We investigated the role of response selection in sequence learning in the serial reaction time (SRT) task, by manipulating stimulus–response compatibility. Under conditions in which other types of learning, like perceptual, response-based, and response-effect learning, were unaffected, sequence learning was better with an incompatible than with a compatible stimulus–response mapping. Stimulus discriminability, on the other hand, had no influence on the amount of sequence learning. This indicates that the compatibility effects cannot be accounted for by a different level of task difficulty. Relating our results to the dimensional overlap model (Kornblum, Hasbroucq, & Osman, 1990), which assumes that incompatible stimulus–response mappings require more controlled response selection than do compatible stimulus–response mapping, we suggest that sequence learning in the SRT task is particularly effective when response selection occurs in a controlled way.

The serial reaction time (SRT) task of Nissen and Bullemer (1987) has become a very popular tool to investigate sequence learning. In the SRT task, participants respond as fast and as accurately as possible to successively presented stimuli. Unbeknown to them, the stimuli are not presented in a random order, but follow a regular sequence. Typically, reaction times (RTs) decrease progressively with practice and increase when a random stimulus sequence is inserted. This shows that the improved performance is due to sequence-specific knowledge. Knowledge acquired in the SRT task is said to be implicit, because learning can occur in the absence of explicit awareness of the sequence structure (for a review see, e.g., Cleeremans, Destrebecqz, & Boyer, 1998). In the present study, we investigated the influence of the response selection process on sequence learning in the SRT task, by manipulating the stimulus–response compatibility (S–R compatibility).

It is known that sequence knowledge can be represented at different levels of information processing (for reviews see, e.g., Clegg, DiGirolamo, & Keele, 1998; Goschke, 1998). For example, there is evidence that learning can be based on perception (e.g., Deroost & Soetens, in press-a; Mayr, 1996; Remillard, 2003; Soetens, Melis, & Notebaert, 2004) as well as on motor responses (Deroost & Soetens, in press-b; Nattkemper & Prinz, 1997; Willingham, Nissen, & Bullemer, 1989). In addition, it seems that associations between responses and subsequent stimuli can also contribute to sequence learning (e.g., Ziessler & Nattkemper, 2001).
In the present study, we examined the influence of intermediate levels of information processing on sequence learning. More specifically, we manipulated stimulus–response compatibility (S–R compatibility) to determine whether the response selection process has an influence on SRT learning. The idea that response selection plays a role in sequence learning was initially put forward by Willingham et al. (1989), who suggested that learning is represented as a sequence of stimulus–response bounds. However, in a later study, Willingham (1999) abandoned this idea and instead proposed that learning is represented as a sequence of response locations. This was because he believed that the response selection hypothesis could not account for the transfer effects that he found from digit to spatial sequences and from incompatible to compatible stimulus–response mappings. Since then, the possible influence of response selection on sequence learning has largely been neglected.

Nevertheless, there are convincing indications that S–R compatibility, which has a selective influence on response selection (e.g., Sternberg, 1969), can have an important impact on learning. For example, in demonstrating that sequence learning is particular effective for spatial information, Koch and Hoffmann (2000) mapped stimulus sequences onto response sequences of either a similar or a dissimilar degree of relational structure, resulting in, respectively, a compatible and incompatible S–R mapping. The authors found that sequence learning tended to be better under low S–R compatibility conditions than under high S–R compatibility conditions.

In the present study, we examined the effects of S–R compatibility on sequence learning more directly. Sequence learning with a compatible S–R mapping was compared to learning with an incompatible S–R mapping. Importantly, varying S–R compatibility allowed us to investigate the role of response selection in a selective way, since other types of learning were unaffected. The stimulus sequence was the same for the compatible and incompatible conditions, so that perceptual learning was not influenced by the manipulation. In addition, the sequences of responses (effectors as well as response locations) and response-effects were simply mirrored between the compatible and incompatible conditions, leaving, respectively, response-based learning and response-effect learning intact.

EXPERIMENT 1

In Experiment 1, we determined the influence of S–R compatibility on sequence learning. The mapping between stimuli and responses was either compatible or incompatible.

Method

Participants
A total of 30 paid volunteers (21 women) participated in the study. Their mean age was 20.5 years. Participants were randomly assigned to one of two experimental conditions: 16 in the incompatible condition and 14 in the compatible condition. None of them had previous experience with SRT or sequence learning tasks.

Stimuli and apparatus
Participants were tested individually in semidarkened cubicles in the psychological laboratory of the Vrije Universiteit Brussel (VUB). The SRT experiment was run on Pentium 4 personal computers with 17-in. screens, using E-prime Version 1.1 software (Schneider, Eschman, & Zuccolotto, 2002).

Design and procedure
On each trial of the SRT experiment, a black dot of 8 mm diameter (or 0.76° visual angle with a viewing distance of approximately 60 cm) appeared in one of four horizontally aligned squares of side 1.5 cm (or 1.4° visual angle), separated by gaps of 2.5 cm (or 2.39° visual angle). Participants were instructed to react as fast as possible to the location of the target dot, while restricting the error rate to a maximum of 5% per block. The “c”, “v”, “b”, and “n” keys, situated on the bottom row of a standard keyboard, operated as response keys and had to be pressed with the middle and index fingers of each hand. In the compatible condition, participants
responded to a leftmost, left, right, and rightmost target by pressing the “c”, “v”, “b”, and “n” key, respectively. In the incompatible condition, the rightmost “n” key corresponded to a leftmost target, the right “b” key to a left target, the left “v” key to a right target, and the leftmost “c” key to a rightmost target.

The SRT experiment consisted of two practice blocks of 50 trials, followed by 15 experimental blocks of 100 trials. At the start of a block, a warning for the upcoming trials appeared, urging participants to rest their fingers lightly on the four response keys. RTs and accuracy were recorded on each trial. The target was presented until the response was made within the allowed response window of 3,000 ms. The next target was presented after a response–stimulus interval of 50 ms. In the case of an incorrect response the word “Error” was presented for 750 ms. No error corrections were possible. After each block of trials, participants received feedback about their error rates and RTs for that particular block. Blocks were always separated by breaks of 30 s.

During practice, the target location changed according to a random sequence that was generated on the basis of a random sample base that differed between participants. All stimulus transitions were allowed during random blocks. In the experimental blocks, except in random Block 13, the location was structured according to a probabilistic sequence with first-order restrictions, which was generated on the basis of the artificial grammar depicted in Figure 1.

The numbers 1, 2, 3, and 4 denote the four horizontal target positions, starting with 1 for the leftmost position until 4 for the rightmost position. The first-order restrictions entailed that each stimulus could be followed by only two of four possible stimulus alternatives. First-order probabilities were always .50, so that the stimulus was followed half of the time by one alternative and half of the time by the other alternative (e.g., 1 is half of the time followed by 1 and half of the time by 4). In Block 13, the stimulus sequence turned to a random order to assess sequence-specific knowledge.

In all structured and random sequences, the four possible stimulus alternatives occurred equally often. The percentage of stimulus repetitions and alternations was the same for structured and random blocks. This was the case for both experiments.

Results and discussion

Errors
The mean error rate per block amounted to 3.3% ($SD = 1.20$) in the compatible condition and 5.2% ($SD = 2.42$) in the incompatible condition. The positive correlation between error rates and RTs showed that there were no indications for a speed–accuracy trade-off in the compatible condition, $r(13) = .54, p < .05$, nor in the incompatible condition, $r(13) = .52, p < .05$. Errors were not analysed further.

Reaction times (RTs)
Erroneous responses as well as responses following an error were excluded from RT analysis, which was always performed on participants’ mean correct RTs. This was done for both experiments. Responses faster than 100 ms and slower than 1,000 ms were considered outliers and were discarded from statistical analysis (2.59%).

To analyse general learning effects, we performed a repeated measures analysis of variance (ANOVA) with block (all blocks with the exclusion of random Block 13) as within-subjects factor and compatibility as between-subjects factor. A significant main effect of compatibility indicated that participants in the compatible condition responded faster than participants in
the incompatible condition, $F(1, 28) = 37.61$, $MSE = 30,994$, $p < .001$. As can be seen in Figure 2, general learning was revealed by a significant RT decrease over blocks, $F(13, 364) = 134.19$, $MSE = 455, p < .001$. Furthermore, general learning was more pronounced in the incompatible condition than in the compatible condition, $F(13, 364) = 12.253$, $MSE = 455, p < .001$.

Subsequently, we estimated the amount of sequence-specific learning by the increase in RT in random Block 13 as compared to the mean of the adjacent structured Blocks 12 and 14. A repeated measures ANOVA, with random Block 13 and the mean of Blocks 12 and 14 as within-subjects factor and compatibility as between-subjects factor, showed that RTs were more elevated in the incompatible condition than in the compatible condition, $F(1, 28) = 32.27$, $MSE = 4,689$, $p < .001$. Moreover, higher RTs in random Block 13 than in the adjacent Blocks 12 and 14 indicated the presence of sequence-specific learning, $F(1, 28) = 582.47$, $MSE = 381$, $p < .001$. Planned comparison tests showed that sequence learning was significant in the compatible condition ($M = 110$ ms), $F(1, 28) = 221.02$, $MSE = 381, p < .001$, as well as in the incompatible condition ($M = 134$ ms), $F(1, 28) = 377.76$, $MSE = 381, p < .001$. More important, however, the significant interaction between sequence learning and compatibility indicated that more sequence learning took place in the incompatible condition than in the compatible condition, $F(1, 28) = 5.86$, $MSE = 381, p < .05$. The effect size of the S–R compatibility manipulation on the learning effect proved to be large, Cohen’s $d$ for $F$-test $= 0.92$.

The results of Experiment 1 showed that more learning occurred in the incompatible condition than in the compatible condition. Since other types of learning were unaffected, this suggests that the response selection process plays a selective role in sequence learning. Alternatively, the results could be explained by a different level of task difficulty. Since responses are faster with a compatible S–R mapping than with an incompatible mapping (e.g., Kornblum, Hasbroucq, & Osman, 1990), it is possible that learning was in fact equal for both conditions, but had less opportunity to be expressed under compatible conditions. When we look at the compatible condition in Experiment 1, the RTs in random Block 13 are higher than those in Block 1, whereas this is not the case in the incompatible condition. This shows that the introduction of the random sequence was particularly disruptive for the compatible condition, suggesting that learning was in fact equal in both conditions.

In order to gather more convincing evidence that the compatibility effects are not the result of a difference in performance, we assessed the influence of task difficulty without affecting response selection. Following the logic of the additive factors methodology (Sternberg, 1969), we manipulated stimulus discriminability, a variable known to influence stimulus identification, but not response selection. Sequence learning was compared for stimuli that were either easy or difficult to discriminate. If the found compatibility effects are due to a difference in task difficulty, learning should be enhanced when stimuli are less discriminable.
EXPERIMENT 2

Method

Participants
A total of 29 paid volunteers (19 women) participated in the study. Their mean age was 22 years. Participants were randomly assigned to one of two experimental conditions: 16 in the easy discriminable and 13 in the difficult discriminable condition. None of them had previous experience with SRT or sequence-learning tasks.

Stimuli and procedure
On each trial, a dot of 8 mm diameter was centrally presented. In the easy discriminable condition, the target could adopt four different shades of grey that were easy to discriminate: white, light grey, dark grey, and black (respectively, luminosity = 240, 160, 80, and 0, with hue = 160 and saturation = 0). In the difficult discriminable condition, the four grey alternatives went from lightest, light, dark, to darkest grey (respectively, luminosity = 180, 165, 135, and 120, with hue = 160 and saturation = 0). In the easy discriminable condition, participants had to press the response keys “c”, “v”, “b”, and “n” for a white, light grey, dark grey, and black dot, respectively. In the difficult discriminable condition, the response keys “c”, “v”, “b”, and “n” corresponded to a lightest, light, dark, and darkest grey dot, respectively. Participants first completed two random practice blocks of 50 trials, followed by 15 experimental blocks of 100 trials. Except in random Block 13, the stimulus alternatives changed according to the same probabilistic sequence as that used in Experiment 1. In Experiment 2, the numbers 1 to 4 of the sequence corresponded to a white, light grey, dark grey, and black stimulus for the easy discriminable condition, and a lightest, light, dark, and darkest grey stimulus for the difficult discriminable condition.

Results and discussion

Errors
The mean error rate per block amounted to 5.0% ($SD = 1.88$) in the easy discriminable condition and 11.6% ($SD = 3.59$) in the difficult discriminable condition. The positive correlation between error rates and RTs showed that there were no indications for a speed–accuracy trade-off in the easy discriminable condition, $r(13) = .88$, nor in the difficult discriminable condition, $r(13) = .96$, both $p < .05$.

Reaction times (RTs)
Responses faster than 100 ms and slower than 1,500 ms were discarded from statistical analysis (1.42%). To assess the difference in task difficulty between the discriminability conditions, a repeated measures ANOVA was performed on the mean correct RTs, with block (all training blocks with the exclusion of random Block 13) as within-subjects factor and discriminability as between-subjects factor. The analysis showed that participants in general responded faster in the easy discriminable condition than in the difficult discriminable condition, $F(1, 27) = 31.87, MSE = 76,316, p < .001$, see Figure 3. A main
effect of block further showed that RTs decreased over training, hereby revealing a general learning effect, \( F(13, 351) = 57.45, \text{MSE} = 812, p < .001 \). General learning also proved to be more pronounced in the difficult discriminable condition than in the easy discriminable condition, \( F(13, 351) = 3.62, \text{MSE} = 812, p < .001 \).

To determine differences in sequence learning between the conditions, the RTs were submitted to a repeated measures ANOVA, with random Block 13 and the mean of the adjacent Blocks 12 and 14 as within-subjects factor and discriminability as between-subjects factor. This analysis confirmed that participants responded slower in the difficult discriminable condition than in the easy discriminable condition, \( F(1, 27) = 29.26, \text{MSE} = 9,316, p < .001 \). Furthermore, RTs were higher in random Block 13 than the mean of the surrounding structured Blocks 12 and 14, indicating sequence learning, \( F(1, 27) = 206.08, \text{MSE} = 1,218, p < .001 \). Planned comparison tests showed that learning took place in both the easy discriminable condition \((M = 138 \text{ ms}), F(1, 27) = 125.47, \text{MSE} = 1,218, p < .001, \) and the difficult discriminable condition \((M = 126 \text{ ms}), F(1, 27) = 85.19, \text{MSE} = 1,218, p < .001 \). However, the interaction between sequence learning and discriminability was not significant, indicating that the amount of sequence learning in the two conditions was similar, \( F(1, 27) = 0.41, \text{MSE} = 1,218, p = .53 \). The effect size for the stimulus discriminability manipulation was not only small, but even opposite to the predicted direction, Cohen's \( d \) for \( F \)-test = 0.25.

The results of Experiment 2 demonstrated that the manipulation had its intended impact on stimulus discriminability; RTs were elevated in the difficult discriminable condition as compared to the easy discriminable condition. General learning effects were also more pronounced in the difficult discriminable than in the easy discriminable condition. However, despite the difference in general learning resulting from the manipulation of level of task difficulty, sequence learning was equal in both conditions. Therefore, the results of Experiment 2 support that S–R compatibility truly affects the learning process and not the expression of the learned knowledge due to a difference in task difficulty.

**GENERAL DISCUSSION**

In the present study, we investigated the role of response selection in sequence learning in SRT tasks. In Experiment 1, we manipulated S–R compatibility and showed that more sequence learning took place under incompatible than under compatible conditions. Since the manipulation left other types of learning, like perceptual, response-based, and response-effect learning, unaffected, this suggests that the response selection process has a selective influence on sequence learning.

However, since responses are much faster with a compatible S–R mapping than with an incompatible mapping (e.g., Kornblum et al., 1990), the two conditions differ in level of task difficulty. Accordingly, one could argue that sequence learning under compatible conditions can only make a small contribution to the response times and that the difference between the incompatible and compatible conditions are actually reflecting a difference in performance, rather than a difference in learning.

If this were true, then other manipulations that affect task difficulty but not response selection should have a similar effect on the amount of sequence learning. This was tested by varying stimulus discriminability in Experiment 2. Making stimulus discriminability more effortful resulted in higher reaction times, as well as in better general learning effects. Nevertheless, sequence learning proved to be unaffected by the stimulus discriminability manipulation. This supports that S–R compatibility truly influences learning and not performance.

More research is required to find out how sequence learning and response selection are precisely related. In general, contemporary models of sequence learning assume that sequence knowledge is acquired through passive, associative learning mechanisms that incorporate increasingly larger units of sequential elements (e.g., Cleeremans & McClelland, 1991). However, these models do
not pronounce upon the precise localization of sequence learning in information processing.

To account for our results, we suggest relating the influence of S–R compatibility on sequence learning to the dimensional overlap model (DOM, e.g., Kornblum et al., 1990). According to this model, response selection proceeds along two parallel routes. When there is dimensional overlap between stimulus and response features, the correct response code is automatically primed, and response selection develops fast. In contrast, without dimensional overlap, stimulus features have to be translated in response features by means of a more complex mapping rule, so that response selection develops along a slower, controlled response-identification route. Under compatible conditions, the two routes lead to the same response, but under incompatible conditions, the incorrectly activated automatic response code must be inhibited in a controlled way before the correct response can be selected. Since learning was better under incompatible conditions, our results suggest that sequence learning is particularly effective when controlled response selection processes are involved.

This proposal would be in line with neuropsychological evidence. In the study of Werheid, Ziessler, Nattkemper, and von Cramon (2003), sequence learning in Parkinson patients was reduced under compatible conditions, as compared to controls, but intact under incompatible conditions. Parkinson’s disease is associated not only with impairments in sequence learning (e.g., Jackson, Jackson, Harrison, Henderson, & Kennard, 1995), but also with a more general malfunction of response selection processes (e.g., Hocherman, Moont, & Schwartz, 2004). If controlled response selection processes crucially contribute to sequence learning, this may explain preserved learning under incompatible conditions.

In conclusion, the present results show that response selection plays an important role in sequence learning, in agreement with the hypothesis proposed by Willingham et al. (1989). Our findings suggest that sequence learning is more effective when response selection processes are controlled. Future research is needed to determine how sequence learning and response selection are precisely related.

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