle, 1988), that is, that no task exclusively involves a single cognitive process. In other words, performance in any situation will always depend on the operation of different processes working at the same time. More specifically, performance in implicit tasks may be "contaminated" by explicit influences and vice-versa. With this "contamination" problem in mind, one can argue that the similar transfer effect observed by Willingham and Goedert-Eschmann in their incidental and intentional conditions was possibly related to implicit learning in the former but to explicit learning in the latter condition.

Using the PDP, we indeed previously reported that similar transfer effects could be essentially attributable to conscious or unconscious knowledge acquisition in two conditions differing only by the pace of the SRT task (Destrebecqz & Cleeremans, 2001). We observed that when a high responding rate was imposed in the SRT task, subjects' exclusion scores were above chance level in the free generation task—suggesting that learning was at least partly based on unconscious knowledge acquisition (but seeWilkinson & Shanks, 2004 for a different result). Goschke (1997; 1998) reported the same pattern of results when the SRT task was performed concurrently with a tone-counting secondary task.

The absence of unconscious influence in any of the four training conditions considered in our experiments does not mean, therefore, that sequence learning may not occur implicitly but only in specific conditions in which participants are prevented to develop stronger sequential representations.

One can also argue that implicit learning took place in our study, in parallel with explicit learning, but that unconscious influence in the generation task was systematically overridden by controlled responding initiated by explicit knowledge about the sequence. In other words, participants were always able to recall explicitly the training sequence and to produce some other response in the exclusion task. This class of interpretation has previously been proposed by Willigham (1998), according to which both conscious and unconscious sequence knowledge co-exist in distinct brain systems, but the conscious system will systematically tend to usurp the control of behaviour.

Our results are insufficient to decide between single- and multiple-systems views of implicit and explicit learning. However, the simulations presented in this paper suggest that the dissociations between different levels of *explicit* knowledge can be accounted for within a single processing system. Previous simulation work also indicates that a connectionist model endowed with a single learning process can simulate dissociations between implicit and explicit learning (Destrebecqz & Cleeremans, 2003). Other models support, however, that implicit and explicit learning depend on separate processing modules (Wallach & Lebiere, 2003, Sun, Merrill & Peterson, 2001). The results of brain imaging studies have also led to the conclusion that different brain networks subtend implicit and explicit sequence learning processes (Grafton, Hazeltine & Ivry, 1995; Rauch et al., 1995). In these studies, however, implicit and explicit processes were exclusively associated with different training phases—a procedure that does not ensure that implicit and explicit components were effectively dissociated during the two training conditions. In a PET scan experiment, (Peigneux et al., 2000) reported the systematic activation of the striatum when participants were presented with a complex probabilistic sequence (see also Rauch et al., 1997). Sequence learning in experiments using this material is typically essentially implicit (e.g., Jiménez, Méndez & Cleeremans, 1996). According to Peigneux et al., the striatum is involved in implicit sequence learning through its participation in the cortical-subcortical motor loop between prefrontal and caudates areas. They further suggested that the striatum is particularly active for the selection of the most appropriate response given the identity of the current target and the context of previous stimuli.

It remains possible, however, that some brain areas are specifically involved in the conscious treatment of sequential material (Clegg, DiGirolamo, & Keele, 1998). In a recent PET study adapting the process dissociation procedure, we reported that anterior cingulate cortex and medial frontal cortex (ACC/MCPF) were specifically involved in conscious control of sequence knowledge in a generation task performed under inclusion and exclusion instructions (Destrebecqz et al., 2003). These results are in line

with previous reports indicating the function of this region in cognitive control (e.g. MacDonald, Cohen, Stenger, & Carter, 2001), and suggest that the role of the ACC/MCPF consists in exerting conscious control over the activity of the striatum that subtends the core mechanism of sequence learning as proposed by Peigneux et al. (2000). The relationship between implicit and explicit learning might therefore not be viewed as reflecting the involvement of independent or mutually exclusive systems but rather the functional interaction between different brain regions subserving different cognitive processes.

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Appendix: SRN parameters

In each condition, eight different networks were each initialized with random weights comprised between –0.5 and 0.5. To simulate the LK and FK conditions, we pre-trained each network by exposing it respectively to 10 and to 100 presentations of the twelve-element sequence prior to the SRT task itself. To introduce variability in the network's performance, normally distributed random noise ($\sigma = 1$) was added to the net input of each receiving unit. Learning parameters were identical in the four conditions and were as follows: slow learning rate = 0.1, momentum = 0.9, fast learning rate = 0.45, fast weight decay = 0.5 (see Cleeremans & McClelland, 1991).