Serial action and perception

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SERIAL ACTION AND PERCEPTION

DISSERTATION

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Chapter 1 Introduction

In everyday life we employ a large variety of perceptual-motor skills that were acquired through practice and interaction with our environment. One may think of handwriting, playing the piano, dancing, communicating or driving a car. A fundamental characteristic of such skills concerns the serial organization of perceptual and/or motor events, which allows for the anticipation of future events on the basis of incoming information, as well as effectively preparing for future action. Acquisition of perceptual-motor skills typically takes place in the relative absence of conscious awareness, and they are therefore often referred to as implicit (see Figure 1).

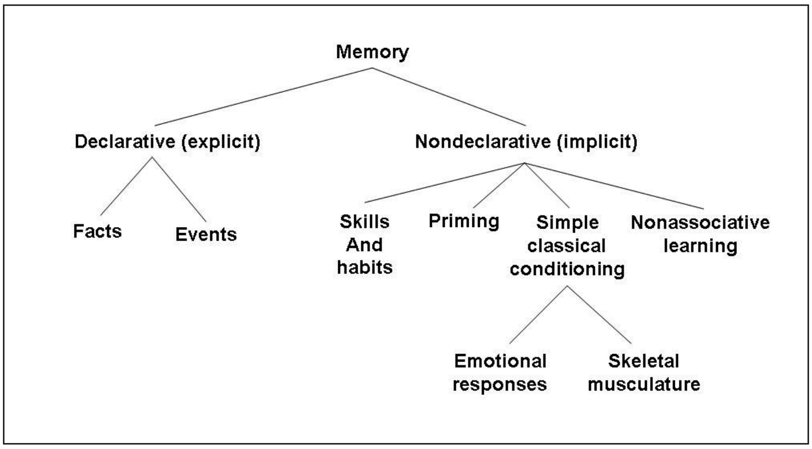

Figure 1. A taxonomy of human memory. Adapted from Squire (2004)

The current dissertation focuses on serial perceptual-motor performance in a particular task called the serial reaction time (SRT) task. In this introductory chapter the SRT task will first be explained in detail. Second, an attempt will be made to outline how the task can be situated within a larger framework of information processing. Third, the main topic of this dissertation will be introduced, i.e., the question of what type of information underlies the representations that are formed during practice in the SRT task. Some major accounts (response-based learning, perceptual learning, and response-effect learning) will be briefly described, but it has to be noted that these accounts will be further elaborated on in the review in Chapter 2. Finally, a brief outline of the empirical work of the current dissertation will be provided.

THE SERIAL REACTION TIME TASK

The serial reaction time (SRT) task, developed by Nissen and Bullemer (1987), has become a major paradigm in studying serial perceptual-motor learning, which constitutes a critical element of skilled behavior. In its basic form, participants are seated behind a screen on which four possible stimulus locations (i.e., placeholders) are presented throughout the experiment. They are asked to rest four designated fingers (e.g., the middle and index fingers of the left and right hand) on the four response buttons (e.g., four keys of a regular keyboard). The precise mapping between the stimulus locations on the screen and the response buttons is explained (typically this mapping is spatially compatible), and participants are required to respond as fast and accurately as possible to the location of successive stimuli presented on the screen (i.e., one of the placeholders lighting up; see Figure 2). After a response is made, the next stimulus appears at a fixed response-to-stimulus-interval (RSI).

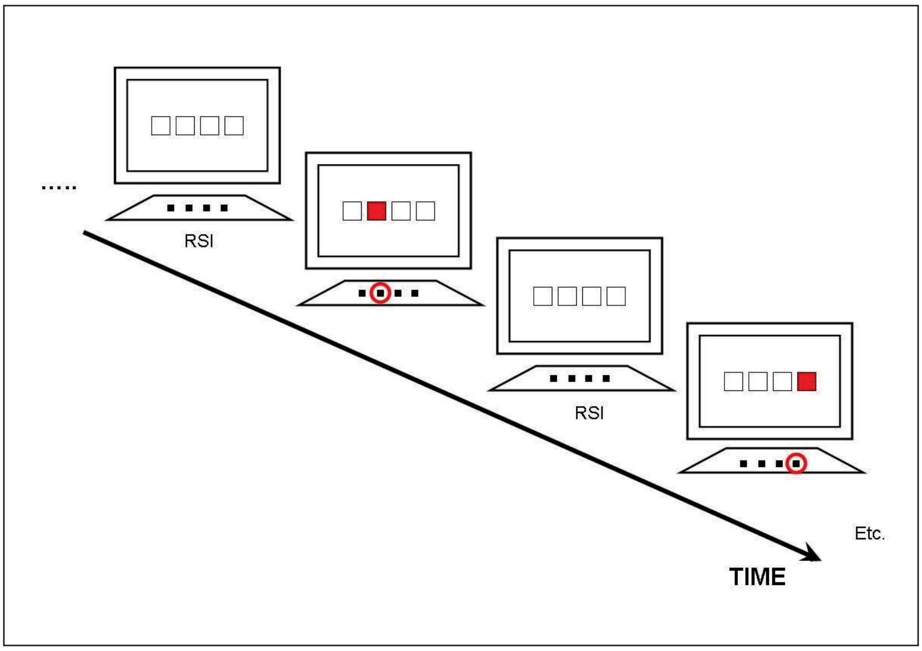

Figure 2. Serial RT task. Participants are seated behind a screen that contains four possible stimulus locations. Their designated fingers are resting on the response buttons. Stimulus and response locations are typically spatially corresponding. For each trial, one of four stimulus locations lights up in the color red, signaling the correct response. After a response is given, the next stimulus location lights up at a fixed stimulus-to-response-interval.

Unbeknownst to the participants, stimulus presentation is pre-structured, either by a fixed deterministic (i.e., noiseless) sequence, a probabilistic (i.e., noisy) version of a deterministic sequence, or a probabilistic finite-state grammar (see Figure 3). Typically, response times and/or error rates decrease with training, indicating that learning has occurred. However, this does not yet enable distinguishing between sequence learning and general practice effects. To separate out the mere effect of sequence learning, a random block of stimuli is inserted at the end of the practice phase: the cost in RT and/or accuracy for this random block relative to its surrounding sequence blocks serves as an index for sequence learning. Participants often show clear sequence learning in this task through direct learning measures (reaction time and accuracy) while this is not accompanied by the ability to clearly describe what was learned. Therefore, sequence learning in the SRT task is referred to as implicit (e.g., Seger, 1994). This resembles the implicit feature of learning and performing that is typically involved in real life examples of perceptual-motor tasks (e.g., dancing, driving a car, etc.).

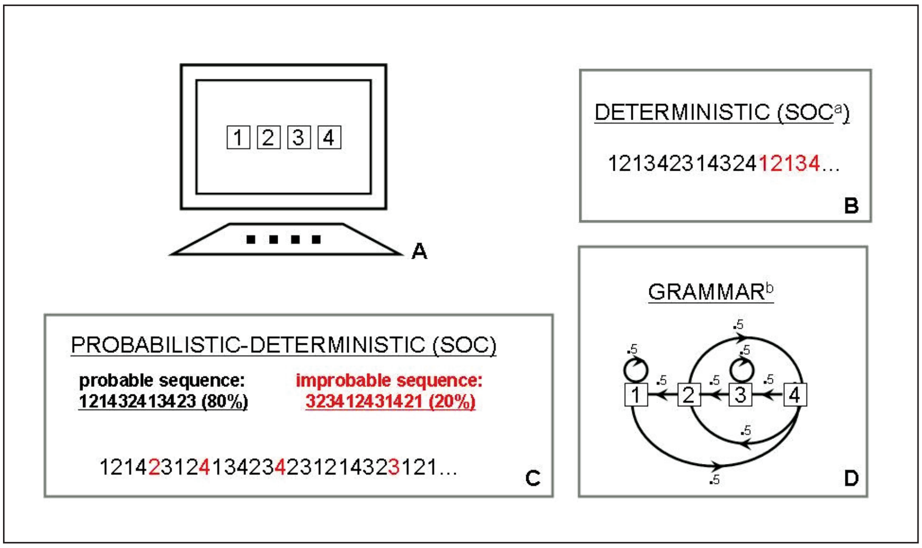

Figure 3. Pre-structuring in the serial RT task. A) stimulus locations are denoted by numbers 1-4, B) example of a deterministic SOC sequence, C) example of a probabilistic version of a deterministic SOC sequence; probable trials are in BLACK, and improbable trials are in RED, D) example of a probabilistic (finite-state) grammar.

Note A: Sequences are often composed entirely of second-order conditionals (SOC): each target location is fully determined by the previous two target locations, such that knowing the previous target location alone provides no information regarding the next target location.

Note B: Example adopted from Deroost and Soetens (2006b); p = 1/N for all transitions (N is the number of possible transitions).

The SRT task has been employed across a wide range of parametric settings (see Table 1); particular settings may be selected on theoretical or methodological grounds, though sometimes well-defined reasons may be absent (e.g., why opt for RSI = 50 ms and not RSI = 200 ms?). The effects of particular parametric changes on performance have been explored to some extent, and performance is generally quite sensitive to these. To name a few examples, it has been reported a) that implicit sequence learning is better with incompatible than compatible stimulus-response (S-R) mappings (e.g., Deroost & Soetens, 2006; Koch, 2007; but see Chapter 6 of this dissertation), b) that implicit sequence learning becomes partly effector-dependent only after extensive practice (e.g., Keele, Jennings, Jones, Caulton & Cohen, 1995; Verwey & Clegg, 2005), c) that explicit sequence knowledge develops mainly with relatively large response-to-stimulus (RSI) intervals (e.g., Destrebecqz & Cleeremans, 2001), and d) that presenting fully randomized trials in a test block can artificially inflate the index for sequence learning (i.e., the difference between sequence and test trials) because of higher proportions of reversals (e.g., 121, 232 or 414; Vaquero, Jiménez & Lupiáñez, 2006). Such sensitivity makes direct comparisons across studies with different parametric settings complicated.

Table 1. Design variations within the SRT paradigm. The column *Variable* denotes the relevant aspect of design, and some examples of variations are given in the *Exemplar settings* column. Note A: in case of probabilistic sequences, a test block may not be needed. Sequence learning can be determined "online" by comparing performance between probable and improbable trials.

Variable	Exemplar settings	Exemplar references
Nature of the structure	• Deterministic sequence • Probabilistic sequence • Finite-state grammar	Abrahamse et al. (2008) Jiménez et al. (2006) Cleeremans & McClelland (1991)
Number of fingers	• 1 finger for all response buttons • 1 finger for each response button	Willingham et al. (2000) Abrahamse et al. (2008)
RSI	0-2000 ms	Destrebecqz & Cleeremans (2001) Willingham et al. (1997)
S-R mapping	• 1 to 1 mapping: each response is uniquely signaled by a particular stimulus • 2 to 1 mapping	Nissen & Bullemer (1987) Clegg (2005)

Variable	**Exemplar settings**	**Exemplar references**
Sequence repetitions during training	• 40	Willingham et al. (2000)
	• 90	Abrahamse et al. (2008)
	• 1300 (exceptional)	Verwey & Clegg (2005)
Spatial S-R mapping	• Compatible	Abrahamse et al. (2008)
	• Incompatible	Deroost & Soetens (2006b)
Stimuli	• Visual stimuli	
	○ Spatial	Abrahamse & Verwey (2008)
	○ Numbers	Koch & Hoffmann (2000b)
	○ Colors	Abrahamse et al. (submitted)
	• Tactile stimuli	Abrahamse et al. (2008)
Test	• Training (between-subject)	Destrebecqz & Cleeremans (2001)
	• Transfer (within-subject)	Willingham et al. (2000)
Test block[a]	• Pure randomization	Robsertson & Pascual-Leone (2001)
	• Pseudo-randomization (e.g., a series of different sequences)	Abrahamse et al. (2008)
	• New sequence	Jiménez & Vázquez (2008)

Training and transfer

The goal in SRT studies is mostly to determine the effect of a particular manipulation on sequence performance. To this end, one can employ a between-subjects manipulation such that different groups of participants are trained on different versions of an SRT task, and compare the amounts of sequence learning between groups (e.g., Deroost & Soetens, 2006; Destrebecqz & Cleeremans, 2001). This approach, however, has two potential pitfalls. First, it is difficult to differentiate between learning itself, and the expression of learning. It may be that different versions of the SRT task allow for differential expression of learning (i.e., the benefit taken from learning; e.g., Frensch, Wenke & Rünger, 1999). Second, it provides no information on possible differences in the particular nature of the learning; it may be that different experimental groups form qualitatively different sequence representations that nonetheless affect response times and accuracy levels to a similar extent.

These issues can both be tackled by employing a transfer phase. Concerning the first problem, one may employ a mixed design: different groups of participants are first trained on different task versions, and then performance is compared in a transfer phase under identical conditions (e.g., Abrahamse, Van der Lubbe & Verwey, 2009). This would provide a fair comparison with respect to the expression of sequence learning. With respect to the second problem, transfer in the SRT task is also the major tool in determining the nature of the representations underlying sequence learning (see Clegg, DiGirolamo & Keele, 1998). The idea is that transfer will occur to the extent that the key features that were included in the sequence representation during training are being maintained at transfer.

A problem with regard to the use of transfer tasks is the potential existence of indirect effects on performance caused by changes employed during the transfer as compared to training. For instance, it may be that transfer to a more difficult version of the SRT task than that employed during training, somehow provokes a strategy of highly controlled S-R processing, thereby suspending all implicit learning effects. Hence, reliable transfer to a more demanding task may be absent because of such a strategy, and not because the particular representation that was formed during training is no longer accessible. The same may be true for transfer to a version that requires additional processing as compared to the training version, without necessarily making it a more difficult task; or even for transfer that only involves completely task-irrelevant changes. Any change may provoke highly controlled S-R processing, thereby providing a confounding variable in the interpretation of knowledge transfer. Some results of the current dissertation (see Chapter 8 for some elaboration) may be explained in part by such an indirect mechanism. However, this issue has not been clearly identified, yet, as direct support for it is lacking.

Overall, though the SRT task may seem to be a fairly simple and straightforward tool in the study of skill acquisition at first sight, its sensitivity to the various parametric differences employed across designs complicates manners. This may be an important reason for the lack of clear understanding with respect to the basic mechanisms of sequence learning. This dissertation focuses on one major issue from SRT literature: what is the nature of the representations that underlie sequence learning in the SRT task? This issue will be discussed in more detail below. However, before doing so, the SRT task will be situated within a larger framework of information processing. Specifically, it will be claimed that the SRT task can be seen as a special case of the typical choice RT task, in which sequential learning facilitates processing within single trials.

SERIAL ACTION IN INFORMATION PROCESSING THEORY

From perception to (single) action: serial processing stages

The information processing approach is a major theoretical framework in cognitive psychology that depicts people or other cognitive agents as input-output mechanisms. The essence of this approach is to see cognition as being essentially computational in nature, with incoming information (i.e., sensory processing) flowing through a set of stages within which certain operations are performed, eventually culminating in a specific (set of) response(s). The goal of cognitive psychology is to understand what happens in the cognitive agent from the early perceptual processing of stimuli until the final execution of responses. In general, this approach has been extremely successful in explaining cognitive phenomena through the use of a large number of experimental paradigms based on the principle of mental chronometry.

Mental chronometry is the use of reaction-time (RT) in perceptual-motor tasks to determine their underlying processes. In his seminal work Franciscus Cornelis Donders (1969) was the first to raise the idea that mental processes take (specific amounts of) time, and therefore that measuring RTs to stimuli can be used to study human cognition. He devised three different types of RT tasks which made up his celebrated “subtraction method”: the simple RT task, the go/no-go task, and the choice RT task.

In a simple RT or detection task participants are required to simply press a button as fast as possible after stimulus presentation. The slightly more complex go/no-go task includes two different stimuli that are being presented in an intermixed manner; one that requires the fast execution of a button press (i.e., similar to the simple RT task) and another that requires restraining from responding at all. Finally, in the choice RT task participants are presented at every trial with one of multiple stimuli, each of which requires a different response.

The RTs are typically fastest on average for the simple RT task, slower for the go/no-go task, and the slowest for the choice RT task. This pattern was interpreted as reflecting the involvement of different processing stages. For instance, in case of the simple RT task, participants solely need to detect the stimulus and execute the prepared response. For the go/no-go task an additional stage was assumed to be required in between detection and execution, namely stimulus identification: a decision has to be made on whether it is the go- or the no-go-stimulus. However, there is still only one response possibility in the go/no-go task, which can be selected (and prepared) even before the trial starts. This is different for the choice RT task, in which a different response is required for each of the different stimuli.

Because it is unknown which response is required after stimulus presentation, a particular response can only be selected after the stimulus is being identified. Thus, the choice RT task was hypothesized to require the involvement of a response selection stage.

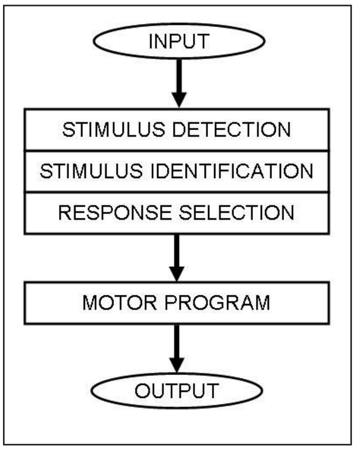

Figure 3. Information processing stages that are assumed for a typical choice RT task. Adapted from Schmidt and Wrisberg (2008).

Overall, information processing in the choice RT task in its simplest form can be considered to involve stimulus detection, stimulus identification, response selection, and response execution through a motor program (see Figure 2). In recent years, this stage model (see Sanders, 1980; 1998; Schmidt & Wrisberg, 2008; Sternberg, 1969) has been modified and extended. For instance, it has been argued a) that information processing across stages is not necessarily serial but also involves temporal overlap of processing at different stages (e.g., Miller, 1993; Miller & Hackley, 1992; Miller, Van der Ham & Sanders, 1995), and b) that more direct routes of information processing may co-exist between stimulus and response, that bypass the various stages (e.g., De Jong, Liang & Lauber, 1994). Moreover, some of its assumptions have been questioned. For example, it is questionable whether mental process can be added or omitted without altering the speed of other processes (i.e., the assumption of pure insertion; e.g., Gottsdanker & Tietz, 1992; Ilan & Miller, 1994; Jansen-Osmann & Heil, 2006; Taylor, 1996; Ulrich, Mattes & Miller, 1999). Despite these modifications, extensions and challenges, however, the core stage-model is still generally accepted as a major tool in describing controlled information processing.

Representing and controlling a single action

At the end of the line of information processing, a particular action is to be executed. Typically, for relatively simple and brief actions the movement pattern (i.e., a fixed series of component actions) that underlies the action seems to be planned/prepared in advance; see Rosenbaum, Cohen, Jax, Van Der Wel & Weiss (2007) for arguments in favor of action preparation. This raises the fundamental question of how this is achieved. One major explanation refers to the existence of motor programs that define and shape the to-be-produced action (see Figure 2). Even though substantial modifications and/or extensions have been proposed with respect to the concept of a motor program (e.g., Keele, 1968; Schmidt, 1975; Summers & Anson, 2009), it is still useful in understanding human behavior and cognition.

Having a program readily at hand that specifies a particular action, is only one part of goal-directed behavior. Another is to know when and how to trigger it into action (i.e., action control). *When* to trigger a particular program could either be internally (i.e, an "internal GO stimulus") or externally (i.e., by an external GO stimulus) determined. An elegant way to deal with the latter, more problematic issue of *how* to trigger the appropriate program is presented by ideomotor logic (e.g., Hommel, Müsseler, Aschersleben & Prinz, 1998). Simply put, ideomotor logic suggests that in order to execute a particular action, an agent endogenously builds up or activates a representation of the desired effect of the action, and this representation is used as a sort of retrieval cue to determine which movement pattern (i.e., motor program) is selected to fulfill the action. A phenomenon that accompanies this logic is that of "executive ignorance": independently of the question whether the mental simulation of the action effects is necessarily a conscious, intentional process (see Herwig & Waszak, 2009 for support that indeed this constitutes an intentional process), people do not need to have much conscious insight in the precise processes that underlie their voluntary actions (e.g., muscle activation and coordination). Merely thinking of the goal triggers the movements necessary to reach it, without much conscious insight into their inner workings; we are aware only of the tip of the action iceberg.

From single to serial action

People do not usually reach their goals by performing single actions in response to single stimuli. Rather, goal-directed behavior involves sequences of actions in response to streams of information from our environment. Specific sequences of (perceptual-motor) actions are often repeated for a particular task; e.g., tying shoe laces, or playing a musical score on the piano (cf. Landau & D'Esposito, 2006). From the notion that the cognitive system is always trying to decrease control demands for task execution, this repetitive feature will be utilized as much as possible: a specific sequence of actions can be represented at a particular level in the hierarchy of control (i.e., sequence learning), and help facilitate ongoing action. As noted above, Nissen and Bullemer (1987) constructed an experimental paradigm to study sequential perceptual-motor learning, the SRT task. From the notion that the SRT task can be considered a special case of the typical choice RT task in which successive trials are presented in a structured fashion, then, it could be argued that the concepts used to explain information processing in the choice RT task are also relevant to the SRT task.

First, the concept of a motor program was used above to explain how action can be pre-shaped and produced. Even though no reference will be made to motor programs in the chapters to follow, some contemplation on the link between motor programs and the SRT task seems justified; especially since the SRT task is often perceived of as a perceptual-motor skill task. The concept of a motor program has had a major influence on theorizing within the field of motor skill and motor control, and is used to define a particular action, in particular the order of a series of component actions that can be prepared and executed in a fast and accurate manner (for a recent review see Summers & Anson, 2009). With respect to a choice RT task, the motor program can be located at the end of S-R processing when a response has to be executed (see Figure 2). Even though this may be most obvious for more complicated actions such as grasping or aiming movements, it is here assumed that even a simple key-press (which typically constitutes the response in a choice RT task) is controlled and triggered into action through a motor program, despite its minimalistic architecture. Hence, a motor program is assumed to be employed within each trial of a choice RT task.

Applying this logic to the SRT task, which can be thought of as a special version of the choice RT task, may create some confusion. In this task, participants typically learn a fixed series of events across trials, i.e., sequence learning, and consensus exists on the major involvement of the response level in sequence learning (e.g., Willingham, 1999; Willingham et al., 2000). Hence, response-related serial order is involved both within trials (even though this may be limited to a minimum for simple key-presses; but see for more complicated actions Shea, Park & Braden, 2006; Ter Schegget, 2009; Witt & Willingham, 2006) and across trials. This prompts the question about whether sequence learning becomes (partly) represented in a “motor program”, such that the motor program is extended across trials, or that sequence learning involves a conceptually different (associative) mechanism? Even though this may be a mere issue of definition, the latter option is defended: motor programs are employed solely within trials of the SRT task, and the sequence learning mechanism across trials is conceptually different from this. The main argument for this is the employment of a response-to-stimulus-interval (RSI), which renders trials in the SRT task to be separated events (for a different view see, for example, Shin & Ivry, 2002). Sequence representations that are formed over practice in the SRT task, then, will not be linked to the concept of a motor program in the current dissertation.

In the discrete sequence production (DSP) task, which seems closely related to the SRT task, the opposite may be argued. In this task, two or more discrete sequences (usually with a length of three to seven elements) are practiced extensively by responding to fixed series of stimuli, with each sequence being practiced for about 500 times (e.g., Verwey, Abrahamse & Jiménez, 2009). Importantly, no RSI is employed in this task, such that the next stimulus follows immediately after a response is registered. It may well be argued that in this task the concept of a motor program includes the representation of order across trials. This claim is supported by the finding that participants with practice become increasingly capable of successfully executing a discrete sequence when only the first stimulus is presented, indicating that visual feedback is no longer necessary (see also Wickens & Hollands, 2000; p. 390-392).

Second, if one considers the SRT task as a special case of the typical choice RT task, it can be argued also that the stage-model, including all of its issues, is relevant to sequence learning in the SRT task; perhaps more than has been recognized in the literature so far. For instance, one may wonder exactly what part of information processing is facilitated through sequence learning, or whether the cognitive subtraction method used to index sequence learning (i.e., the performance differences between sequential and random blocks) should take into consideration possible violations of the assumption of pure insertion. In addition, it could be meaningful to adopt the stage-like architecture from the information processing approach in reasoning about the mechanism(s) underlying sequence learning in the SRT task, which is a notion that will be further elaborated on in Chapter 2. Overall, the SRT task has become one of the most productive tools in the study of (implicit) perceptual-motor learning over the last decades, but still relatively little consensus seems to exist with respect to the position of the task within a broader framework of information processing, as well as with respect to the mechanisms underlying sequence learning in this task.

COGNITIVE MECHANISMS OF SERIAL LEARNING

One major issue in the SRT literature concerns the precise nature of sequence learning in the SRT task. However, this issue actually relates to a number of questions. Below we will briefly discuss three of such issues, the third of which constitutes the main topic of this dissertation.

Chunking versus statistical learning

A first question that speaks to the nature of sequence learning in the SRT task, is whether it involves the memorization of specific sequence fragments (i.e., chunking), or the extraction of first- or higher order transitions (i.e., statistical learning). From the notion of statistical learning, responding to each trial drives the system to encode the relevant dimension, update the transition probabilities in accordance to the observed trial, and prepare for the next trial as predicted by the probability context up to that trial (e.g., Jiménez, 2008). Some authors have proposed that, in addition to statistical learning, sequence learning in the SRT task can also be based on chunking (e.g., Koch & Hoffmann, 2000a). Chunking may be seen as an alternative account to statistical learning, mainly to resolve the problem of possible capacity limitations that may be related to the extensive, online computations needed for statistical learning.

Reasoning solely from the dichotomy between chunking and statistical learning as mechanisms underlying sequence learning, statistical learning may already be considered self-evident because of the observation that sequence learning occurs also in cases that chunking is highly unlikely; for instance, in case of probabilistic sequences (e.g., Schwaneveldt & Gomez, 1998) each sequence fragment is pierced by deviating information once in a while, thereby probably deterring the chunking process. Moreover, simple grammars as used in the study by Deroost and Soetens (2006) also do not allow for chunking, and learning in that study again supports statistical learning. In contrast, the empirical support for chunking in the SRT task is rather sparse (see Jiménez, 2008, for a discussion on this). This may be somewhat surprising given the generally accepted role of chunking in the DSP task (e.g., Verwey, 1996; Verwey, Abrahamse & Jiménez, 2009)[1].

So, despite strongly suspecting its existence, chunking of sequential information in the SRT task has not yet clearly been identified, and it thus needs further exploration.

Implicit learning

A second issue that relates to the nature of sequence learning in the SRT task concerns the implicit-explicit distinction. Thinking about learning, most people would probably assume it to be a strategic and conscious process that serves to accomplish a specific and explicitly defined goal. However, many skills seem to be acquired in the relative absence of direct awareness, a process referred to as implicit learning. For instance, while learning to play a sport we do not continuously pay attention to the dynamic regularities that describe our body movements, yet they develop with practice. The definition and operationalization of the concept of implicit learning have been heavily debated over the years, and various alternatives have been proposed. To list some definitions of implicit learning:

a) An alternate mode of learning that is automatic, nonconscious, and more powerful than explicit thinking for discovering nonsalient covariance between task variables (Mathews, Buss, Stanley, Blanchard-Fields, Cho & Druhan, 1989)
b) A situation neutral induction process whereby complex information about any stimulus environment may be acquired largely independently of the subjects' awareness of either the process of acquisition or the knowledge base ultimately acquired (Reber, 1993)
c) Learning that "a) happens in an incidental manner, without the use of conscious hypothesis-testing strategies, b) happens without subjects acquiring sufficient conscious knowledge to account for their performance on tests of their learning, c) is of novel material, rather than involving activation of previously acquired representations, and d) is preserved in patients with amnesia" (Seger, 1998)
d) A learning process that "is unaffected by intention" (Stadler & Frensch, 1994)
e) Improvements that occur in a person's capability for correct responding as a result of repeated performance attempts and without the person's awareness of what caused the improvements (Schmidt & Wrisberg, 2008).

It is noteworthy that different aspects can be stressed in defining implicit learning. First, whereas some definitions only consider the learning process, other definitions take into account the retrieval processes in addition. Second, the label implicit can be taken synonymous with either unconscious or incidental; put differently, it may stress either the end-product of learning (i.e., are participants unaware of the knowledge acquired over practice?), or the learning process itself (i.e., is learning incidental and effortless?). However, these two characteristics may be intrinsically related to each other, and many definitions of implicit learning are actually a combination of these. For a more comprehensive outline on how to define implicit learning, please refer to Frensch (1998), who concluded from an in-depth analysis of the implicit learning literature that the scientifically most useful definition of implicit learning stresses the nonintentionality/automaticity of the learning process. Finally, it should also be considered that implicit learning as observed in Task A may not necessarily be comparable to implicit learning as observed in Task B (Frensch & Rünger, 2003).

It has been debated whether the SRT task involves an implicit component in terms of an unconscious end-product, or not. Simply put, two conflicting perspectives can be identified on this matter. According to some authors there are clear indications of the existence of implicit learning (though it is at the same time recognized that a fixed operational definition of so called implicit learning is still an issue of debate). Hence, the learning in implicit-learning paradigms such as the SRT task reflects the ability to learn complex information without any awareness of what is being learned; in other words, such mechanisms reflect a kind of learning that occurs outside of conscious control and that is qualitatively different from explicit-learning mechanisms. Other authors have opposed this point of view–not necessarily the idea that learning can be implicit (i.e., unconscious) under some conditions, but rather the validity of the empirical support that has been presented to demonstrate the existence of such implicit-learning mechanisms (e.g., Shanks, 2005).

Measuring implicit learning

In order to make any conclusive claims about implicit learning and its characteristics, it is needed to separate out influences from explicitly learned information. Various tools have been suggested and employed across the literature to estimate the amount of explicit knowledge for a particular (group of) participant(s). Initially, most of these tools were variations of (free or forced) recall and recognition tasks, based on the idea that performance on such explicit tasks would reflect only the presence of explicit knowledge. However, it is now recognized that performance on cognitive tasks is seldom or never purely explicit or implicit, but rather consists of a mix of both (process-purity problem; Curran, 2001).

To tackle the process-purity problem, Destrebecqz and Cleeremans (2001) suggested to adopt Jacoby’s (1991) process dissociation procedure (PDP) methodology and applied it to sequence learning in the SRT task while employing a second-order conditional (SOC; each element can be fully predicted only on the base of the two proceeding elements) sequence. In their study, the PDP test was completed after an initial training phase (with an RSI of either 0 or 200 ms), and consisted of an inclusion and exclusion task. In the inclusion task, participants are instructed to reproduce as much of the sequence as they can in 96 successive key-presses executed at own will. Conversely, in the exclusion task, they are instructed to freely[1] generate a sequence of 96 key-presses while preventing at best to include parts of the sequence involved in the training phase. To analyze performance, inclusion and exclusion scores can be calculated from these series of 96 key-presses by counting the number of correctly reproduced chunks of three elements (as it was a SOC sequence). The inclusion score is thought to reflect learning of the sequence in general, containing both implicit and explicit contributions. Successful performance on the exclusion task, however, requires a certain amount of control that can be said to be specific for explicit knowledge (Destrebecqz & Cleeremans, 2001), and thus exclusion scores are thought to reflect mainly implicit learning.

Destrebecqz and Cleeremans (2001) hypothesized that the group practicing with a 200 ms RSI would develop higher sequence awareness than the group practicing with a 0 ms RSI, because of the extra time to contemplate on the task performance for the former group. In line with this expectation, it was shown that indeed the group with the 200 ms RSI obtained higher scores on the inclusion task then the group with a 0 ms RSI, and that the former, but not the latter, group could successfully perform the exclusion task. Arguably, the PDP task is currently the most reliable tool in disentangling implicit and explicit sequence knowledge.

Overall, it seems that the whole discussion on awareness has reached a status quo among researchers. Most of them would probably vote in favor of an implicit learning component in the SRT task, but they have at the same time accepted the fact that it is difficult to single out its precise contribution and characteristics. A possible way out of this is to employ probabilistic sequences. These have been shown to allow little development of explicit sequence knowledge, even when explicitly instructed to search for regularity. Comparison can then be made between these probabilistic sequences, and the more typical deterministic sequences (which allow explicit knowledge to develop), in order to investigate potential differences between implicit and explicit learning (e.g., Jiménez, Vaquero & Lupiánez, 2006).

Informational content of sequence representations

Finally, and this is the main topic in the current dissertation, over the last decade a large number of studies have explored the informational contents of the representations that underlie sequence learning (for reviews see Clegg et al., 1998, and Chapter 2 of this dissertation). In general, there exists substantial support in the literature for three underlying mechanisms. Notably, from the notion of a stage model of information processing, all these three mechanisms can be traced back to the formation of associations between (response and/or stimulus) features from ongoing S-R processing. First, in the typical SRT task the order of successive stimuli presented to the participants is fixed, so it is possible that they learn a sequence of stimulus features (e.g., stimulus location, color, etc.; i.e., perceptual learning). However, inherent to the fixed order of stimuli, the responses are also structured. A second possibility, then, is that participants learn a fixed series of response features (e.g., response location; i.e., response-based learning). Third, every stimulus can be perceived as an action effect of the previous response, such that performance enhancement in the SRT task could also be explained by participants learning a sequence of R-S compounds (i.e., response effects learning). Because the order of successive stimuli and responses are so inherently bound to each other in the typical SRT task, it is often hard to disentangle the contribution of each to overall sequence learning. Attempts to do so, have produced rather conflicting results, with some studies advocating a stimulus-based account of sequenced learning, and others arguing in favor of a predominantly response-based account.

For a more comprehensive overview of this particular issue, please refer to Chapter 2 of this dissertation. For now it suffices to say that, even though response-based learning has generally been considered to dominate the learning process since a couple of studies by Willingham and colleagues (i.e., response-location learning; Bischoff-Grethe et al., 2004; Willingham, 1999; Willingham et al., 2000), over the last decade ample support has arisen for the notion that stimulus information plays an important role in sequence learning as well. This has been one of the major incentives for the empirical work in Chapters 3-6 of this dissertation.

OVERVIEW OF THIS DISSERTATION

This dissertation focuses on the informational content that underlies the representations that are being formed during serial learning in the SRT task. Chapter 2 presents a comprehensive overview of the various accounts that have been proposed over the last decades. Moreover, seeing that strong support exists for a number of underlying mechanisms, an attempt was made in that chapter to reconcile these mechanisms within a multilevel framework. It is suggested that a particularly well-known model suggested by Keele and colleagues (i.e., Keele, Ivry, Hazeltine, Mayr & Heuer, 2003) could play an important role in this regard. Most of the empirical chapters (Chapter 3-6) that follow the review chapter are based on the notion that stimulus information is involved in sequence learning (either perceptual or response-effect learning), for which evidence has been mounting over the last decade (e.g., Clegg, 2005; Remillard, 2003; Song, Howard & Howard, 2008).

Chapter 3 presents a study on the potential existence of context dependencies in perceptual-motor skill acquisition. Specifically, participants are trained in an SRT task with a number of fixed, seemingly task-irrelevant perceptual features (i.e., placeholder shape, placeholder position and display color). A subsequent transfer phase explores the effect of changing these features. Importantly, a comparison is made between two different groups of participants that trained either with a fixed or pseudo-random sequence of trials, in order to determine the sequence-specific impact.

In Chapter 4 it is explored to what extent the tactile domain can be employed in guiding perceptual-motor sequence learning. Whereas the SRT task is typically performed while employing visual stimuli on a computer screen, in Chapter 4 sequence learning is compared between the typical, visual SRT task, and a tactile SRT task in which the stimuli are presented tactilely to the fingers. Moreover, it is determined to what extent sequence knowledge is transferable across the visual and tactile modalities.

From the notion that stimulus information has a role in sequence learning, Chapters 5 and 6 explore the effect of response cue redundancy. Specifically, in Chapter 5 congruent visual and tactile stimuli are employed during training in the SRT task, and performance is compared to conditions with either single visual or single tactile stimuli. Additionally, in a subsequent transfer phase, each participant is tested on all three stimulus conditions in order to enable a comparison between the different training groups under equal conditions. Chapter 6 employs a similar design as Chapter 5, but now with the position and color features of the stimuli serving as redundant response cues.

The last empirical study as presented in Chapter 7 does not focus on the role of stimulus information, but rather aims at exploring the effect of response selection processes on sequence learning by manipulating spatial stimulus-response compatibility. From previous work it has been suggested that incompatible mappings produce better implicit sequence learning than compatible mappings (e.g., Deroost & Soetens, 2006b; Koch, 2007), and two experiments in this chapter further test this claim.

Finally, Chapter 8 presents a brief review on how to interpret the findings in the SRT literature (including some of the empirical work of this dissertation) from an applied perspective. More specifically, it denotes how the development of training programs for perceptual-motor tasks may benefit from the findings obtained from the SRT task.

NOTES

1. Typically, in the DSP task it is observed that some key-presses within a sequence are executed consistently slower than others. This is thought to reflect spontaneous segmentation of the sequence into chunks.

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Chapter 2

Representing serial action: A dynamic approach

Abstract

One major issue in the sequence learning literature concerns the representational base of sequence learning. A number of different types of associations have been proposed in this regard, and the review presented in the current paper shows that strong support has been obtained for three of them: associations between successive stimulus features, associations between successive response features, and associations between successive response-to-stimulus-compounds. A dynamic approach will be proposed in which the associations that underlie sequence learning are not predetermined with respect to one particular type of information, but rather develop according to an overall principle of activation. Such an approach enables the integration of a rich and seemingly equivocal literature. Moreover, it is here proposed that substantiating such an integrative approach can be achieved by a synthesis with the dual system model as depicted by Keele, Ivry, Mayr, Hazeltine and Heuer (2003).

Abrahamse, E. L., Jiménez, L., Verwey, W. B. & Clegg, B. A. (*Manuscript under review*).

INTRODUCTION

The ability to sequence information and actions lies at the very heart of skilled performance, and is of long-standing interest (e.g., Lashley, 1951). Nissen and Bullemer (1987) developed the serial reaction-time (SRT) task, a paradigm that has become widely-used to study sequence learning (for reviews see Clegg, DiGirolamo & Keele, 1998; Keele, Ivry, Mayr, Hazeltine & Heuer, 2003; Rhodes, Bullock, Verwey, Averbeck & Page, 2004; Robertson, 2007).

In its basic appearance, the SRT task is a continuous four choice reaction time task in which participants respond to the location of the stimulus. A fixed response to-stimulus-interval (RSI) separates successive events. Unbeknownst to the participants, stimulus presentation is sequential; i.e. individual events either follow a certain rule, or they are presented as a fixed-length string of events that is repeated continuously. Decreases in reaction times (RTs) and/or error percentages (PEs) with practice provide evidence that learning has occurred. To differentiate sequence learning from general practice effects, a random block of stimuli is inserted towards the end of the practice phase. The cost in RT and/or accuracy of this random block relative to the surrounding sequence blocks serves as an index for sequence learning. Often participants are apparently unable to (fully) express their sequence knowledge in other ways (e.g., recognition and free recall tests) than through the direct performance measures, and learning is characterized as implicit (e.g., Cleeremans, Destrebecqz, & Boyer, 1998; Seger, 1994; but see Shanks, 2005).

The SRT task has provided the foundation for a highly productive area of research featuring behavioral, imaging (e.g., Curran, 1998; Hazeltine & Ivry, 2003), patient (e.g., Dominey, 2003; Doyon, 2008), animal (e.g., Christie & Dalrymple-Alford, 2004; Nixon & Passingham, 2000), developmental (e.g., Meulemans, Van Der Linden, & Perruchet, 1998; Wilson, Maruff, & Lum, 2003), and computational approaches (e.g., Cleeremans, 1993; Cleeremans & Dienes, 2008). With its relatively fast acquisition and objective index of sequence-specific performance gains, it offers an easy laboratory tool in the study of sequence learning. Moreover, the paradigm mimics important properties of real life learning situations, as both our actions and many of the naturally occurring events that surround us entail some inherent structure.

At the same time, the broad scope of sequencing can make investigation and interpretation in the SRT task more complicated than its relatively simple design might suggest. A full evaluation of human sequence learning phenomena touches upon a wide range of aspects of cognitive functioning (such as perception, attention, consciousness, motor control, memory, language, learning, etc.). This complexity is also apparent in the sensitivity of the paradigm to even relatively minor parametric manipulations, sometimes making straightforward comparisons between studies difficult. For instance, variations in the stimulus-to-response mapping (e.g., Deroost & Soetens, 2006c) or the RSI (e.g., Destrebecqz & Cleeremans, 2001) have been shown to influence sequence learning.

The nature of sequence representations

One of the central issues for SRT research and related fields over the last two decades has been the nature of sequence learning: What exactly is being learned and how is this knowledge represented in the brain (Clegg et al., 1998; Goschke, 1998; Hazeltine, 2002; Stadler & Roediger, 1998)? This issue can be divided into three sub-questions. First, there is the question of whether sequence learning in the SRT task is necessarily explicit, or whether it could also be implicit (e.g., Destrebecqz & Cleeremans, 2001; Frensch, 1998; Jiménez, Vaquero & Lupiáñez, 2006; Shanks & St. John, 1994)? This inherently brings about the difficult question of how to define and operationalize implicit learning in the first place (Frensch & Rünger, 2003). Second, it can be debated whether sequence learning involves the extraction of statistical information inherent to the underlying sequence, or a discrete process of memorizing and using specific fragments of the sequence (e.g., Jiménez, 2008; Koch & Hoffmann, 2000a). Third, the nature of sequence learning may refer to the precise informational content underlying the sequence representation that is being formed during training. The current review will focus on this latter issue, which has already produced a rich literature of equivocal and even contradictory findings (see Table 1).

Different types of knowledge have been suggested to underlie the learning of behavioral sequences, such as perceptual, response-effect, and response location knowledge. To satisfactorily cope with all the disparate findings that are associated with these single-level accounts, a comprehensive framework of sequence learning must involve a multi-level configuration. However, few attempts exist in the literature to substantiate such an integrative framework. Rather it remains all too common to embrace the simple dichotomy of stimulus- versus response-based sequence learning, with individual findings being interpreted as supporting one while arguing against the other.

One major exception to this practice of testing single mechanism accounts is the dual system model proposed by Keele, Ivry, Mayr, Hazeltine, and Heuer (2003). This model offers an integrative description of sequence learning that includes two parallel association systems; a set of unidimensional modules that each operate on a single dimension, and a multidimensional module operating both within and across dimensions. However, the model as currently instantiated does not always readily lend itself to testable predictions because of its abstract nature, unfortunately leaving its current role in the field often restricted to an explanatory model. For example, within this dual system model the central concept of a dimension is not operationally defined, and no subsequent studies have attempted to tackle the role of dimensions in sequence learning. Here we outline one way in which progress can be made, through providing a more tangible link of this model to the forms of sequence learning more frequently discussed in SRT literature.

Below we review recent progress on the nature of sequence learning, borrowing both from the SRT literature as well as from other paradigms. It shows that strong empirical support exists for various mechanisms underlying sequence learning. Building from an integrative approach, then, a synthesis is proposed between these multiple single-level mechanisms, and the more overarching but somewhat abstract model depicted by Keele et al. (2003). In doing so, we aim to a) further integrate seemingly opposing findings in the literature, b) revisit and extend the dual system model based on recent literature, c) create new predictions based on this model, and d) inspire new ways of thinking about the nature of sequence learning in general.

MULTIPLE SINGLE-LEVEL ACCOUNTS

One of the crucial questions within SRT literature concerns exactly which associations underlie sequence learning. In general, two decades of investigation on this issue has identified a number of such associations, with relatively strong support for three of them: response-location, perceptual, and response-effect learning (see Table 1). These can be traced back to the formation of associations within and between stages of information processing (e.g., Sanders, 1990, 1998; see Figure 1). We will next discuss in detail these forms of sequence learning, as well as a few less documented alternatives (i.e., abstract learning, learning at the response selection stage).

Table 1. Overview of studies that provide support for (V) or against (X) the different forms of sequence learning that are discussed in the literature. Please note that for each study we restricted ourselves to the main interpretations described by the authors themselves. Occasionally, the authors themselves acknowledged that their results could not distinguish between perceptual and response-effect learning; in these cases we placed the V-sign in between cells.

<table>
<tr><th rowspan="2">Reference</th><th rowspan="2">Response – based</th><th colspan="2">Stimulus-based</th><th rowspan="2">Response selection</th><th rowspan="2">Abstract</th></tr>
<tr><th>Perceptual</th><th>Response-effect</th></tr>
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<tr><td>Gheysen et al. (2009)</td><td>V</td><td>V</td><td>–</td><td>–</td><td>–</td></tr>
<tr><td>Goschke & Bolte (2007)</td><td>–</td><td>–</td><td>–</td><td>–</td><td>V</td></tr>
<tr><td>Hazeltine (2002)</td><td>–</td><td>–</td><td>V</td><td>–</td><td>–</td></tr>
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<tr><td>Kinder et al. (2008)</td><td>–</td><td>–</td><td>–</td><td>X</td><td>–</td></tr>
<tr><td>Koch & Hoffmann (2000b)</td><td>V</td><td>V</td><td>–</td><td>–</td><td>–</td></tr>
<tr><td>Mayr (1996)</td><td>V</td><td>V</td><td>–</td><td>–</td><td>–</td></tr>
<tr><td>Nattkemper & Prinz (1997)</td><td>V</td><td>X</td><td>–</td><td>–</td><td>–</td></tr>
<tr><td>Price & Shin (2009)</td><td>–</td><td>V</td><td>–</td><td>–</td><td>–</td></tr>
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<tr><td>Ruessler & Roesler (2000)</td><td>V</td><td>X</td><td>–</td><td>–</td><td>–</td></tr>
<tr><td>Schwarb & Schumacher (2008)</td><td>–</td><td>–</td><td>–</td><td>V</td><td>–</td></tr>
<tr><td>Stadler (1989)</td><td>–</td><td>V</td><td>–</td><td>–</td><td>–</td></tr>
<tr><td>Song et al. (2008)</td><td>–</td><td>V</td><td>–</td><td>–</td><td>–</td></tr>
<tr><td>Stöcker et al. (2003)</td><td>–</td><td>–</td><td>V</td><td>–</td><td>–</td></tr>
<tr><td>Vakil et al. (2000)</td><td>V</td><td>V</td><td>–</td><td>–</td><td>–</td></tr>
<tr><td>Verwey & Clegg (2005)</td><td>V</td><td>–</td><td>–</td><td>–</td><td>–</td></tr>
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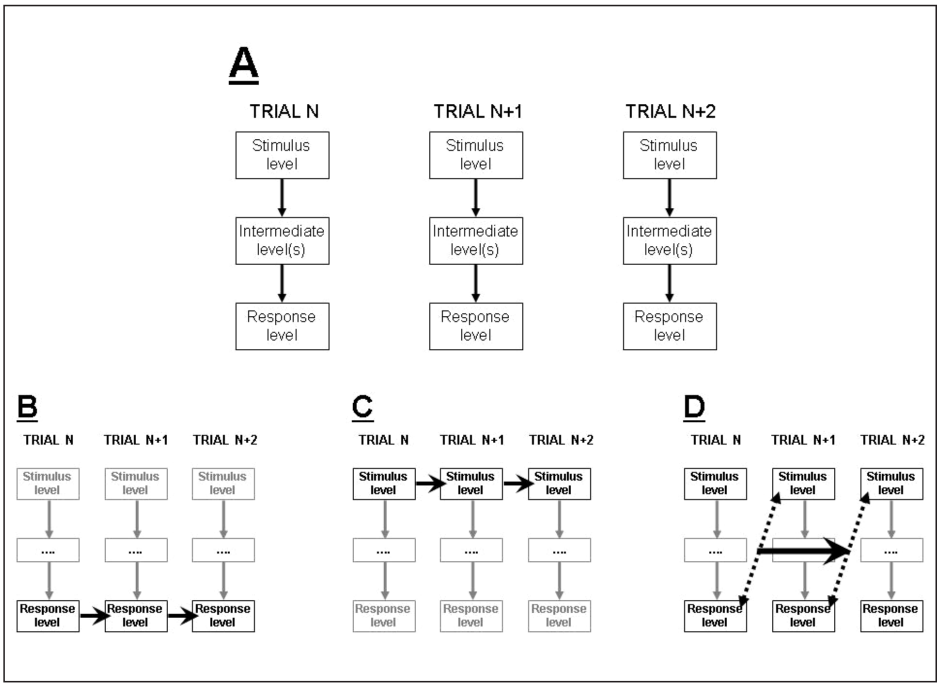

Figure 1. Information processing and sequence learning in the serial RT task. During early training, or in blocks with (pseudo-)randomly structured trials, performance involves the same basic information processing stages as a typical (four-)choice RT task (1A): processing at the stimulus level (e.g., encoding, identification), processing at intermediate levels (e.g., response selection) and processing at the response level (e.g., programming, execution). With training, associations may develop across trials between successive response features (1B), between successive stimulus features (i.e., perceptual learning; 1C), or between successive response-to-stimulus compounds (i.e., response-effect learning; 1D).

Response-based learning

Response-based learning refers to the formation of associations between successive response features (see Figure 1A). One initially perplexing pair of findings in sequence learning was the observed absence of effector-specific sequence learning in the SRT task (e.g., Cohen, Ivry & Keele, 1990; Keele, Jennings, Jones, Caulton & Cohen, 1995), whereas imaging and patient studies clearly indicate the involvement of motor areas in the brain (e.g., Grafton, Hazeltine & Ivry, 1995; Grafton, Hazeltine & Ivry, 1998; Willingham & Koroshetz, 1993). Willingham, Wells, Farrell and Stemwedel (2000) offered a resolution to this apparent paradox by stressing the role of response locations. In their study it was observed a) that participants showed no reliable transfer when the stimulus sequence was maintained, but response locations were changed, and b) that participants showed transfer from a crossed-hand training phase to a normal hand test phase only when the sequence of response locations was maintained, and no transfer when the sequence of finger movements was maintained.

Willingham and colleagues proposed an account based on response location learning: participants primarily learn a sequence of response locations, independent of the specific effectors used to act on these locations. This response location account was further supported by various subsequent studies.

The conclusion that sequence learning is not effector specific does not fit well with the notion that in many real life tasks that involve sequential action, such as writing and typing, performance is typically affected by employing different effectors or effector groups (e.g., Hicks, 1974; Gentner, Larochelle & Grudin, 1988; Jordan, 1995). Moreover, effector-specific sequence learning effects have been found in studies with monkeys (e.g., Rand, Hikosaka, Miyachi, Lu, Nakamura, Kitaguchi & Shimo, 2000). Verwey and Clegg (2005) noted that these types of situations featuring effector-specific learning involve greater amounts of practice than is typical for the SRT task. In line with another study employing the discrete sequence production (DSP) task (Verwey & Wright, 2004), Verwey and Clegg (2005) were able to detect an effector-specific component of sequence learning in the SRT task after extended practice, in addition to the typical effector-independent learning (see also Berner & Hoffmann, 2008; Deroost, Zeeuws & Soetens, 2006). This finding suggests that at least two possible types of response-based representation can occur concurrently within the SRT task (see also, Richard, Clegg, & Seger, 2009, for evidence of a potential third type of representation, direction of movement). However, there remain some unresolved questions about effector-specific learning with extended practice. For instance, it may indicate that, with extensive practice, the triggering of particular finger movements becomes increasingly automatic. Alternatively, the same result could also be accounted for by assuming that over training a body-based egocentric representation is progressively replaced by a hand-specific spatial reference frame (see Verwey, Abrahamse & Jiménez, 2009).

Overall, response-based learning, and more specifically response location learning, is arguably the dominant model of implicit sequence learning in the typical SRT task. It is supported by a wealth of behavioral findings (e.g., Nattkemper & Prinz, 1997; Willingham, 1999; Deroost & Soetens, 2006a), and fits well the frequently observed involvement of motor areas in the brain (e.g., Bischoff-Grethe, Goedert, Willingham & Grafton, 2004; Grafton, Hazeltine & Ivry, 1995; Grafton, Hazeltine & Ivry, 1998; Grafton, Hazeltine & Ivry, 2002). Additionally, this account is congruent with the typically observed impaired sequence learning in clinical populations characterized by motor deficits (for a review see Doyon, 2008). For instance, a meta-analysis by Siegert, Taylor, Wheatherall and Abernethy (2006) suggested that patients with Parkinson’s disease are significantly impaired on implicit sequence learning.

However, while response-based sequence learning is well documented, on its own it cannot easily incorporate various other findings in the literature that have been mounting over the last decade.

Stimulus-related learning

Stimulus-based sequence learning may refer to any associations underlying sequence learning that involve stimulus features. On the one hand, this pertains to associations between successive stimulus features (either within or between single features, such as color, shape, and location), typically referred to as perceptual learning (see Figure 1B). On the other hand, associations may be formed between current response features and subsequent stimulus features (remember that in the typical SRT task, fixed and relatively small RSIs are employed, enabling each new stimulus to be interpreted as a direct effect of the preceding response), coined response-effect learning (see Figure 1C). Both these forms of sequence learning have received support in the literature, though specific experimental designs have sometimes made it impossible to disentangle their contributions (e.g., Abrahamse, Van der Lubbe & Verwey, 2008; Clegg, 2005; Jiménez et al., 2006).

Abrahamse, Van der Lubbe, and Verwey (2008) showed that sequence learning does not always transfer well between different sets of stimuli (but see Abrahamse, Van der Lubbe & Verwey, 2009; Willingham, 1999). Specifically, they observed only partial transfer from visual stimuli on a screen to tactile stimuli presented directly to the fingers to respond. As response sequences were always identical, across both training and transfer phases and across stimulus conditions, these results suggest at least some role for stimulus modality. Along the same lines, Jiménez et al. (2006) observed no transfer when participants were first trained in a typical SRT setting, and then tested in an adapted version with distracters appearing at the non-target positions. Again, the response (location) sequence was maintained during testing. Finally, Clegg (2005) mapped two stimulus locations on each of two response keys. Response latencies increased when stimulus locations deviated from the learned sequence over a test phase, even when the response features remained the same (i.e., the stimulus did not appear at the expected location, but rather at the alternative location that was mapped onto the same response). These results indicate that features of the stimuli are implicated in sequence learning, but cannot distinguish between perceptual learning of a sequence of stimuli, or the acquisition of sequence knowledge based on response-effect contingencies.

Perceptual learning

Some definitions of perceptual learning confine it to (relatively long-lasting) changes to an organism's perceptual system (e.g., Goldstone, 1998). However, in the context of sequencing, perceptual learning refers to the possibility that stimulus features (such as location and shape) become bound into a higher level sequence representation, thereby facilitating responding to that series of stimuli when they reappear.

Empirical support for the involvement of stimulus locations in sequence learning that is independent from response related processes stems mainly from studies in which a) no overt responding was required[1] (i.e., observational learning), or b) stimulus location followed a sequential structure independent from the response sequence. With regard to the former, Howard, Mutter and Howard (1992) reported similar performance in a transfer phase from subjects who had been responding throughout the experiment and those who had previously only observed the sequence. Willingham (1999) suggested that sequence learning through observation involved explicit rather than implicit learning. He observed no performance improvements on structured versus random trials after eliminating all subjects that showed relatively high awareness of the sequence (see also Kelly & Burton, 2001). However, Song, Howard and Howard (2008) also found sequence learning with observation alone in an alternating serial reaction time (ASRT) task, which has been claimed to produce little sequence awareness (Howard et al., 2004). Hence, it seems as if implicit sequence learning can develop from merely observing sequential order.

Various other studies have employed a fixed sequence of stimulus locations, while responses followed an independent, sometimes (pseudo-)random, sequence (e.g., Deroost & Soetens, 2006a; Mayr, 1996; Remillard, 2003). This can be achieved by presenting a task-relevant stimulus feature (e.g., shape or color) across multiple potential stimulus locations. For instance, Remillard (2003; see also Deroost & Soetens, 2006b) employed a design in which six different stimuli, consisting of the letter pairs "xo" and "ox", were simultaneously presented at six fixed locations on the screen. An underline marked the location of one of the letter pairs, and participants were instructed to respond as fast as possible to the identity of the marked letter pair. While the identities of those target letter pairs, and therefore the response series, were unstructured, the stimulus location changed according to an independent probabilistic sequence. The sequence of stimulus locations was reliably learned, even though there the response-related information was unstructured.

Similar findings have been reported by Mayr (1996) and Deroost and Soetens (2006a). The task-irrelevant stimulus locations were sequentially structured over trials, while responses were made to a different, independent sequence of colors of the stimuli. Again, sequence learning based on stimulus locations was observed. Interestingly, Deroost and Soetens (2006a) showed that learning of the sequence of stimulus locations was strongest in (or even restricted to) the situation in which subjects practiced a concurrent sequence of responses. When the response series was unstructured, little or no stimulus location learning seemed to develop.

Support for the ability to implicitly extract regularity from input, such as with learning a fixed sequence of stimuli, also stems from other paradigms than the SRT task. For instance, Saffran, Johnson, Aslin & Newport (1999) exposed subjects to continuous sequences of non-linguistic auditory stimuli whose elements were organized into ‘tone words’ on the basis of statistical information. Adults could reliably extract this regularity, and, more importantly, the same was true even for 8-month-old infants. Most likely, the latter were not engaged in explicit learning. Likewise, the visual statistical learning (VSL) paradigm, in which subjects are presented with a long series of visual stimuli, has shown implicit learning of statistical relationships among these stimuli (e.g., Turk-Browne, Isola, Scholl & Treat, 2009). Given some of the surface similarities between the tasks, it is not implausible that the system underlying VSL is working also during SRT training, at least under some conditions. Finally, Olson and Chun (2001) showed that spatial attention can be guided to a target location on the basis of learned, sequentially structured event durations, event identities, and spatial-temporal event sequences, even when subjects were unaware of the regularity (see also Clohessy, Posner & Rothbart, 2001; but see Smyth & Shanks, 2008).

Response-effect learning

A second proposed stimulus-related form of sequence learning is so called response-effect learning, that is, sequence learning based upon associations between compounds of responses and subsequent stimuli. In an ingenious study, Ziessler and Nattkemper (2001) employed a flexible stimulus-to-response mapping that allowed them to vary the stimulus sequence while the response sequence was maintained. Predictable response-to-stimulus relationships improved serial learning, and the authors went as far as to state that “R-S learning is … the major learning mechanism working under serial learning conditions” (p. 612).

Further support for R-S learning was provided by a study of Hoffmann, Sebald and Stoecker (2001). They mapped different tones as task-irrelevant response-effects to the response keys and observed improved sequence learning as long as each tone was consistently and uniquely mapped onto a response (Experiment 1; see also Stoecker, Sebald & Hoffmann, 2003). Moreover, for participants who had adapted to a contingent key-tone mapping during training, performance was significantly impaired when the mapping between response-keys and tones was changed in a transfer block (Experiment 2). Stoecker et al. (2003) extended these findings by showing that the benefit from tones as task-irrelevant and contingent response-effects only occurs when the tones are mapped ascending to response-keys from left to right, thus in a highly compatible manner.

These findings illustrate that response-effect associations benefit sequence learning. However, it remains uncertain whether this kind of component could play the major role attributed to it by some of its proponents. For instance, it is unclear how this type of representation could account for findings like those reported by Willingham (1999; Experiment 3; see also Abrahamse, Jiménez, Deroost, Van den Broek & Clegg, unpublished data[2]), in which reliable transfer was observed when the stimulus patterns change while the response sequence is maintained, thus breaking the R-S coupling. In addition, one may wonder how response-effect learning relates to sequence awareness. Response-effect learning fits well with the ideomotor approach to action control, which points to the important role played by the mental anticipation of the sensory effects of a movement in the actual production of that movement (e.g., Hommel, Müsseler, Aschersleben & Prinz, 2001). Even though the ideomotor approach does not specify whether this anticipation is necessarily a conscious process, it seems as if this mental anticipation comes close to implying some sort of conscious intention (e.g., Herwig & Waszak, 2008). It may be wondered, then, whether response-effect learning could be taken as a mechanism underlying truly implicit knowledge. Below we will propose that response-effect learning occurs within the multidimensional module as depicted by Keele et al. (2003), which is the module supporting explicit learning.

Other forms of representation

Although most of the existing evidence of sequence learning can be classified along the dichotomy between stimulus- and response-related learning, this does not cover the whole range of possibilities. At least two more alternatives are discussed in the literature. Extensive support for these alternatives is currently absent (see Table 1), but that may be partly due to the relative complexity of exploring these accounts (especially at a behavioral level).

Response selection stage

One of the less discussed possibilities concerns learning at intermediate stages of information processing, such as the response selection stage: Can implicit sequence learning be based on a series of S-R associations? Initially, this idea was put forward by Willingham, Nissen and Bullemer (1989), and some further support for it has been reported (even though Willingham and colleagues themselves abandoned the idea when it did not match with later findings; e.g., Willingham, 1999; Willingham et al., 2000). First, Schwarb and Schumacher (2009) found that spatial sequence learning relies on many of the same brain areas as spatial response selection. According to their interpretation, this would be in line with theories that localize sequence learning at the level of response selection processing. Second, sequence learning has been found to be better for spatially incompatible than spatially compatible S-R mappings (Deroost & Soetens, 2006c; Koch, 2007). Again, from the notion that incompatible mappings force more controlled response selection processes, this would fit with a response selection account.

However, while these results indicate a link between response selection and sequence learning, they do not provide direct support for the idea that implicit sequence learning is actually based on S-R associations. In addition, equally strong support has been reported against a response selection account of sequence learning. Hoffmann and Koch (1997) demonstrated that changes in the (non-spatial) stimulus-response compatibility have no impact on sequence learning, and Kinder, Rolfs and Kliegl (2008) showed that sequence learning occurs even under very high S-R compatible conditions (i.e., needing little response selection processing). Finally, results from a study by Abrahamse, Jiménez, Deroost, Van den Broek and Clegg (unpublished data) suggest that it is perhaps explicit, but not implicit sequence learning that benefits from incompatible S-R mappings. Accordingly, the advantage for the incompatible S-R mappings as reported in Deroost and Soetens (2006c) and Koch (2007; Experiment 1), was not found in this study when a probabilistic sequence was employed, thereby hindering the development of explicit learning. Notably, Koch (2007) already speculated about the possibility that explicit learning modulated the effect of spatial S-R mappings, but he claimed that the sample sizes in his Experiment 1 "were probably too small to give meaningful results when the groups were post-hoc classified into explicit and implicit learners" (p. 265).

Abstract learning

In some implicit learning paradigms (e.g. Abstract Grammar Learning; AGL) that seem related to the SRT task, abstract knowledge has been claimed to develop with training (e.g., Gomez & Schvaneveldt, 1994; Knowlton & Squire, 1996; Gomez, 1997; see also Francis, Schmidt, Carr, & Clegg, 2009). Abstract knowledge refers to knowledge that is independent from any surface information, such as stimulus or response features, but rather is related to some generally applicable rule. Although some abstract knowledge has been shown to generalize between different surfaces in AGL procedures, questions remain about whether learning and transfer of an underlying abstract structure is dependent on explicit memory retrieval (Gomez, 1997).

Based on the findings with AGL tasks, Dominey, Lelekov, Ventre-Dominey and Jeannerod (1998) explored abstract sequence learning in the SRT task. They trained subjects on a sequence with both predictable surface (i.e. the stimulus order) and abstract structure, half of them being kept naïve as to the abstract structure (i.e. implicit group), and half of them receiving explicit information about the rule determining the abstract structure as well as the instruction to use the rule (i.e. explicit group). Both groups showed sequence learning, but only subjects from the explicit group were able to transfer their knowledge to an isomorphic sequence (i.e. a different surface structure with the same underlying abstract rule). Two additional experiments in that study further supported this finding, and, overall this study thus strongly indicates that abstract learning is conditional upon explicit processing.

A different conclusion was suggested by Goschke and Bolte (2007), who introduced the serial naming task. In this task, subjects had to respond to pictures of objects simply by naming them. Whereas the individual objects were presented in a random order (thus implying a random order of the naming responses as well), the underlying semantic categories to which the objects belonged were structured. Participants learned this abstract sequence of categories, even in cases in which they showed no or little explicit knowledge of the structure on subsequent reproduction and recognition tests. Thus although the SRT paradigm currently has no direct evidence for abstract learning, this type of finding certainly raises the possibility that such learning may occur.

To summarize, ample empirical support (see Table 1) exists for different types of associations underlying sequence learning in the SRT task, most notably associations between successive stimulus features (perceptual learning), successive response features (response-based learning) and successive response-to-stimulus couplings (response-effect learning). In contrast, the results are very sparse and somewhat contradictory concerning the involvement of either sequences of response-mapping decisions, or abstract, categorical regularities (see also Table 1).

A MULTILEVEL APPROACH

The idea of a distributed network of sequence learning mechanisms is not new in the SRT literature. Most commonly, it has referred to different mechanisms for explicit and implicit sequence learning (e.g., Hazeltine, Grafton & Ivry, 1997; Willingham & Goedert-Eschmann, 1999). Over the last decade, however, it has also been suggested occasionally that implicit sequence learning itself involves a distributed network of systems, although the precise qualification of the proposed levels varies considerably (e.g., Abrahamse et al., 2008; Bapi, Doya & Harner, 2000; Clegg et al., 1998; Deroost & Soetens, 2006a; Deroost & Soetens, 2006b; Keele et al., 2003; Seger; 1997; Witt & Willingham, 2006). This suggestion matches the observation that various distinct brain areas are associated with implicit sequence learning and/or performance (for a review see Hazeltine & Ivry, 2003, and see Shendan, Searl, Melrose & Stern, 2003, for support of hippocampal involvement in addition).

Indeed, from examining the myriad of studies on the nature of sequence learning above, it seems apparent that a single-level account encompassing all observations from the sequence learning literature has become increasingly unattainable. Though it is common and productive in cognitive science to take an oppositional view around a dichotomy of options (see Newell, 1973), with regard to the different forms of learning identified in literature (and reviewed above) we aim here to integrate these forms into a multilevel account, rather that seeking to dismiss some. It is noteworthy that various models on related paradigms have paralleled such a move towards a multilevel configuration in order to capture the diverse, sometimes paradoxical findings; such as with category learning (Ashby & Casale, 2003), repetition priming (Race, Shanker & Wagner, 2008), and discrete sequence learning (Verwey, 2003).

In depicting the nature of sequence learning in the SRT task, then, we need a framework that captures, beyond an explicit learning component, the multilevel configuration of implicit learning. Various models across related paradigms, and varying substantially in their scope, seem to relate more or less to the issue (e.g., Ashby & Casale, 2003; Keele et al., 2003; Race, Shanker & Wagner, 2008; Verwey, 2003; Willingham, 1998). Two models that do so explicitly for sequence learning are the parallel processor model proposed by Verwey (2003), and the dual system model developed by Keele et al. (2003). The dual system model will be extensively elaborated on below, but, briefly, it consists of a multidimensional module that is sensitive for regularities both within and across different types of information (i.e., dimensions), and a set of unidimensional modules that are each specifically tuned to one particular type of information. The parallel processor model (Verwey, 2003) comprises a general purpose processor that works in different modes while using different inputs, and two specialized single purpose processors. Hence, on close inspection, these models share a main structure, with one system serving as an overarching processor, accompanied by a set of independent modules that are information-specific. The correspondence between these models can be seen as converging evidence for the feasibility of such a processing architecture in sequence learning.

We will build upon the model depicted by Keele et al. (2003) in attempting to integrate the various forms of implicit sequence learning present in the literature. This model was firmly grounded in the existing SRT literature, and it was developed to be plausible from a neuro-physiological perspective. Regardless of this choice of framework, however, the core idea is that qualitatively different sequence representations can develop. We focus initially on three forms that have received the most convincing support to date: perceptual (location) learning, response-effect learning and response location learning (see Table 1). As stated above, these three forms can all be said to develop from associations within or between stages of information processing (e.g., Sanders, 1990, 1998; see Figure 1). For now, potential contributions to sequence learning of response selection and abstract processing are not directly addressed.

The dual system model

Keele et al. (2003) proposed a multidimensional and a unidimensional association system to be the representational base of complex sequential skills (see Table 2). The unidimensional system is composed of a set of modules that are each capable of associating within a single dimension, whereas the multidimensional system enables associations both within and across dimensions. Apart from this difference in associative abilities, the two systems differ in attentional requirements and the potential development of awareness. Learning within the unidimensional system is automatic, entirely implicit, and independent of attentional effort (i.e., unselective) because of its encapsulation. Sequence learning thus occurs for regularity present within any single dimension, even in the presence of uncorrelated (task-relevant) information within other dimensions. In contrast, the multidimensional system needs to be protected against these uncorrelated, noisy streams of information in order to do its job. This is achieved by making learning dependent on selective attention, so that the multidimensional system would associate only within and across attended dimensions. This makes this system the natural origin of explicit sequence knowledge: learning that starts accruing implicitly in that system could end up becoming explicit when attentional processing gets focused on the structured relations.

Table 2. Overview of the main characteristics of the uni- and multidimensional systems of the dual system model proposed by Keele et al. (2003). PC: parietal cortex; SMA: supplementary motor area; MC: motor cortex; OC: occipital cortex; MTC: medial temporal cortex; ITC: inferior temporal cortex; IFC: inferior frontal cortex; DLPFC: dorsolateral prefrontal cortex; PMC: premotor cortex.

Unidimensional system	**Multidimensional system**
Dorsal stream (PC, SMA, MC)	Ventral stream (OC, MTC, ITC, IFC, DLPFC, PMC)
Uninterpreted stimuli	Categorized stimuli
Implicit	Implicit-Explicit (the natural source of awareness)
Set of modules	Single module
Within dimensions or modalities (encapsulation)	Within and between dimensions or modalities
Unconditional access	Access to the system only for attended signals
Egocentric coding of locations	Allocentric coding of locations

These two systems combine into a powerful sequence learning device. However, we believe that the model has not evolved to its full potential since its publication. Of the (approximately) 137 citations that the Keele et al. (2003) paper received up to the writing of this paper, it becomes clear that its role is mostly limited to providing a post-hoc framework from which to interpret particular observations, or even merely a general background overview. Obviously, some studies have provided support for or against certain claims that were made by Keele et al. (2003). For instance, confirmation of involvement of hippocampal system in implicit sequence learning (e.g., Shendan et al., 2003; Ergorul & Eichenbaum, 2006) strengthens the dual system model's account of a possible congruency between the hippocampal structures of the brain and the hypothesized multidimensional system (both are said to underlie cross-dimensional associations). In contrast, studies by Liu, Lungu, Waechter, Willingham & Ashe (2007) and Witt, Ashe and Willingham (2008) provided evidence against the model's prediction that coding of locations in the ventral system should take place in an allocentric space (see also Willingham, 1998). Below we will attempt to account for such a discrepancy in terms of task set.

Despite these individual counterexamples, the point remains that the dual system model has rarely been the subject of investigation itself; the possible predictions that come from it have not been put to the test. Perhaps one reason for this is related to the lack of detailed specification on the workings of the model's main features. For instance, regarding the relation between attentional processes and sequence learning, a clear strength of Keele et al.'s (2003) dual system model was shifting the emphasis away from resource-based (i.e., processing limitation) accounts to selective attention (see also Jiménez & Méndez, 1999; Jiménez & Vázquez, 2005), even though the two may be inextricably linked to each other (e.g., Lavie, 1995; Lavie & Tsal, 1994). However, in claiming that only the multidimensional system is dependent on selective attention, the model seems to let the workings of the unidimensional system somewhat underspecified, implying the rather bold assumption that learning in this system will not be restricted in any way, and hence that it would unselectively associate all predictive information contained within a single dimension. Below we will discuss two studies that seem to contradict such a strong claim.

Another more central problem that surely has deterred progress in exploring this model has to do with the rather abstract description of the concept of a dimension, which lies at the core of the distinction between unidimensional and multidimensional modules. As stated above, this creates a gap between the various forms of sequence learning empirically explored in the literature, and the specific predictions of the model. However, given that Keele et al. (2003) actually provided some clear hints on the interpretation of their concept of a dimension, the gap may not be theoretical in nature, but rather arises just because the relation between the framework and the various forms of sequence learning that have been studied to date has not yet been made explicit. In the next sections of this paper, we will offer a way to bridge this gap, and discuss further implications.

Synthesis

A possible strength of the Keele et al. (2003) dual system model for sequence learning is that it provides a framework for integrating the multiple forms of sequence learning for which exist strong empirical support across the literature, by mapping these onto its two systems. However, due to the abstract nature of the model, this mapping has not yet been clearly identified. Here we propose that this mapping can be made explicit by defining dimensions mainly in terms of stimulus and response features: A dimension in the dual system model is regarded as equivalent to a specific feature, either at the stimulus level, or at the response level.

On a trial by trial base, performing the SRT task initially involves the same three basic information processing stages as a typical (four-)choice RT task: stimulus encoding, response selection, and response execution (e.g., Donders, 1969, Sternberg, 1969, Sanders, 1990, 1998). However, due to the sequential regularity presented across trials in the SRT task, something extra happens over practice that enables participants to speed up performance through associative learning: a sequence representation is formed on the basis of the fixed order of events. The benefit taken from this memory representation becomes clear if, after some amount of practice, the sequential structure is removed from the task and RTs and error percentages increase. As we have seen above, the sequence representation may be based on various specific features or combinations of features available across processing stages (see Figure 1).

The two systems of the Keele et al. (2003) model may thus be interpreted as *associative learning systems that associate between (mainly the most) active feature representations from ongoing S-R processing stages, thereby enabling the facilitation of future action*. In doing so, the model more or less automatically generates the three main forms of sequence learning discussed above (i.e., S-S, R-R, and R-S associations), thus providing an integrative perspective on these. Obviously, the focus of each of the unidimensional modules is restricted to a single feature, whereas the multidimensional system can temporarily associate various features with the aid of some central maintenance system.

It has to be noted that this interpretation of the two systems is not so far removed from that hinted by Keele et al. (2003) themselves: “the term dimension has generally been used interchangeably with modality, and we maintain this convention” (p. 317). However, by refining the definition of the concept of a dimension as referring to features of ongoing S-R processing stages, rather than overall modalities, the model becomes more directly relatable to a large literature on the nature of sequence learning. Making explicit the coupling between the concept of a dimension on the one hand, and the various stimulus and response features claimed to be involved in sequence learning on the other hand, enhances the dual system model as a predictive model for future research, and inspires new ways of thinking about sequence learning in general.

The multidimensional system

By defining the concept of a dimension as referring to specific stimulus and response features, the multidimensional system is allotted the capability of associating between a) successive instances of one particular stimulus or response feature (e.g., perceptual and response location learning), b) successive instances of different stimulus features or different response features (e.g. predictive relations between current shapes and next locations, such as in Jiménez & Méndez, 1999), c) successive instances across stimulus and response features (e.g., response-effect learning), or d) successive instances of rich compounds such as whole objects. Whereas the former of these alternatives is shared with the unidimensional system (see below), the latter three are exclusively assigned to the multidimensional system, as they imply associating across dimensions.

As noted already by Keele et al. (2003), Jiménez and Méndez (1999) provided evidence in support of the notion that associating between stimulus features of a different kind is restricted to the attention-dependent multidimensional system. Specifically, they observed for all participants sequence learning on a primary task – responding to the locations of stimuli. However, at the same time a sequential contingency was built between the shape of each stimulus and the next stimulus location (thus across stimulus features). This contingency was learned only when participants needed to pay attention to the shape feature through a secondary counting task; hence, learning the sequential associations between different features of a series of stimuli was conditional upon attentional selection. This can nicely be interpreted from a perspective that relates the concept of a dimension to specific features within stimulus- or response-modalities, rather than to overall modalities.

Even though it has never been directly explored, the suggested re-conceptualization of the dual system model has similar implications for response-effect learning. Response-effect learning refers to the formation of sequence representations that are built from cross-dimensional compounds of features from a response and a subsequent stimulus. Such learning would be restricted to the multidimensional system, implying that these sequence representations would be accessible for conscious processing, and conditional upon attentional processing. Some indirect support for the close relationship between awareness and response-effect learning is provided by the observations that a) studies supporting response-effect learning typically report relatively high overall awareness scores (e.g., Ziessler & Nattkemper), and b) groups of participants that benefit from response-effect learning do consistently demonstrate higher levels of awareness than those that could not (e.g., Hoffmann, Sebald & Stoecker, 2001; Stoecker, Sebald & Hoffmann, 2003), though not always significantly so (the latter may be partly due to a lack of sensitive and process-pure awareness tests; Destrebecqz & Cleeremans, 2001; Shanks & St. John, 1994).

Zirngibl and Koch (2002) reported further results congruent with a relationship between response-effect sequence learning and awareness. They found that sequence learning in a serial RT task was facilitated for verbal responses, as compared to manual ones. The authors themselves suggested that this difference in sequence learning could be traced back to differences in the distinctiveness and salience of the naturally occurring response feedback (i.e., response effects). Importantly, this difference in sequence learning was not found in those subjects who showed a significant behavioral learning effect but no explicit knowledge. This indicates that implicit learning could not be substantially boosted by the more salient response effects that are arguably provided by verbal responding.

Finally, support for the notion that response-effect learning does not arise in the absence of attentional processing, stems from a study by Deroost, Zeischka and Soetens (2008). They had subjects responding to the location of a red circle, while at each trial a task-irrelevant blue circle was simultaneously presented at a different location. The locations of both circles followed two independent sequences and, in line with earlier findings (Cock, Berry & Buchner, 2002), participants acquired sequence learning even about the irrelevant sequence of blue circles: a negative priming effect was obtained when the sequence of the task-irrelevant circle was imposed on the target circle. Interestingly, however, the amount of sequence learning (i.e., negative priming) obtained in these conditions was equivalent regardless of whether or not the two sequences were synchronized (i.e., running in phase because of equal sequence length). This implies that the overall configuration formed by the red and the blue circles was not bound with the previous response to form a response-effect association, arguably because such response-effect associations entail different dimensions, and thus only associate features which are selectively attended (i.e., the target circle).

Overall, there is at least indirect evidence consistent with the notion that response-effect learning is restricted to the multidimensional system, and thus tightly coupled to attentional processing and consciousness accessibility. In terms of mapping the multidimensional system onto the ventral processing pathway (Keele et al., 2003), for example, it could be predicted that disruption (e.g., by using transcranial magnetic stimulation) of ventral (and not dorsal) stream processing would impair response-effect learning. This type of predictions only arises from an integration of the more abstract dual system model with the types of representation discussed within the empirical work in the sequence learning field. While the veracity of this particular prediction remains one for future research, the general point remains that such testable predictions become more readily available from connecting the dual system model with the specific processes implicated in sequence learning.

The unidimensional system

In Keele et al's (2003) model, the encapsulated modules are proposed to take up automatically on those regularities occurring within a single dimension. From the notion that dimensions are equivalent to specific stimulus or response features, associations in these modules would arise between successive tokens of a given stimulus or response feature. It has been suggested that color (and sometimes also shape) information might often be outweighed by spatial information in the dorsal processing stream (e.g., Glover, 2004; Milner & Goodale, 2007; Ungerleider & Mishkin, 1982). So, it is possible that the dorsal, unidimensional system for sequence learning could be predominantly focused on associating between spatial features, such as location (cf. Koch & Hoffmann, 2000b).

Keele et al. (2003) regard the functioning of the unidimensional system as fully automatic and unselective, with associations forming regardless of attention. However, true automaticity has been hard to find within human information processing. For instance, even the Stroop interference effect, viewed for a long time as the gold standard of automaticity, has been shown to be reduced or eliminated under some conditions (e.g. Tzelgov, Henik & Berger, 1992). In this respect, Deroost and colleagues (i.e. Deroost & Soetens, 2006a; Deroost et al., 2008) have recently provided some interesting findings with respect to how unidimensional sequence learning could depend on the fulfillment of certain constraints. We will here discuss these findings because of their strong relevance to the dual system model.

As noted above, Deroost et al. (2008) observed negative priming when a sequence of locations of a task-irrelevant stimulus (presented simultaneously with the imperative stimulus during training) was later imposed on the locations of the imperative stimulus in a transfer phase. However, no such negative priming was observed when the imperative stimuli were presented in random order during training. This is a complicated set of findings, especially when considering the proposed automaticity and unselectivity of the unidimensional system: Why was the task-irrelevant, unidimensional regularity not detected and utilized by a unidimensional module?

One may argue that one particular unidimensional module is tuned to stimulus location information overall, regarding both the relevant and irrelevant location information, and thus unable to detect regularity in the irrelevant information when it is interspersed by random information from the relevant stimulus (rendering the pattern as a whole to be irregular). However, the same study provides evidence against this account: in their Experiment 2, the authors found that a similar amount of negative priming occurred independent of the synchronization (i.e., running in phase or not) between the relevant and irrelevant sequences, while out of sync relevant and irrelevant sequences also produce an irregular overall sequence of stimulus locations. Hence, in the design of Deroost et al. (2008), the relevant and irrelevant stimuli seem to provide independent, unidimensional sequential structures to be learned, and not one overall, unidimensional sequence of (combined relevant and irrelevant) stimulus locations. Then, how to explain the absence of learning of the irrelevant, single dimension in a unidimensional module when the imperative stimuli were presented in random order?

Deroost et al. (2008) themselves may have provided an answer to this question. They explained their findings in terms of attentional processing: responding to predictable stimuli may have released attentional capacity that could be used to process the task-irrelevant sequence (in line with the Lavie model of selective attention; Lavie, 1995; Lavie & Tsal, 1994). Such a dependence on attentional processing is a characteristic assigned to the multidimensional system, and this explanation therefore implies that the irrelevant, unidimensional sequence was not learned within the unidimensional system; thus opposing true unselectivity of this system.

Further results that reinforce this suspicion were provided by Deroost and Soetens (2006a). They replicated the study of Mayr (1996), in which subjects show learning of a sequence of task-irrelevant stimulus locations when responding to a different dimension of the stimuli (e.g., color). Interestingly, and in strong analogy with the study by Deroost et al.

(2008), learning about the sequence of task-irrelevant locations only occurred when the imperative stimuli were also sequentially structured. Again, this could well be explained by released attentional capacity due to the fixed sequence of task-relevant stimuli (see Deroost et al., 2008). However, from the dual system model outlined by Keele et al. (2003) one would have expected the unidimensional system to automatically pick up on the fixed series of (task-irrelevant) locations. Clearly this was not the case, once more suggesting that learning of task-irrelevant information does not occur within the unidimensional system, even when it involves just a single dimension.

Overall, the findings by Deroost and colleagues at the very least indicate that learning in the unidimentional system does not arise immediately from any interaction with a structured environment, and thus highlight the importance of assessing the conditions which constrain sequence learning about unidimensional relations. A possible way to approach this issue might be to restrict the unidimensional system as described by Keele et al. (2003) to information that is strongly action-related, which would be in line with the view that the dorsal processing route is mainly involved in online action control (e.g., Glover, 2004). Learning about task-irrelevant regularity, then, would be confined to the multidimensional system, and thus dependent on attentional processing. However, further exploration and contemplation is needed in order to justify such a strong claim.

DETERMINANTS OF LEARNING: TASK SET

From the notion that qualitatively different sequence representations can develop in the SRT task, an important question arises on what precisely determines the effective nature of the sequence representation in a specific condition. It seems clear that not all the different kinds of learning depicted in the literature (i.e., perceptual, response-effect and response location learning) always develop in parallel: Many examples are known of studies in which the sequential order of at least one of these three levels is maintained over a transfer test, but nevertheless no reliable transfer is observed (e.g., Abrahamse, Jiménez, Deroost, Van den Broek & Clegg, unpublished data[2]; Jiménez et al., 2006; Willingham et al., 2000). Hence, instead of developing multiple sequence representations in parallel, as predicted by Keele et al.'s (2003) unidimensional system, the brain typically tailors a specific sequence representation to the task at hand (cf. Memelink & Hommel, 2006). This may be individually determined, for example based on visual-spatial ability, or personality variables such as "openness to feelings" (a subscale of the NEO-PI-R personality inventory; see Norman, Price, Duff & Mentzoni, 2007). However, probably more relevant in accounting for the equivocal findings across literature is the concept of task set.

Task set can be loosely defined as the set of cognitive processes that are actively maintained during task performance (e.g., Sakai, 2008). Although, to the best of our knowledge, this concept has not been used in an explicit way to account for differences in sequence learning results, the prediction that task set should constrain sequence learning arises directly from the view of implicit learning as an obligatory result of active processing (e.g., Jiménez & Méndez, 1999; Logan, Taylor & Etherton, 1996). If, as Logan et al., put it, “people learn what they attend to and express what they learned in transfer if they attend to the same things in the same way” (p. 620), then probably it would simply not be accurate to ask what is learned in a sequence learning paradigm, but rather we should ask how the acquisition and the expression of sequence learning is affected by the specific processing priorities stressed by a given task set. A growing number of studies make explicit the importance of task set in determining implicit sequence learning effects.

One example of the effects of task set in sequence learning was demonstrated by Deroost and Soetens (2006b). As noted above, they explored the influence of processing spatial information on implicit sequence learning in an adapted version of the SRT task. In their study responses were based upon the identity of stimuli, while stimuli were presented at a fixed sequence of task irrelevant locations. Responses to the target could depend either on a single feature of the target (i.e. its color) or on the spatial relation between two of its features (i.e. “xo” vs. “ox”). Learning about the task-irrelevant sequence of locations was observed in the latter case, when the task relevant information required spatial processing, but not in the former one, when the response was determined independently from any spatial feature. These results suggest that spatial processing of relevant information sets the stage for learning about regularity across spatial features of the stimuli.

Another pattern of results that might be re-interpreted in terms of the specific task demands is that reported in Willingham et al. (2000, Experiment 1). In this study, the authors failed to obtain transfer between different response location configurations, even though the stimulus sequence on the screen remained unchanged over the transfer phase. Given that there is now ample evidence in favor of the existence of a perceptual component in sequence learning, and that the large number of participants tested precluded any power concerns, one may wonder why perceptual learning effects did not arise under the particular conditions in their study. Again, the specific task set established in this experiment could provide us with a useful approach to this question. When participants are told to respond using a set of neatly defined response locations on a fixed keyboard, and when they are instructed to use only one finger to act on all of these response locations, task demands could be taken to strongly emphasize the processing of the response locations (simply because the task requires moving the finger between these response locations), hence rendering a representation of the sequence in terms of the series of response locations to be most effective.

But what could be expected if the task would not have such well defined response locations, such as when it requires to keep track of a moving target with a mouse cursor (Chambaron, Ginhac, Ferrel-Chapus & Perruchet, 2006) or, even more realistically, to respond with a racquet as in playing a game of tennis? Would procedural learning in these tasks also be based on representing a sequence of response locations? There is no need to say that this would render the underlying skill extremely rigid and dysfunctional. One may even wonder whether the dominance of response locations in the study by Willingham et al. (2000) could already be changed after a small change in task set, such as performing the SRT task with four fingers (one for each response button) instead of one. In this case, the task of executing a response no longer strongly emphasizes the programming of a movement to a specific response location, because the fingers are already in place. We surmise that, in such a design, reliable transfer could be observed over changes of specific response locations, at least when the spatial stimulus-response compatibility is not radically altered between training and transfer, as it was in Willingham et al. (2000, Experiment 2).

Focusing on the impact of the task set could also be useful in explaining why, under some conditions, one can fail to obtain evidence for an allocentric representation of a sequence, despite the fact that allocentric coding has been proposed as the default representation mode for the multidimensional learning system. Witt & Willingham (2008) and Liu et al. (2007) reported this failure to find evidence for an allocentric representation of a sequence, in conditions in which participants were instructed to use a single effector (either a single finger or a mouse cursor) to act upon all response locations. Here again, we surmise that this task set emphasizes the coding of response locations, thereby reinforcing learning about that aspect of the task. Obviously, for such a task set an egocentric reference frame is the most useful, as otherwise a translation from allocentric to egocentric codes would be needed to effectively act upon these locations. It would be interesting to see whether allocentric coding can be observed when participants learn about a sequence of stimulus locations in conditions in which these locations do not coincide with the response locations. For example, in the spatial sequence learning designs employed by Mayr (1996) and Deroost and Soetens (2006a), where participants responded to the color of a stimulus appearing on each trial at one of a predictable series of locations, it is an open question whether the spatial sequence would be learned within an allocentric or an egocentric frame of reference.

In sum, there is growing evidence that sequence learning in the SRT task may be highly sensitive even to seemingly trivial task parameters, such as the response effectors used, the response-to-stimulus-interval (see Destrebecqz & Cleeremans, 2001), and spatial processing of task relevant information. Acknowledging this may be important in order to deal with the frequently observed equivocal or even conflicting findings in the literature. To finish this section, it is worthwhile noting that, just as the training conditions may affect what is learned in a sequence learning task, the conditions in which learning is tested may also determine how learning is expressed during a transfer phase. Again, by relying on Logan et al.'s (1996) quote, people not only learn what they are effectively processing for the task at hand, by they also "…express what they learned in transfer if they attend to the same things in the same way". This implies that in addition to comparing the amount of sequence learning obtained in a training procedure, it is important to assess the impact of manipulating certain parameters over a transfer task on the expression of the previously acquired knowledge.

CONCLUSION

The ability to represent sequential order in many different ways is in line with the notion that sequential behavior is fundamental to human functioning, and is supported both by neuropsychological and behavioral findings. In the current paper we presented a review and assessment of the type of associations underlying implicit sequence learning in the serial RT task. Strong empirical support exists for the formation of associations between successive stimulus features (perceptual learning), successive response features (response-based learning) and successive response-to-stimulus compounds (response-effect learning). We propose that the strong oppositional thinking, usually between response-based and perceptual learning, should be replaced by a more dynamic, integrative approach that takes into consideration how the task set and task context modulate the acquisition and the expression of sequence learning. According to an overall principle of activation, we assume that the associations that underlie sequence learning are not predetermined with respect to one particular type of information, but rather develop from the most active representations from ongoing S-R processing.

Substantiating such an integrative approach can be achieved by our proposed synthesis with the dual system model as depicted by Keele et al. (2003). This has mutual benefits. First, integration of existing, smaller scale forms of sequence learning is provided by a well-known multilevel model, the development of which is firmly grounded in major SRT studies. Second, the current re-framing directly links the dual system model to recent findings on sequence learning as obtained in the SRT task, thereby introducing new questions and predictions, and enhancing the overall testability of the model. Crucially, this approach shifts the emphasis from the old question "what is the nature of sequence learning?" to a whole new set of questions concerning what precisely determines the nature of sequence learning and its dynamics. Future research faces the challenge of trying to understand and classify the rules of this complex dynamics. Let's just beware of looking like that bunch of blind men, discussing on how an elephant looks like by relying on one's own, apparently objective, but reduced grasp.

NOTES

1. Related studies employed instructions in which participants were required to respond only to the stimulus appearing at one particular location, and not other locations (e.g., Vakil et al., 2000; Berger et al., 2005). This revealed similar results as the studies in which no responding was required at all: sequence learning takes place independent of responding.
2. In this unpublished study we observed no transfer from a compatible to an incompatible stimulus-to-response mapping, even though the response (location) sequence was maintained. In line with the study by Willingham (1999), however, reliable transfer was observed the other way around.

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Chapter 3 Context dependent learning in the serial RT task

Abstract

This study investigated the development of contextual dependencies for sequential perceptual-motor learning on static features in the learning environment. In three experiments we assessed the effect of manipulating task irrelevant static context features in a serial reaction-time task. Experiment 1 demonstrated impaired performance after simultaneously changing display color, placeholder shape, and placeholder location. Experiment 2 showed that this effect was mainly caused by changing placeholder shape. Finally, Experiment 3 indicated that changing context affected both the application of sequence knowledge and the selection of individual responses. It is proposed either that incidental stimulus features are integrated with a global sequence representation, or that the changed context causes participants to strategically inhibit sequence skills.

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INTRODUCTION

Research on verbal memory tasks has revealed better retrieval performance if the original learning context is reinstated during test administration (Smith & Vela, 2001). A variety of context stimuli have been shown to reduce performance when changed, including background music (Smith, 1985), physiological state (Eich, 1980), and general physical environment (Godden & Baddeley, 1975; Eich, 1985). Wright and Shea (1991) extended the examination of the effects of task irrelevant context on verbal memory performance to the reproduction of perceptual-motor responses. They proposed a model in which they discriminate between stimuli that are explicitly identified as essential to task performance (intentional) and those that are not (incidental). In their study participants practiced three keying sequences, with numbers to indicate the elements of each sequence. Each sequence was consistently paired during practice with a combination of a particular display color, a specific tone, a certain position on the screen, and a particular placeholder shape. Subsequently changing these incidental stimuli impaired key pressing performance. This finding was interpreted as support for the notion that motor skills can be context dependent.

However, because the incidental stimuli consistently co-varied with the intentional stimulus, associative learning instead of a general context effect might explain the effects reported by Wright and Shea (1991). It can be argued that through their strong temporal relationship with the intentional stimulus, the incidental stimuli became more or less intentional with practice. We propose that incidental context features should be further subdivided into those that co-vary with the intentional stimulus, and those that are continuously present during training, independently of the presence of intentional stimuli (static features). The purpose of the present study is to examine the potential contextual dependency of motor skill learning on static context features.

To our knowledge context-dependence has not been investigated before with the serial reaction-time (SRT) task (Nissen & Bullemer, 1987). In this task participants are required to respond as fast and accurately as possible to the location of successively presented stimuli. Unbeknownst to the participants, however, the stimuli follow a specific order. With practice, reaction times (RTs) turn out to decrease. To make sure that that improvement is not a general effect of practice, a random or pseudo-random block of stimuli is presented at the end of the practice phase. The increase in RTs and/or errors in this random block relative to the final sequence blocks serves as an index for sequence learning. As participants are often not able to tell that the stimuli followed a particular order after the experiment, the task is said to involve implicit sequence learning. The SRT task has become one of the major paradigms for studying implicit learning (for reviews see e.g. Keele, Ivry, Hazeltine, Mayr & Heuer, 2003; Stadler & Frensch, 1998).

We suspect that dependencies on static context are most pregnant for implicitly learned perceptual-motor skills as the effects of implicit sequence learning are mostly described as more vulnerable to changes in its triggering conditions (Jiménez, Vaquero, & Lupiáñez, 2006), and “tend to be less manipulable and more context bound” (Berry & Dienes, 1993, p. 13; but see Willingham, 1997, for critical commentaries on the difference in flexibility between implicit and explicit memory). Because implicit learning is said to be highly stimulus-driven it may be directly affected by changes of stimulus input (even if task irrelevant). Designed to study implicit learning, the SRT task may thus be a promising candidate for revealing context dependent motor skills. We tried to reduce explicit learning by using a response-to-stimulus interval (RSI) of 0 ms in the current experiments (see Destrebecqz & Cleeremans, 2001).

EXPERIMENT 1

In Experiment 1 participants responded to the onset of stimuli presented in a fixed order in a typical serial RT task. After they practiced this sequence in a specific context (with a particular placeholder location, display color, and placeholder shape), we changed these context features. We hypothesized that if certain features of the incidental context are stored in memory along with response events, in this case while performing a SRT, then changing these features would impair performance.

Method

Participants

Sixteen students at the University of Twente participated in exchange for course credits. They were aged between 18 and 30, had no hand or vision problems, and were naïve as to the purpose of the study.

Apparatus and setting

Stimulus presentation, timing, and data collection was achieved using the E-prime© 1.1 experimental software package on a standard Pentium© IV class PC. Stimuli were presented on a 17 inch Philips 107T5 display running at 1,024 × 768 pixel resolution in 32 bit color, and refreshing at 85 Hz. The viewing distance was approximately 50 cm, but not strictly controlled.

Procedure

The task consisted of a typical SRT task (Nissen & Bullemer, 1987), and involved twenty blocks of trials. The experiment started with two random blocks, in which stimulus position did not follow a particular pattern, to prevent participants from discovering the pattern in an initial attempt. These blocks were followed by 16 sequence training blocks, a transfer block, and finally one more sequence training block. Each of these blocks started with four random trials and was followed by nine repetitions of a 12-element sequence. Participants were instructed to respond as fast and accurately as possible, using the middle and index finger of both hands to press the c, v, b, and n keys on the keyboard. A correct response was defined as the participant pressing the appropriate key within a 2-s time limit. Erroneous responses were signalled to the participants, after which the next stimulus was presented after a 2-s interval. This relatively long interval was intended to motivate the participant to prevent errors. Short 1 min breaks were provided in between blocks. The sequence consisted of second order conditional (SOC) transitions: 121342314324 (Reed & Johnson, 1994). In a SOC sequence all elements and pairs of elements occur equally frequent. Consequently, performance cannot improve from just learning that certain elements or element pairs occur more often than others.

Each display provided both intentional and incidental stimuli. The intentional stimulus consisted of filling one of the four horizontally aligned placeholders with red. The incidental stimuli consisted of the color of the screen background, the placeholder location, and the shape of the placeholders. In Context A we used a white display, with four rectangular placeholders at the top of the screen. Context B involved a dark grey display, with four triangular placeholders placed at the bottom of the screen. From a viewing distance of 50 cm, stimulus angle measured 2.3° × 2.0° for the rectangles, and 2.3° × 2.7° for the triangles. To make the distance between the placeholders identical in contexts A and B, the triangles were clustered with the first and third triangle pointing upwards, and the second and fourth triangle pointing downwards. Training and testing with either Context A or Context B was counterbalanced across participants: half of the participants trained with Context A, and encountered Context B during transfer at Block 19, while the other participants trained with

Context B and were tested with Context A. Just before the context was changed in Block 19, participants were informed that some changes would occur on the screen, but that in other respects the task would remain the same.

Finally, participants performed a free generation task to examine the extent to which they were aware of the order of the sequence elements. This involved telling them that there had been a 12-element fixed order, and then having them write down the complete 12-element sequence that according to them had been repeated during the experiment (Witt & Willingham, 2006).

Results

Reaction-time task

RT analyses excluded erroneous key presses, and RTs exceeding the criterion of mean plus 3 standard deviations. This eliminated less than 5% of the data in the acquisition and the test phase. Also, the four random trials at the beginning of each block were excluded from analysis. Mean reaction times and accuracy scores were calculated for each block, for each participant.

Practice phase

Figure 1 shows the mean RT for each block. We performed a repeated measure ANOVA on reaction times with Block (18; Blocks 1 to 18) as a within-subject variable. This analysis revealed a significant effect for Block, $F(17,255)=59.0$, $p < 0.0001$, indicating improvement with practice.

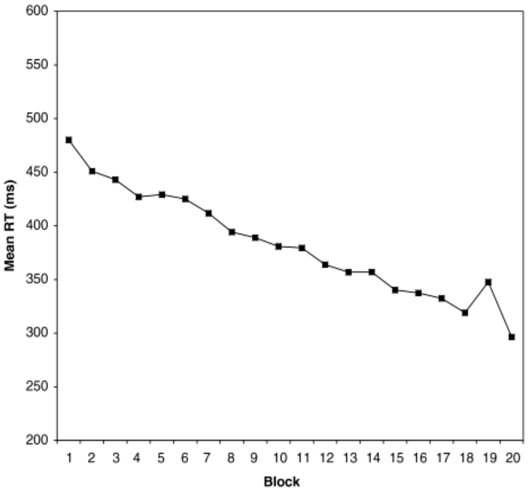

Figure 1. Mean RT for Blocks 1–20 in Experiment 1. In Block 19 display color, placeholder shape, and placeholder location were simultaneously changed.

Test phase

Rather than changing the order of the elements, as is typical in the SRT task, we changed the context in Block 19. The effect was tested with another repeated measures ANOVA on reaction times with Block (2; mean of Blocks 18 and 20, versus Block 19) as within-subject variable. As depicted in Fig. Fig. 1,1, reactions were slower in Block 19, $F(1,15) = 39.0$, $p < 0.0001$, confirming that performance decreased with context change.

Finally, to perform an error analysis, we used an arcsin transformation (Winer, Brown & Michels, 1991) to stabilize variances. Then a repeated measures ANOVA was run on these transformed error scores for the practice phase with Block (18) as a within-subject variable. This showed no significant results. A similar analysis on the mean error percentages of Blocks 18 and 20 versus Block 19 did not reveal reliable differences either. Error percentages were around 2.5% for Block 18, 19 and 20.

Awareness

An awareness score was calculated by counting the number of correctly generated 3-element chunks in the free generation task, and dividing this number by 12, as participants could generate a maximum of twelve correct chunks. The awareness score (mean = 0.36) was compared to chance level (which is 0.33 as no repetitions were allowed) of generating correct sequence chunks with a one-sample t test (Destrebecqz & Cleeremans, 2001). This indicated that across the entire group the mean awareness score did not differ reliably from chance level, $t(15) = 0.6$, $p = 0.5$. Inspection of individual awareness scores indicated that awareness varied amongst the participants. However, grouping participants according to their awareness scores (low versus high awereness) and including this as an independent variable in the above ANOVAs did not produce reliable awareness effects, and these analyses have therefore not been reported.

Discussion

The purpose of Experiment 1 was to test the hypothesis that sequential skills as assessed with the serial RT task may become dependent on the context they have been acquired in, even if this context remains fixed during training. If so, performance should be impaired when the training context is changed. The results from Experiment 1 support this idea for the combined effect of changing display color, placeholder location and placeholder shape.

EXPERIMENT 2

Experiment 1 indicates that changing seemingly task irrelevant features can impair performance. The question remains, though, whether all three incidental context features had been equally effective. Experiment 2 was conducted to assess the separate contributions of each individual context feature used in Experiment 1.

Method

Participants

Forty-eight first year bachelor students at the University of Twente participated in exchange for course credits. They were aged between 18 and 30, had no vision or arm problems, and were naïve as to the purpose of the study.

Apparatus and setting

Apparatus and setting were the same as in Experiment 1.

Procedure

The procedure was the same as for Experiment 1, except now there were three groups of participants. In one group the effect of display color (white versus gray) was tested, in the second group the effect of the placeholder shape (rectangular versus triangular) was tested, and in the third group the effect of the location of the four placeholders on the computer screen (top versus bottom) was tested. The feature combinations actually used are summarized in Table 1. The use of either Context A or B for practice in a particular context group was counterbalanced across participants. Participants were randomly assigned to groups.

Results

Reaction-time task

RT analyses excluded erroneous key presses, and RTs exceeding a criterion of mean plus 3 standard deviations. The latter requirement eliminated less than 5% of the data across the acquisition and test phases. Also, the four random trials at the beginning of each block were excluded from analysis. Mean reaction times and accuracy scores were calculated for each block, for each participant.

Table 1. Contexts A and B as used with the three experimental groups of Experiment 2.

Experimental Group	Feature	Context A	Context B
Display color	Display color	*White*	*Grey*
	Placeholder shape	*Rectangular*	*Rectangular*
	Placeholder location	*Middle*	*Middle*
Placeholder shape	Display color	*White*	*White*
	Placeholder shape	*Rectangular*	*Triangular*
	Placeholder location	*Middle*	*Middle*
Placeholder location	Display color	*White*	*White*
	Placeholder shape	*Rectangular*	*Rectangular*
	Placeholder location	*Top*	*Bottom*

Practice phase

A Group (3; color, shape, location) × Block (18) repeated measures ANOVA on reaction times was performed with Block as within-subject variable. This showed an effect for Block, $F(17,765) = 102.5$, $p < 0.0001$, but no significant Group main effect, $F(2,45) = 1.8$, $p = 0.15$, or Block by Group interaction, $F(34,765) = 0.6$, $p = 0.8$. This indicates that learning did not differ across groups (see Figure 2). The same analysis was performed on transformed error scores, but this revealed no reliable differences at all (Fs < 1.2, ps > 0.25).

Test phase

Another Group (3; color, shape, location) × Block (2; mean of Blocks 18 and 20 versus Block 19) ANOVA on reaction times was performed with Block as within-subject variable. This resulted in a significant Block effect, $F(1,45) = 12.4$, $p < 0.005$, and a Block by Group interaction, $F(2,45) = 18.6$, $p < 0.0001$. Separate paired-sample t tests on Block 19 versus the mean of Blocks 18 and 20 were carried on for all three groups. Bonferroni correction yielded an α of 0.013. This resulted in a significant effect for the placeholder shape group, $t(15) = 4.7$, $p < 0.0001$, but not for the placeholder location group, $t(15) = 2.5$, $p = 0.03$, or the display color group, $t(15) = 2.1$, $p = 0.05$. So, performance was significantly impaired after changing the placeholder shape in the test phase while changing the location on the screen or changing the display color failed to produce a significant effect (see Figure 2).

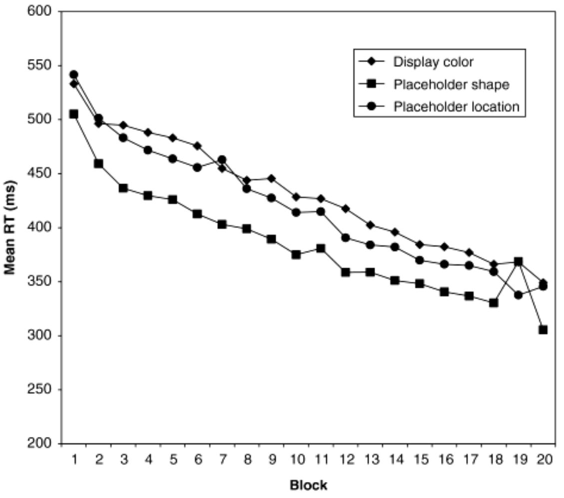

Figure 2. Mean RT per experimental group for Blocks 1–20 in Experiment 2. In Block 19 for each group another context feature was changed.

Finally, a repeated measures ANOVA on arcsine-transformed error scores was performed for the means of Blocks 18 and 20 in comparison with those of Block 19. This revealed a significant Block by Group interaction, $F(2,45) = 5.2$, $p < 0.01$. Paired-sample t tests for each group ($\alpha = 0.013$ after Bonferroni correction) showed a significant Block effect only for the placeholder shape group, $t(15) = 4.0$, $p < 0.005$, with error percentages amounting to 3.3, 3.9 and 2.9% for Blocks 18–20. The other two were far from significant (ts < 0.8, ps > 0.4; error percentages were always below 4%).

Awareness

Awareness was calculated in the same way as in Experiment 1. A one-way ANOVA was performed on awareness scores with Group as between-subject variable (mean awareness scores were 0.35, 0.33, and 0.33 for the display color, placeholder shape, and placeholder location groups, respectively). This indicated no reliable differences between groups, $F(2,45) = 0.06$, $p = 0.9$. Then the difference between the awareness score and chance level was tested for each group separately. This indicated no reliable differences (ts < 0.5, ps > 0.6), thus again this indicates that learning was mainly implicit. Again, inspection of individual awareness scores showed that some participants had some awareness. Therefore, we also performed analyses with low and high awareness as independent variable. This did not produce any reliable effects, while keeping the relevant findings of this experiment intact.

Discussion

Experiment 2 suggests that placeholder shape had produced almost the entire context effect in Experiment 1, even though display color may have contributed, too. Participants were less able to efficiently apply their sequence knowledge when placeholder shape had been changed: During the test block, they showed significantly increased response latencies, and produced more errors. This indicates that performance had become dependent on the task-irrelevant shape of the stimulus, and not significantly so on display color and placeholder location.

EXPERIMENT 3

The results of Experiments 1 and 2 demonstrate that performance in the serial RT task became context dependent in the course of practice. However, in the test block of those experiments we manipulated just the context and not the order of the individual elements (i.e. the sequence). As responding to individual stimuli may well continue to be used in the serial RT task we are not yet able to determine whether the context change affected sequencing skill or response selection skill. Experiment 3 was aimed at testing whether the context effect we obtained in Experiments 1 and 2 was associated with response selection (which should affect random and fixed sequences, but random more than fixed), with sequencing skill (which should influence just fixed sequences), or with both (which should affect fixed sequences more than random). To that end, we had a group of participants perform in an experiment that was identical to the placeholder shape condition of Experiment 2, but in which there was no fixed sequence. We then compared the obtained results with those of the placeholder group in Experiment 2.

Method

Participants

Sixteen first year bachelor students at the University of Twente participated in exchange for course credits. They were aged between 18 and 30, had no vision or arm problems, and were naïve as to the purpose of the study.

Apparatus and setting

Apparatus and setting were identical to those in Experiments 1 and 2.

Procedure

The procedure was identical to that of the placeholder shape group in Experiment 2, except that this time the stimuli were ordered in a pseudo-random way. The pseudo-random blocks in this experiment consisted of nine different SOC sequences that were randomly picked from a pool of twelve, with no element and sequence repetitions allowed. This procedure was repeated for every next random block.

Results

All RT analyses excluded erroneous key presses, and RTs exceeding a criterion of mean plus 3 standard deviations. The latter requirement eliminated less than 5% of the data. Mean reaction times and accuracy scores were calculated for each block and for each participant. Because the procedures in Experiments 2 and 3 were identical, the analyses used the data from the placeholder shape group of Experiment 2.

Practice phase

RTs obtained in Experiment 3 are depicted in Fig. Fig. 33 along with those assessed with the placeholder shape group of Experiment 2. An Order (2; random versus sequential) × Block (18) repeated measures ANOVA on reaction times was performed with Block as within-subject variable. This showed significant main effects for both Block, $F(17,510) = 30.5$, $p < 0.0001$, and Order, $F(1,30) = 6.7$, $p < 0.05$, and a significant Block by Order interaction, $F(17,510) = 20.4$, $p < 0.0001$. As expected, this indicates that participants in the random SRT condition showed less improvement with practice than the participants in the normal SRT (see Fig. Fig. 33).

The same analysis was performed on transformed error scores. This produced no significant results, even though Block almost reached significance, *F*(17,510) = 1.8, $p = 0.07$, indicating a trend towards less errors with practice (error percentages were always below 5%).

<u>Test phase</u>

An Order (2; random versus sequential) × Block (2; mean of Blocks 18 and 20 versus Block 19) repeated measures ANOVA on reaction times was performed with Block as within-subject variable. This produced significant main effects for both Block, *F*(1,30) = 26.9, $p < 0.0001$, and Order, *F*(1,30) = 16.2, $p < 0.0001$, and a significant Block by Order interaction, *F*(1,30) = 5.2, $p < 0.05$. This interaction demonstrates that context had a stronger effect in the sequence group of Experiment 2 than in the random group of Experiment 3. Experiment 2 already reported that changing placeholder shape significantly increased RT, *t*(15) = 4.7, $p < 0.0001$. We then performed a paired-sample t test to determine whether changing placeholder shape had reduced performance in Block 19 for the random group too. This appeared to be the case, *t*(15) = 2.4, $p < 0.05$. Taken together, these results show that changing the placeholder shape has a dominant effect on applying sequence knowledge, but that response selection skill was affected too.

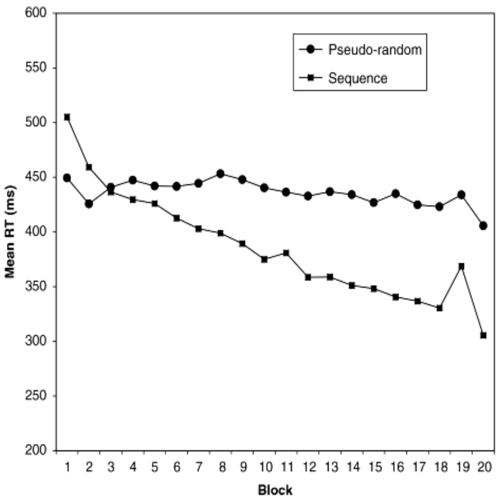

Figure 3. Mean RTs for the group practicing with a pseudo-random sequence (Experiment 3) and the group practicing with a fixed sequence (taken from Experiment 2). In both groups, Block 19 involved changing placeholder shape.

A similar repeated measures ANOVA was performed on arcsin transformed error percentages. This revealed a significant main effect for Block, $F(1,30) = 13.6$, $p < 0.005$, but no Block by Order interaction, $F(1,30) = 2.4$, $p = 0.1$. Error percentages amounted to 2.7 and 3.9% for the mean of Block 18 and 19, and Block 20, respectively.

Discussion

In Experiment 2 we showed that the impaired performance in Experiment 1 after changing the context was mainly caused by changing placeholder shape. However, it remained unclear whether this feature affected sequencing skill, or perhaps some residual selection of responses on basis of the stimulus, that is assumed to continue with implicitly learned sequences. Experiment 3 clearly shows that it was primarily the application of sequence knowledge that was affected by this context change, as this manipulation disrupted performance more in the normal SRT condition than the random SRT condition. In line with earlier conclusions (Shea & Wright, 1995), Experiment 3 demonstrates also that response selection had become a skill that is affected by this context change.

GENERAL DISCUSSION

The main purpose of this study was to determine whether sequential movement skills as obtained in the serial RT task may become susceptible to changes in the context, as has been demonstrated with various memory tasks (e.g., Smith & Vela, 2001). We manipulated only static context features. Our results indicate that, in addition to response selection skill (Shea & Wright, 1995), sequential skill in the SRT task becomes susceptible to the task irrelevant shape of the placeholder that contained the imperative stimuli, though there was a trend in Experiment 2 that changing background colour had a detrimental effect too. Changing the placeholder location revealed a trend towards better performance at the test block. This latter effect may well be a motivational effect: any change will trigger renewed attention to the task at hand.

The current findings show that the serial RT task is a useful paradigm for exploring contextual dependent motor skill acquisition. However, the mechanism underlying the influence of incidental perceptual features on sequence performance remains largely unclear. Below we will elaborate on two general alternatives to account for the current findings. The first is derived from the notion that stimulus features are becoming part of a global sequence skill representation. Second, the change in context could have affected performance in a less direct manner, as it may have brought participants to inhibit existing sequence skills.

A number of different levels of serial learning have been proposed by various authors. From the perceptual learning view, sequence learning is predominantly based on associations between successive stimuli (stimulus-to-stimulus or S–S learning). In contrast, the motor learning account states that associations are formed mainly between successive responses (response-to-response or R–R learning). Additionally, other studies support sequence learning on intermediate levels of information processing (e.g. Deroost & Soetens, 2006), or as a kind of response effect learning (response-to-stimulus or R–S learning; Ziessler & Nattkemper, 2001). There is growing consensus that sequence learning is predominantly response based, as learning on the motor level is supported by many behavioural (Nattkemper & Prinz, 1997; Willingham, 1999) and neuropsychological (e.g. Bischoff-Grethe, Goedert, Willingham & Grafton, 2004; Grafton, Hazeltine & Ivry, 1995) studies. The role of perceptual learning on the other hand is still heavily debated. In line with other studies (e.g. Abrahamse, Van der Lubbe & Verwey, 2007; Remillard, 2003; Mayr, 1996), the current study adds support to the notion that sequence learning in a SRT task is not completely motor based (i.e. independent of the stimuli), as changing a stimulus feature that was not directly relevant to the task (i.e. the placeholder shape) had a clear effect on performance. The representation underlying sequence skill, then, may include incidental stimulus information (either through S–S associations, R–S associations, or learning at intermediate levels of information processing), implying that when these features are changed, the skill representation can no longer be as easily retrieved from memory (maybe under certain conditions incidental features of the rest of the task environment are also included, as display color almost produced a reliable effect). This is in line with the notion that sequence learning is partly produced by an automatic associative process (Jiménez & Méndez, 1999), on the condition that it involves only that information that has been selected for processing (e.g. Frensch & Miner, 1994), including some features that may not be crucial to task execution. The role of co-activation in memory systems to account for automatic associations is fundamental to many learning theories (e.g. Logan, 1988). Future research will be needed to explore the role of selective attention for the development of context dependability of sequential skills in more detail.

A second explanation may be worth mentioning here. Above we propose a rather direct influence of incidental stimulus features on sequence performance, as they may have been integrated in a global sequence representation. However, changing the perceptual stimulus features may have also influenced performance in a less direct manner, that is, through an increased tendency for more direct control by the participants (Luis Jiménez, personal communication). The idea is that when features of the task or task environment change, participants may no longer (trust to) rely on their implicit skills (see also Schneider & Fisk, 1982; Moore & Stevenson, 1994). Rather, they are strategically evaluating the task and its environment, while inhibiting automatic processes. So, the present context effect could be caused also by strategic inhibition of sequencing skill, rather than by difficulty in memory retrieval.

In conclusion, changing the context (i.e. the placeholder shape, and possibly also the display color) has a clear effect on sequencing skill. This may have been caused by the impeded retrieval of a global sequence representation from memory (implying that sequence learning in the SRT task is not predominantly motor-based), or by strategic inhibition of sequencing skills. Further research is needed to explore the mechanism underlying the present findings in more detail.

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Chapter 4 Asymmetrical learning between a visual and tactile serial RT task

Abstract

According to many researchers, implicit learning in the serial reaction-time task is predominantly motor based and therefore should be independent of stimulus modality. Previous research on the task, however, has focused almost completely on the visual domain. Here we investigated sequence learning when the imperative stimuli were presented tactilely to the fingers. Learning in this task was compared to sequence learning in a typical visual task, using very similar experimental conditions. The results indicate that sequential learning occurs in the tactile task, though to a lesser degree than in its visual counterpart. Furthermore, there was similar cross-modal transfer in both directions, meaning that transfer from the visual to the tactile task was partial. It is proposed that sequence learning involves a stimulus-specific component in the visual but not in the tactile task.

Abrahamse, E. L., Van der Lubbe, R. H. J. & Verwey, W B. (2008). *The Quarterly Journal of Experimental Psychology*, *61*, 210-217.

INTRODUCTION

One of the fundamental aspects of human adaptive behaviour is the ability to detect and utilize regularities that are inherent to the environment. A major paradigm for studying sequence learning is the serial reaction time (SRT) task introduced by Nissen and Bullemer (1987). In this task participants are required to respond fast and accurately to the location of successively presented stimuli. Unbeknownst to the participants, however, stimuli follow a particular order, and, with practice, reaction times (RTs) decrease. The common procedure to differentiate sequence learning from general practice effects is to present a random block of stimuli at the end of the practice phase. The cost in RT and/or accuracy of this random block relative to the final sequence blocks serves as an index for sequence learning. Often participants are unable to express their sequence knowledge, and then their learning is said to be implicit. Learning in the spatial SRT task has been studied rigorously, but almost exclusively while using visual stimuli. In the current study, we investigated sequence learning in the SRT task with stimuli presented tactilely to the fingers.

As noted above, learning in the SRT task is said to be predominantly implicit as it mostly takes place in the absence of awareness of sequence structure. With increasing practice, however, explicit sequence knowledge will also develop. Explicit knowledge is thought to be highly controllable and flexible with respect to transfer manipulations (except to changes in semantic sense between encoding and retrieval; Willingham, 1997). The nature of human implicit sequential skills appears to be more complicated. Several views can be distinguished. The perceptual learning view asserts that people primarily learn the structure of the stimulus sequence in that associations are formed between successive stimuli (stimulus-to-stimulus or S-S learning; e.g., Remillard, 2003). In contrast, the motor learning account states that learning is primarily based on the response sequence, associating successive responses to each other (response-to-response or R-R learning; e.g., Hoffmann, Martin, & Schilling, 2003; Nattkemper & Prinz, 1997). In addition, Ziessler and Nattkemper (2001) found strong empirical support for response effect learning, in that processing of a stimulus in a sequence is facilitated by the effect of the response just given (i.e., response-to-stimulus or R-S learning). Finally, it has been suggested that participants may learn the order of stimulus-response (S-R) associations (Willingham, Nissen, & Bullemer, 1989).

There is growing consensus that implicit sequence learning is predominantly motor based, though not specific to effectors (Keele et al., 1995; Willingham, Wells, Farell, &

Stemwedel, 2000; but see Verwey & Clegg, 2005). Motor learning in the SRT task is supported by a considerable number of behavioural (e.g., Deroost & Soetens, 2006a; Nattkemper & Prinz, 1997; Willingham, 1999) and neuropsychological studies (Bischoff-Grethe, Goedert, Willingham, & Grafton, 2004; Grafton, Hazeltine, & Ivry, 1995; Rsseler & Rsler, 2000), whereas the development of perceptual implicit learning is still being heavily debated. Willingham (1999, Willingham et al., 2000) argued that results supporting perceptual learning are based either on explicit rather than on implicit learning, or on a particular kind of motor learning (i.e., eye movements). Moreover, Deroost and Soetens (2006a) showed that perceptual learning, if it occurs, does not add to performance in terms of response times when the motor sequence is also structured. They independently manipulated the sequence of stimulus locations and motor responses, and the separate learning of motor responses did not differ reliably from the combined learning of the motor and stimulus location sequences. In conclusion, sequence learning in an SRT task is generally believed to be dominated by either motor-based (in case of implicit learning) or explicit processes. As both of these processes can be assumed to be independent of stimulus features and modality, near-perfect transfer of learning is expected when the same sequence of responses is determined by a new type of stimuli within the same modality (e.g., Willingham, 1999), or by stimuli that are presented through a different modality from the one used during training.

Previous research on the SRT task has focused almost exclusively on the visual domain, limiting the generalizability of the motor-based view. Here we investigated sequential learning in a tactile SRT task (i.e., participants responded with the finger that was stimulated by a vibro-tactile stimulus), while comparing it to learning in a visual SRT task under similar experimental conditions. At transfer, then, the participants who trained with tactile stimuli were tested with visual stimulus presentation, and the participants who were trained with visual stimuli were tested with tactile stimulus presentation. If implicit sequence knowledge is indeed predominantly motor based, performance in the tactile SRT task should be similar to performance in the visual SRT task. Furthermore, near-perfect cross-modal transfer is expected in both directions. From any other view (i.e., S-S, S-R order, and R-S learning) than the motor-based account, transfer should affect performance because the stimuli are changed.

METHOD

Participants

Informed consent was obtained from 24 right-handed students (16 women; mean age of 21.5 years) from Twente University who participated in the experiment in exchange for course credits. The study was approved by the ethics committee of the Faculty of Behavioural Sciences from Twente University.

Apparatus and stimuli

Stimulus presentation, timing, and data collection were achieved using the Presentation 10.1 experimental software package on a standard Pentium© IV class PC. Visual stimuli were presented on a 17-inch Philips 107T5 display running at a resolution of 1,024 by 768 pixels in 32-bit colour, with a refresh rate of 85 Hz. The viewing distance was approximately 60 cm, but this was not strictly controlled. Visual stimuli were four white, 1.5° × 1.0° horizontally outlined rectangles with a total length of 8.0° visual angle, continuously presented on a black background. The target stimulus consisted of the filling in red of one of the rectangles. Vibrotactile stimuli were delivered to the fingers by using miniature loudspeakers (8 Ω; 35 × 20 × 8 mm), taped to the proximal phalanx of the ring and index fingers of both hands (stimuli to adjacent fingers appeared difficult to discriminate). Tactile stimuli consisted of clearly detectable triangle-wave tones of 200 Hz being amplified by two stereo amplifiers (2 × 8 W). To hold experimental settings as similar as possible, all participants (including those practising with visual stimuli) were carrying the loudspeakers throughout the experiment. Participants were wearing a headphone presenting white noise at a loudness level that prevented them from using the tones as auditory spatial cues. Moreover, participants could not see their hands as these were covered by a box.

Procedure

All participants were presented first with one pseudorandom block of tactile stimuli, requiring them to respond as accurately as possible, with speed being irrelevant (a criterion of 95% accurate was employed before allowing participants to continue). All participants performed well on this test of tactile stimulus discrimination. Then, half of the participants were trained on a SRT task with the imperative stimuli presented to them tactilely to the fingers, followed by a visual test of the task (tac-vis group), while the other half practised visually followed by a tactile test (vis-tac group). Participants were randomly assigned to conditions, and they were instructed to respond as fast and accurately as possible to the stimuli, with positions from left to right on the screen (for the visual SRT task) and loudspeakers from left to right on the fingers; (for the tactile SRT task) corresponding to the a, f, k, and ' keys, respectively, on a regular QWERTY keyboard. Participants were further instructed to use the ring and index fingers of the left hand on the a and f keys, and the index and ring fingers of the right hand on the k and ' keys. A correct response was defined as the participant pressing the appropriate key within a 1.5-s time limit. Erroneous responses were signalled to the participants, after which the next stimulus was presented after a 1-s interval. Stimuli were always presented until responding. Short 1-min breaks were provided in between blocks, with a more extended break after the sixth training block in which the experimenter briefly entered the room to check whether everything went all right (participants in a pilot study of the tactile SRT task had expressed a loss of concentration half way the experiment, probably as the task is rather demanding).

The 12-element sequence consisted of second-order conditional (SOC) transitions: 242134123143. In a SOC sequence every location is determined by the previous two locations, and performance cannot improve from learning the frequencies of individual elements or element pairs. The training SRT task consisted of 1 pseudorandom block at the start, then 10 sequence blocks, 1 pseudorandom block, and finally a sequence block. Each block contained 108 trials (nine complete sequences), implying that the sequence had been carried out 90 times before the second pseudorandom block started. The pseudorandom blocks in the training phase consisted of a series of 9 different SOCs that were randomly picked from a pool of 12, with no element and sequence repetitions allowed. Pseudorandom blocks were never repeated for the same participant. To determine the amount of sequence learning after training, the mean RT and mean error percentage of the combined blocks 11 and 13 were compared with the mean RT and error percentage of the pseudorandom block 12 (hereafter referred to as Test Phase 1). Response-to-stimulus-interval (RSI) was always 200 ms.

In a second test phase, transfer to stimulus presentation within the other modality was assessed: Participants who trained with tactile stimuli were tested with visual stimuli, and vice versa. The transfer phase consisted of a pseudorandom block (Block 14), a sequence block (Block 15), and another pseudorandom block (Block 16). Each of these blocks consisted of only 48 trials to prevent learning during this test phase as much as possible. Pseudorandom blocks consisted of a series of 4 different SOCs that were randomly picked from a pool of 12, with no element and sequence repetitions allowed. Again, pseudorandom blocks were never repeated for the same participant. Transfer was measured by comparing the mean RT of the combined pseudorandom Blocks 14 and 16 with the mean RT of Block 15. The comparison between sequential and pseudorandom blocks implies that we can exclude any effects of sequence-unspecific learning (such as S-R mapping or stimulus discriminability) that may differ between visual and tactile stimulus presentation. Mean RTs and error percentages were calculated for every participant for each of the 16 blocks.

Finally, participants filled in a questionnaire to indicate awareness. First, they were asked to select one of the following statements describing best the experiment they had just carried out: (a) stimulus presentation was completely random; (b) some fingers had to respond more often than others; (c) sometimes I wanted to respond before stimulus presentation; and (d) stimulus presentation was mostly structured. Second, the existence of a 12-trial repeating sequence was revealed, and in a free generation task participants were asked to write down the complete sequence that they thought had been repeated during the experiment. The number of correctly generated three-element chunks in the free generation task was counted for every participant, and this number was divided by 12 (as participants could generate a maximum of 12 correct chunks) to obtain an awareness score between 0 and 1. Chance level of producing correct chunks of three was 0.33 as no repetitions were allowed. Third, they were asked to select their sequence from six alternatives in a recognition task.

RESULTS

Training

Figure 1 shows the results from the training phase and the first and second test phases. A repeated measures analysis of variance (ANOVA) was performed with block (10; Blocks 2 to 11) as within-subject variable and group (2; tac-vis vs. vis-tac group) as between-subject variable. This showed a block main effect, $F(9, 198) = 26.5$, $p < .0001$, and a main effect of group, $F(1, 22) = 20.9$, $p < .0001$. Then, a repeated measures ANOVA was performed on arcsin-transformed error scores, with block (10; Blocks 2 to 11) as within-subject variable and group (2; tac-vis vs. vis-tac group) as between-subject variable. This revealed that across Blocks 2 to 11 participants in the tac-vis group produced more errors than participants in the vis-tac group (4.9% vs. 2.7%), $F(1, 22) = 12.5$, $p < .01$.

Figure 1 suggests that there is a strong effect of the extended break in between Blocks 6 and 7, as RTs suddenly show an unusually rapid decline. To examine this effect, for each group separately, we performed paired-sample t tests for every pair of successive blocks from Block 2 to Block 11. Bonferroni correction yielded a new critical p-value of .006. Only the difference between Blocks 6 and 7 reached significance, for both the tac-vis group, $t(11) = 6.0$, $p < .001$, and the vis-tac group, $t(11) = 4.8$, $p < .001$. So, surprisingly, the extended break after Block 6, in which the experimenter entered the room, affected the results similarly for both groups. We would like to argue that this sudden decrease of RTs is mainly caused by motivational aspects.

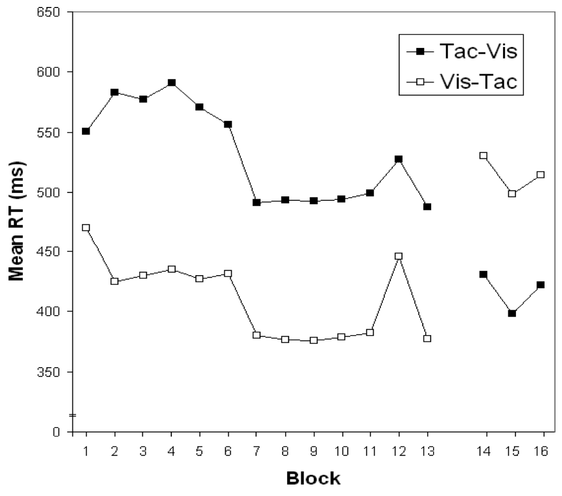

Figure 1. Mean reaction times for the training and test phases (1: Blocks 11–13; 2: Blocks 14–16) for the group that trained with tactile stimuli and was tested with visual stimuli (tac-vis), and the group that trained with visual stimuli and was tested with tactile stimuli (vis-tac). Blocks 1, 12, 14, and 16 involved combinations of different SOC sequences (i.e., pseudorandom).

Finally, we examined sequence-unspecific learning in both groups by comparing pseudorandom Blocks 1 and 12. A repeated measures ANOVA was performed with block (2; Blocks 1 and 12) as within-subject variable and task (2) as between-subject variable. This indicated a main effect of block, $F(1, 22) = 5.6$, $p < .05$, and a main effect of task, $F(1, 22) = 8.0$, $p < .05$. The interaction was far from significant ($F < .01$), indicating that sequence-unspecific learning was similar in the visual and tactile practice groups.

In conclusion, results of the training phase suggest that both sequence-specific and sequence-unspecific learning are comparable between both groups.

Test Phase 1

A repeated measures ANOVA was performed with block (2; mean of Blocks 11 and 13 vs. Block 12) as within-subject variable and group (2; tac-vis vs. vis-tac group) as between-subject variable (see Figure 1). This revealed significant main effects of block, *F*(1, 22) = 68.1, *p* < .001, and group, *F*(1, 22) = 10.8, *p* < .01, and a significant Block Group interaction, *F*(1, 22) = 7.2, *p* < .02. To further examine the interaction, paired-sample t tests were performed on the means of Blocks 11 and 13 versus Block 12 for both tasks. This revealed reliable effects for both the tac-vis group, *t*(11) = 3.5, *p* < .01, and the vis-tac group, *t*(11) = 8.8, *p* < .001.

Overall, both groups showed sequence learning, while the interaction reveals more sequence learning in the vis-tac group than in the tac-vis group. A repeated measures ANOVA on arcsin-transformed error scores with block (2; means of Blocks 11 and 13 vs. Block 12) as within-subject variable and group (2; tac-vis vs. vis-tac group) as between-subject variable, revealed main effects for both block, *F*(1, 22) = 14.3, *p* < .01, and group, *F*(1, 22) = 5.6, *p* < .05. Error scores for Blocks 11/13 and Block 12 were 4.2% and 6.1% for the tac-vis group, and 3% and 4% for the vis-tac group, respectively.

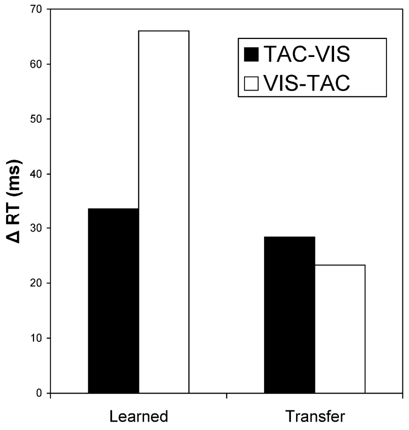

Figure 2. The learning effect (“learned”; the difference between the means of Blocks 11 and 13 and Block 12) versus the transfer effect (“transfer”; the difference between the means of Blocks 14 and 16 and Block 15) for the two groups.

Test Phase 2

A repeated measures ANOVA was performed with block (2; mean of Blocks 14 and 16 vs. Block 15) as within-subject variable and group (2; tac-vis vs. vis-tac group) as between-subject variable (see Figure 1). This revealed main effects of block, *F*(1, 22) = 13.8, *p* < .001, and task, *F*(1, 22) = 9.2, *p* < .01. The absence of a block by group interaction, *F*(1, 22) = 0.1,

$p = .70$, suggests comparable transfer for both groups, even though the vis-tac group was significantly slower on the tactile SRT task than the tac-vis group was on the visual SRT task. A similar analysis was performed on error scores, which revealed no reliable effects: Error scores were always below 5%.

So, even though the vis-tac group showed significantly more sequence learning in Test Phase 1, transfer to the other modality was comparable between groups in Test Phase 2. To combine both test phases in one analysis, we calculated a learning score (the difference between the means of Blocks 11 and 13 and Block 12) and a transfer score (the difference between the means of Blocks 14 and 16 and Block 15) for each participant (see Figure 2). Then, a repeated measures ANOVA was performed with phase (2; learning score and transfer score) as a within-subject variable and group (tac-vis vs. vis-tac group) as a between-subject variable. This revealed a reliable effect of phase, $F(1, 22) = 10.2$, $p < .01$, and a reliable Phase Group interaction, $F(1, 22) = 6.2$, $p < .05$. Separate paired-sample t tests showed that the learning score of the vis-tac group was substantially higher than the transfer score, $t(11) = 3.5$, $p < .01$, while this was not the case for the tac-vis group, $t(11) = 0.6$, $p = .6$. Thus, whereas the tac-vis group showed perfect transfer when encountering the visual SRT task in the second test phase, the vis-tac group was only able to partly transfer sequence knowledge to the tactile SRT task at Test Phase 2.

Awareness

Answers to both the first and the third questions from the questionnaire indicated low awareness for both groups. Only four participants from each group expressed that they had noticed some regularity during the experiment, and only one participant from each group selected the right alternative in the recognition task. An independent t test was then performed on awareness scores between the tac-vis group (mean awareness score of .30) and vis-tac group (mean awareness score of .42). This showed that awareness was somewhat higher in the vis-tac group, $t(22) = 2.3$, $p < .05$. Then, a one-sample t test (one-tailed as we expected these scores to be on or above chance level) was performed on the awareness scores of both groups separately to compare them with chance level of producing correct chunks of three (which is 0.33). This showed that the awareness score of the tac-vis group did not differ reliably from chance level, $t(11) = 1.0$, $\mathrm{p} = .8$, whereas the awareness scores of the vis-tac group did, $t(11) = 2.0$, $p < .05$. Thus, in contrast to the tac-vis group, the vis-tac group showed some explicit knowledge. Finally, for each group separately, we calculated bivariate correlations between the awareness scores and the learning and transfer scores. This revealed no reliable correlations (*p*s > .1), indicating that higher awareness was not associated with more learning or transfer.

DISCUSSION

To the best of our knowledge, the current study is the first to show sequence learning in a spatial (i.e., with both spatially arranged stimuli and responses) SRT task with stimuli presented outside the visual domain. Performing an SRT task with stimuli presented tactilely to the fingers clearly resulted in sequence learning, though to a lesser degree than in the visual counterpart. Learning in the tactile SRT task is hardly surprising as implicit sequence learning is said to be at least partly motoric, and at the motor level the tactile and visual SRT tasks are similar. The question remains, though, why sequence learning in the tactile SRT task was less than that in the visual SRT task. One may argue that the significantly longer response latencies in the tactile SRT task hindered the formation of R-R associations (as the interval between responses is longer). However, this seems unlikely as other studies have shown similar sequence learning across groups that differed in general speed of responding (e.g., Deroost & Soetens, 2006b; Destrebecqz & Cleeremans, 2001).

At first sight, the observed difference in awareness may be a more reasonable explanation for the lower sequence learning rate with tactile stimuli. Elsewhere, higher awareness has been associated with better sequential skill: Participants with more explicit knowledge showed considerably higher RT gains (Mayr, 1996; Rsseler & Rsler, 2000; Zirngibl & Koch, 2002; but see Destrebecqz & Cleeremans, 2001). However, this explanation falls short if we also consider the findings from the second test phase. As noted before, explicit knowledge is supposed to be highly flexible when it comes to stimulus modality, as the same explicit rules can be applied independently of the stimulus modality. If the observed difference in RT gains between the tactile and visual SRT task during training is indeed caused by higher awareness of participants performing the visual SRT task, then higher transfer would also be predicted from the visual to the tactile SRT task than from the tactile to the visual SRT task. This was clearly not the case. Moreover, even though there was a significant difference in awareness scores between groups, awareness in the visual training SRT task was still low (remember that only 4 out of 12 participants of each group noticed at all a sequential structure during training). Finally, no significant correlations were found between awareness scores and the amounts of sequence learning and transfer in each group.

Therefore, we argue that differences in explicit sequence knowledge cannot account for the current results.

Implicit sequence learning in a visual SRT task is thought to be predominantly motor based. Performance in such a task should therefore be unaffected when the stimuli are subsequently presented through the tactile modality. This is not what was observed in the current study, as only partial transfer was found from visual to tactile stimulus presentation. As noted above, this cannot be accounted for by explicit processes. Therefore, the current results are not supporting a predominantly motor-based perspective on implicit sequence learning with visual stimuli: Performance was substantially impaired when, after training with visual stimuli, stimuli were suddenly presented tactilely, even though the response sequence was maintained. Additionally, if sequence learning is indeed predominantly motor based, we should have observed similar sequence learning in the tactile and the visual SRT task. This is clearly not what we found, as participants training with the visual SRT task showed more sequence learning than those training with the tactile SRT task.

This suggests that pure motor-based processes are not as dominant in sequence skill as is proposed by many authors, as the nature of the triggering conditions remains important. Whereas a predominantly motor-based perspective on implicit sequence learning cannot account for the current results, previous research has made clear that sequence learning in a SRT task cannot be predominantly stimulus based either (the latter is further supported by the partial, but still considerable, transfer from the visual to the tactile SRT task in the current study). In line with various authors (e.g., Mayr, 1996), then, we propose that multiple components (i.e., a motor-based and a stimulus-specific component) of sequence learning developed in parallel for the vis-tac group. The stimulus-specific component may involve S-S, S-R order, and/or R-S associations. Only the motor-based component transferred to the subsequent tactile SRT task, whereas switching stimulus modality prevented transfer from the stimulus-specific component (as this component was no longer applicable with tactile stimuli).

Additionally, a stimulus-specific component seems not to have developed in parallel to a motor-based component for the tac-vis group, thereby explaining both the lesser sequence learning during training (relative to the vis-tac group) as well as the near-perfect transfer to the visual SRT task. The absence of a stimulus-specific component in the tac-vis group might be due to the lower spatial resolution of the tactile than the visual domain (remember that tactile stimuli to adjacent fingers were hard to distinguish). Furthermore, in terms of a pure S-S explanation, it may also reflect the absence of eye movement learning. Finally, as the tactile stimuli were so near to the effectors, participants may not have acquired stimulus-specific sequence learning in the training phase because the tactile stimuli provided no additional spatial information on top of the spatial response sequence. Further research is needed to investigate this issue in more detail.

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Chapter 5

Sensory information in perceptual-motor sequence learning: visual and/or tactile stimuli

Abstract

Sequence learning in serial reaction time (SRT) tasks has been investigated mostly with unimodal stimulus presentation. This approach disregards the possibility that sequence acquisition may be guided by multiple sources of sensory information simultaneously. In the current study we trained participants in a SRT task with visual only, tactile only, or bimodal (visual and tactile) stimulus presentation. Sequence performance for the bimodal and visual only training groups was similar, while both performed better than the tactile only training group. In a subsequent transfer phase, participants from all three training groups were tested in conditions with visual, tactile, and bimodal stimulus presentation. Sequence performance between the visual only and bimodal training groups again was highly similar across these identical stimulus conditions, indicating that the addition of tactile stimuli did not benefit the bimodal training group. Additionally, comparing across identical stimulus conditions in the transfer phase showed that the lesser sequence performance from the tactile only group during training probably did not reflect a difference in sequence learning but rather just a difference in expression of the sequence knowledge.

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INTRODUCTION

One crucial aspect of motor performance is the ability to learn sequences of movements. Typically, motor sequence learning is studied using button-pressing tasks such as the serial reaction time (SRT) task or the discrete sequence production (DSP) task, in which participants are required to respond to single stimuli presented visually on a screen. However, in daily life we simultaneously encounter multiple sources of sensory information across different modalities.[1] Whereas the effect of bimodal, congruent stimuli has been extensively explored with respect to trial by trial performance in simple and choice reaction time (RT) tasks (e.g., Frens, Van Opstal & Van der Willigen, 1995; Giard & Peronnet, 1999; Rowland & Stein, 2007), far less is known about the impact of such stimulus pairs on sequence learning across trials. In the current study we explored whether congruent and temporally synchronized visual and tactile stimuli enhance learning of a sequence of actions in an SRT task.

In its basic form, the SRT task requires participants to respond fast and accurately by pressing the buttons corresponding to the locations of successively presented visual stimuli (e.g. Nissen & Bullemer, 1987). Unbeknownst to them, however, stimulus presentation is structured, and reaction time (RT) decreases with practice. To differentiate sequence learning from general practice effects, a random block of stimuli is inserted at the end of the practice phase. The cost in terms of RT and/or accuracy (i.e., sequence effect) of this random block relative to its surrounding sequence blocks serves as an index for sequence learning. Often, participants are unable to express their sequence knowledge in other ways than reflected by RT and accuracy scores, and learning is said to (partly) have taken place implicitly.

The nature of the representation underlying implicit learning is still being debated. Whereas response-based learning is the dominant and best documented account in literature (e.g., Bischoff-Grethe, Goedert, Willingham & Grafton, 2004; Grafton, Hazeltine & Ivry, 1995; Nattkemper & Prinz, 1997; Rüsseler & Rösler, 2000; Willingham, 1999; Willingham, Wells, Farrell & Stemwedel, 2000), recently support is mounting also for sequence learning that involves stimulus features: response-effect learning (e.g., Stöcker, Sebald & Hoffmann, 2003; Ziessler & Nattkemper, 2001) and perceptual (location) learning (e.g., Deroost & Soetens, 2006; Mayr, 1996; Remillard, 2003). This prompts investigation on the effects that different sensory environments have upon sequence learning (e.g., Abrahamse, Van der Lubbe & Verwey, 2008; Jiménez & Vázquez, 2008; Robertson & Pascual-Leone, 2001; Robertson, Tomos, Maeda & Pascual-Leone, 2001). Robertson and colleagues (Robertson &

Pascual-Leone, 2001; Robertson et al., 2001) recognized the fact that we are continuously surrounded by multiple sources of sensory information in the real world. They explored sequence learning in an SRT task in which required responses were signaled through redundant position and color cues. They reported that, compared to either single cue condition (position or color), sequence learning was augmented with combined position and color cues.

The latter supports the notion that perceptual-motor skill acquisition can benefit from multiple sources of congruent information, at least within the visual domain. However, it remains unclear whether these findings would extend to congruent stimuli presented through different sensory modalities. It is known from simple detection and choice RT tasks that presenting congruent stimuli across modalities sometimes results in additive or even superadditive sensory interactions (e.g., Miller & Ulrich, 2003; Santangelo, Van der Lubbe, Olivetti Belardinellt & Postma, 2008; Stein & Meredith, 1993), indicating that information from the different sensory sources gets integrated along the time-course of S-R processing. This integration of bimodal stimuli has been found to occur both at early and late(r) sensory-perceptual processing stages, and seems to be conditional on the spatial proximity and/or temporal synchrony of the separate stimuli (e.g., Atteveldt, Formisano, Blomert & Goebel, 2007; Harrington & Peck, 1998; Helbig & Ernst, 2007; Teder-Sälejärvi, Di Russo, McDonald & Hillyard, 2005; Murray, Molholm, Michel, Heslenfeld, Ritter, Javitt, Schroeder & Foxe, 2005). From the notion that sensory information plays a role in the formation of the representations underlying sequence learning (e.g., Clegg, 2005; Remillard, 2003), one may expect that the enriched perceptual events that follow from (integrated) bimodal stimuli produce stronger sequence representations than those obtained with single stimuli.

Recently, Abrahamse et al. (2008) introduced a new version of the SRT task in which stimuli were presented tactilely to the fingers, and learning was compared to the typical visual version of the SRT task. Sequence learning was reliably observed for both stimulus conditions, but it appeared to be better for the condition with visual stimuli. In a subsequent transfer phase, for both visual and tactile training groups we assessed transfer of sequence learning to the other modality. It seemed that transfer was perfect from tactile to visual stimuli, but only partial the other way around. As we will elaborate on below, though, these findings deserve some closer inspection because of methodological issues.

In the current study, we extended the study of Abrahamse et al. (2008) by adding a condition in which congruent visual and tactile stimuli were presented simultaneously. Hence, participants were trained either with congruent visual and tactile stimuli (bimodal training group), with visual stimuli only (visual only training group), or tactile stimuli only (tactile only training group). This allowed us to investigate the employment by the cognitive system of redundant visual and tactile stimuli, each of which has been shown to produce sequence learning when presented alone (i.e., Abrahamse et al., 2008). In a subsequent transfer phase, transfer to all three stimulus conditions (i.e. visual, tactile and bimodal transfer test) was assessed for each training group. The transfer of sequence knowledge to new conditions is one of the major tools in exploring the nature of sequence learning (Clegg, DiGirolamo & Keele, 1998). Thus, exploring whether sequence knowledge acquired in one stimulus condition could readily be applied to different stimulus conditions provides indications on the nature of the representation underlying sequence learning. In this respect, the transfer test to the initial training condition offered a clear baseline for transfer. Additionally, comparing across identical stimulus conditions at transfer allows controlling for effects of the training stimulus condition on just the expression of sequence knowledge: It has been shown a number of times that sequence knowledge is better expressed under some experimental conditions than others (e.g., Deroost, Coomans & Soetens, 2009; Frensch, Lin & Buchner, 1998).[2] Finally, and closely related to the latter, assessing performance across one or more identical stimulus conditions allows comparing performances with more or less similar baseline RTs, thereby circumventing the debate of whether differences in baseline RTs should be considered in determining the amount of sequence learning (some authors have chosen to normalize the data for baseline differences; e.g., Robertson & Pascual-Leone, 2001).

We would like to stress that for both the training and transfer phase our main interest was whether the bimodal training group would benefit from the addition of tactile stimuli in comparison to the visual only training group. The bimodal training group was logically expected to show better sequence learning than the tactile only training group due to the availability of visual stimuli (since visual stimuli have been shown to produce better sequence learning than tactile stimuli only; Abrahamse et al., 2008).

As a minor aim of the current study, the transfer phase allowed us also to explore in more detail the findings and interpretations of the study by Abrahamse et al. (2008). First, in our previous study we reported better sequence learning for participants training with visual stimuli than for those training with tactile stimuli. However, we never tested both training groups simultaneously under identical stimulus conditions in the transfer phase. Therefore, we were unable to distinguish between genuine differences in sequence learning versus differences in just performance. The second observation we want to further examine is the seemingly partial transfer from visual to tactile stimuli, while transfer appeared perfect the other way around. Abrahamse et al. (2008) tested transfer by comparing between performances from the training phase and a subsequent transfer phase, thus with unequal amounts of training. Moreover, blocks in the training and transfer phase comprised unequal amounts of trials, possibly affecting the expression of sequence learning. The current study can provide a cleaner measure of transfer as both stimuli are employed in counterbalanced order during transfer, thus balanced in the amount of training.

To summarize, in the current study a first attempt was made to investigate the role of bimodal stimulus presentation in sequence learning. This acknowledges the continuous stream of multiple sensory inputs we face from the real world. We combined visual and tactile stimuli in a bimodal condition and compared sequence performance to that under single stimulus conditions. As noted above, the most interesting comparison would be between the visual only and the bimodal training groups, examining whether adding tactile stimuli to a typical visual setting is beneficial to sequence learning. Additionally, we attempted to replicate the findings by Abrahamse et al. (2008) in a more elaborate transfer design.

METHOD

Participants

Sixty-six undergraduates (40 women, mean age of 21 years, three left-handed) from the University of Twente (Enschede, The Netherlands) gave their informed consent to participate in the experiment in exchange of course credit. They had normal or corrected to normal vision. The current study was approved by the local ethics committee.

Stimulus and apparatus

Stimulus presentation, timing, and data collection were achieved using the Presentation 10.1 experimental software package on a standard Pentium© IV class PC. Visual stimuli were presented on a 17 inch Philips 107T5 display running at 1024 by 768 pixel resolution in 32 bit color, with a refresh rate of 85 Hz. From a viewing distance of approximately 60 cm (this was not strictly controlled), placeholders consisted of four white, 1.5° × 1.0° horizontally outlined rectangles with a total width of 8° visual angle, continuously presented on a black background. The target stimulus consisted of the filling in red of one of these rectangular placeholders. Vibro-tactile stimuli were delivered to the fingers by using four miniature loudspeakers, taped to the proximal phalanx of the ring and index fingers of both hands (cf. Abrahamse et al., 2008). Tactile stimuli consisted of clearly detectable 200 Hz triangle-wave vibrations, generated by the computer and amplified by two 2 × 8 W stereo amplifiers. For the bimodal SRT task condition, the visual and tactile stimuli were carefully synchronized using an oscilloscope (onset and offset differences amounted to 0 ± 5 ms). All participants had the loudspeakers attached to the fingers throughout the experiment, in order to hold experimental settings as similar as possible for all three training groups. Furthermore, participants wore headphones presenting white noise at a loudness level that prevented them from using the tones as auditory spatial cues, while a cover over their hands prevented them from seeing their hands.

Procedure

All participants were first tested on a block of randomly presented tactile stimuli, in which they were required to react as accurately as possible. Only participants reaching in this single block a criterion of 95% accuracy were allowed to continue with the main experiment. Then participants were randomly assigned to one of three groups for the training phase, in which an SRT task was performed: the visual only training group (21 participants), the tactile only training group (23 participants), or the bimodal training group (22 participants). In the former two, single stimuli (visual or tactile, respectively) were used as targets in the training phase, whereas both stimuli were presented simultaneously for the bimodal training group. Participants were required to respond with the ring and index fingers of both hands on the A-, F-, K-, and ‘- keys of a QWERTY keyboard to stimuli from left to right, respectively (pilot studies indicated that using adjacent fingers increased errors in the tactile condition). A correct response was defined as the participant pressing the appropriate key within a 1.5-s time limit. Erroneous responses were signaled to the participants, after which the next stimulus was presented at a 1-s interval. Stimulus presentation always continued until a response was given. Short 30-sec breaks were provided in between blocks. The training phase consisted of a pseudo-random block, 10 sequence blocks, a pseudo-random block and finally another sequence block, for a total of thirteen blocks. The increase of response time in the pseudo-random block 12, relative to the mean response time of blocks 11 and 13, was used as an index for sequence learning. During sequence blocks a 12-item second order conditional (SOC) sequence (242134123143; numbers from 1 to 4 are denoting stimulus locations from left to right) was repeated nine times for a total of 108 trials per block. The pseudorandom blocks consisted of a series of nine different SOC sequences, with no element and sequence repetitions allowed. Pseudorandom blocks were never repeated for the same participant. The response-to-stimulus interval (RSI) was always 210 ms.

After this training phase, participants were tested in a fully within-subject design for transfer to each of the three stimulus conditions, i.e. a transfer test with just visual stimuli, a transfer test with just tactile stimuli, and a transfer test with combined visual and tactile stimuli (bimodal transfer test). The order of these three transfer tests was counterbalanced across participants. For each transfer test, three blocks of stimuli were presented: a pseudo-random block, a sequence block, and another pseudo-random block. The sequence block in every transfer test involved four repetitions of the same 12-item sequence as practiced in the training phase, for a total of 48 trials (less trials were used than in the training phase to reduce sequence learning in the transfer phase as much as possible). The pseudo-random blocks in each transfer test now consisted of a series of four randomly picked SOC sequences, with no element and sequence repetitions allowed. Again, pseudo-random blocks were never repeated for the same participant. In all other aspects the transfer phase was identical to the training phase.

After the transfer phase, participants were tested for their awareness of the practiced sequence by the process dissociation procedure (PDP; Destrebecqz & Cleeremans, 2001) task. The PDP consisted of two free generation tasks of 96 key presses, first under inclusion instructions (i.e. participants were required to reproduce as much of the experimental sequence as possible), and subsequently under exclusion instructions (i.e. participants were required to avoid the experimental sequence as much as possible). In the latter task, participants received the additional instruction that no strategy was allowed to facilitate performance (such as constantly repeating a small and unfamiliar set of key presses). For each participant the same stimuli were used in the PDP task as in the training phase. In order to enhance motivation, a €20- reward was promised for the five participants performing best on the PDP task (see Fu, Fu & Dienes, 2007).

RESULTS

Erroneous key presses and correct responses with RTs three standard deviations above the mean were excluded from analyses. This eliminated less than 5% of the data in both the acquisition and the test phases. Then, for each of the remaining participants, mean RTs and error percentages (PEs) were calculated for each block in both the training and transfer phases.

Awareness

An awareness score was calculated for both the PDP inclusion and exclusion tasks by counting the number of 3-element chunks (which constitute the basis of an SOC sequence) corresponding to the SOC sequence used in the training phase, and dividing this number by the maximum number of correctly produced chunks of three (which is 94), in order to create an awareness index ranging from zero to one.

A mixed ANOVA was performed on awareness scores for the PDP, with Task (2; inclusion versus exclusion) as within-subject variable, and Training Group (3; visual only training group, tactile only training group and bimodal training group) as between-subject variable. This produced a reliable Task main effect, $F(1,63) = 12.5$, $p < 0.01$, indicating more correctly produced chunks of three sequence elements in the inclusion (mean awareness score = 0.45) than the exclusion task (mean awareness score = 0.38). The main effect for Training Group, and the more important Task × Training Group interaction were far from significant (ps > 0.80). We then compared the inclusion and exclusion scores (collapsed across groups as there were no reliable group differences) to chance level (0.33), demonstrating that both inclusion, $t(65) = 6.7$, $p < 0.001$, and exclusion scores, $t(65) = 5.8$, $p < 0.001$, exceeded chance level. Thus, overall, there are indications of both explicit (i.e. the inclusion score exceeding the exclusion score) and implicit (both inclusion and exclusion scores exceeding chance level) sequence learning. Importantly, however, sequence awareness did not differ reliably between training groups.

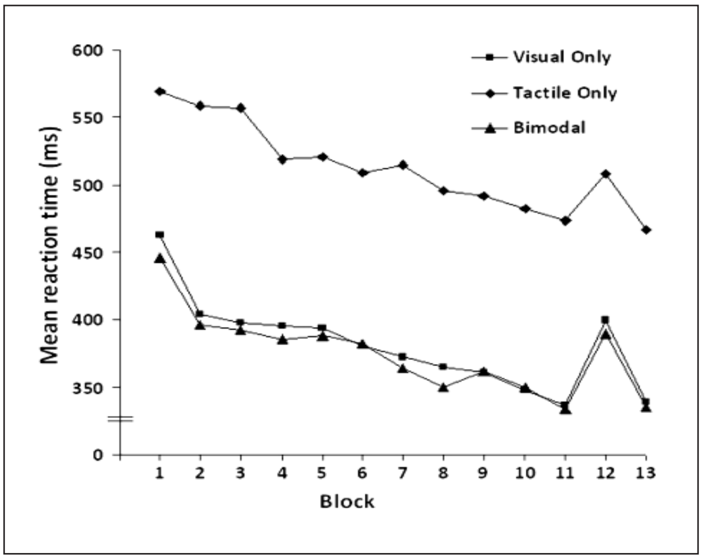

Figure 1. Mean reaction times (ms) for the visual only, tactile only, and bimodal training groups in the training phase. Blocks 1 and 12 are pseudo-randomly structured, while the rest is sequential.

Training

Blocks 2 to 11

Mean RT's were analyzed for Blocks 2 to 11 (see Figure 1) in a mixed ANOVA with Block (10; Blocks 2 to 11) as within-subject variable and Training Group (3; visual only training group, tactile only training group and bimodal training group) as between-subjects variable. This indicated reliable main effects for both Block, $F(9,567) = 25.7$, $p < 0.001$, and for Training Group, $F(2,63) = 20.1$, $p < 0.001$. There was no significant Block × Group interaction ($p = 0.50$). The main effect of Block confirmed learning during training. With regard to the Training Group main effect, subsequent post-hoc analyses (Tukey HSD) showed that the tactile only training group responded slower in general than both the visual only training group, $p < 0.001$, and the bimodal training group, $p < 0.001$, whereas there was no reliable difference between the visual only and the bimodal training groups ($p = 0.98$).

Similar analyses on PEs indicated that the tactile only training group produced more errors on average than the visual only training group, $F(1,42) = 9.5$, $p < 0.01$, and a strong tendency to produce more errors than the bimodal training group ($p = 0.06$). Across all blocks and all groups, PEs never exceeded 5%.

In conclusion, the time course of learning appeared the same for the different training groups, but participants in the tactile training group were generally slower in responding than the visual only and bimodal training groups.

Blocks 11/13 versus block 12

The critical comparison with respect to sequence learning is between the mean of Blocks 11 and 13 and the mean of Block 12 (see Fig. 1). A mixed ANOVA was performed with Block (2; mean of Blocks 11 and 13 versus Block 12) as within-subject variable and Training Group (3; visual only training group, tactile only training group and bimodal training group) as between-subject variable. Reliable effects were found for Block, $F(1,63) = 190.9$, $p < 0.001$, Training Group, $F(2,63) = 20.7$, $p < 0.001$, and the Block by Training Group interaction, $F(2,63) = 3.4$, $p < 0.05$. The main effect of block indicated reliable sequence learning overall. The main effect of Training Group was rooted in slower RTs in general for the tactile only training group than for both the visual only, $F(1,42) = 21.9$, $p < 0.001$, and the bimodal training groups, $F(1,43) = 24.5$, $p < 0.001$. Further investigation of the Block by Training Group interaction revealed larger sequence effects for both the visual only (sequence effect = 60 ms), $F(1,42) = 6.5$, $p < 0.05$, and the bimodal training groups (sequence effect = 56 ms), $F(1,43) = 3.4$, $p < 0.05$, than for the tactile only training group (sequence effect = 38 ms). There was no reliable difference in sequence effect between the visual only and bimodal training groups ($p = 0.51$).

Similar analyses on PEs showed that sequence learning was also reflected in PEs, $F(1,63) = 35.9$, $p < 0.001$, but no reliable differences were observed between training groups ($p = 0.91$). Finally, there was a tendency for the tactile only training group to produce more errors in these final three blocks of the training phase than the visual only and bimodal training groups ($p = 0.06$).

Overall, sequence performance during training was better with either visual or visual/tactile combined stimuli than with only tactile stimuli. Most importantly, however, the bimodal training group did not show a reliable benefit from the addition of tactile to visual stimuli.

Transfer

Transfer scores were calculated for each participant and for each transfer test (visual, tactile, bimodal) by taking the difference in RT between the sequence block and its two surrounding pseudo-random blocks (see Figure 2). Thus, transfer scores indicate how readily sequence knowledge from the training phase can be applied across the different stimulus conditions in the transfer phase.

One-sample t-tests (test-value = 0) showed positive transfer to all three stimulus conditions for the visual only training group, $t(20) > 2.9$, $p < 0.01$, for the tactile only training group, $t(22) > 3.5$, $p < 0.01$, and for the bimodal training group, $t(21) > 1.8$, $p < 0.05$.

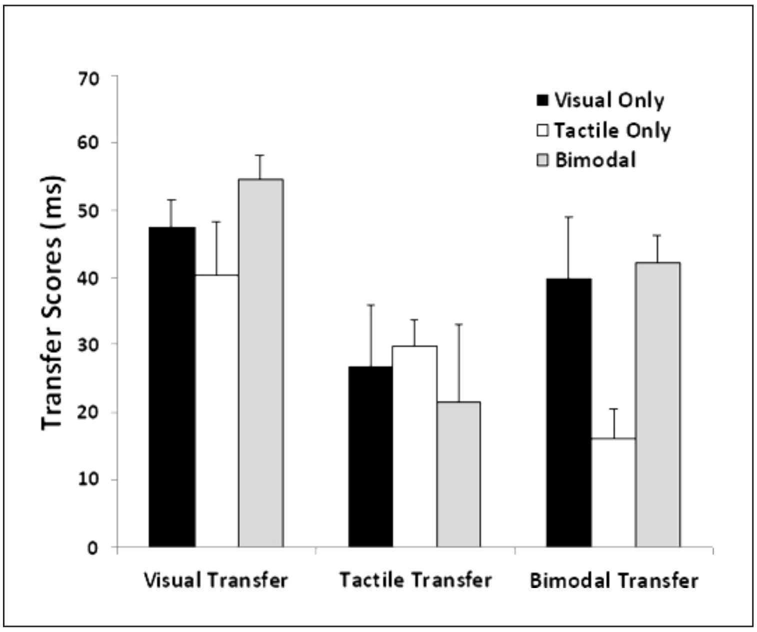

Figure 2. Mean reaction times (ms) for the visual only, tactile only, and bimodal training groups in the training phase. Blocks 1 and 12 are pseudo-randomly structured, while the rest is sequential.

Then we performed a MANOVA with the three transfer scores (visual, tactile and bimodal) as dependent variables, and with Training Group (3; visual only training group, tactile only training group, bimodal training group) as a fixed factor. This produced a reliable effect for Training Group, $F(6,122) = 2.5$, $p < 0.05$. Exploring this effect in more detail, reliable differences were observed between training groups only on the bimodal transfer scores, $F(2,63) = 5.7$, $p < 0.01$, but not on the visual and tactile transfer tests ($ps > 0.20$). Further exploration showed that both the visual only training group, $t(42) = 2.4$, $p < 0.05$, and the bimodal training group, $t(43) = 4.3$, $p < 0.01$, showed better transfer to the bimodal transfer test than the tactile training group. There was no difference between the visual only and bimodal training groups on the bimodal transfer test ($p = 0.80$).

Comparable analyses with just the visual only and bimodal training groups, the main comparison of interest in this study, also showed more or less comparable sequence learning on the two remaining transfer tests (i.e., visual and tactile; $p > 0.18$). Thus, this strengthens the observation from the training phase that the bimodal training group did not benefit from the additional availability of the tactile stimuli when compared to the visual only training group.

As mentioned above, a second aim was replicating the findings from Abrahamse et al. (2008). Comparing the visual only and tactile only training groups across the visual and tactile transfer tests showed no reliable differences ($p > 0.40$). This indicates that the difference found in sequence effects during training with visual versus tactile stimuli in both the current study and in Abrahamse et al. (2008) mainly reflect performance differences, and not reduced sequence learning in the tactile training group. Finally, paired-sample t-tests between the visual and tactile transfer scores for the visual only training group showed smaller sequence effects on the visual than the tactile transfer test, $t(20) = 2.1$, $p < 0.05$, whereas for the tactile only training group more or less similar sequence effects were observed for the visual and tactile transfer tests ($p = 0.25$). The latter findings replicate those from our previous study (Abrahamse et al., 2008).

Analyses on PEs provided no new information, as all reliable differences were in the same direction as the findings on RTs mentioned above (and thus no speed-accuracy trade-offs occurred). For the sake of brevity we decided not to report them.

DISCUSSION

The current study aimed at exploring the impact of adding congruent tactile stimuli to a typical visual SRT task, knowing that tactile stimuli by themselves can produce reliable sequence learning (Abrahamse et al., 2008). This investigation is particularly interesting as sequence learning in the real world is likely to be guided by multiple sources of sensory information. From the notion that stimulus information has a significant role in sequence learning (e.g., Clegg, 2005; Remillard, 2003) we predicted that congruent bimodal stimuli would enhance the strength of sequential representations. However, no indications were observed here that the combination of tactile and visual stimuli affected the amount and/or nature (i.e. explicit versus implicit) of sequence learning, as compared to single visual stimuli. Performance on the SRT task was highly comparable for the bimodal and the visual only training groups, even when assessed under identical stimulus conditions in the transfer phase. Moreover, no differences were observed on the PDP task, indicating that the groups did not differ significantly in sequence awareness either.

It has been shown several times that stimulus information plays a role in sequence learning, at least under some conditions (e.g., Clegg, 2005; Remillard, 2003). This prompted investigation of the effects of multiple congruent stimuli in sequence learning, an issue touched upon before only by Robertson and colleagues (i.e., Robertson & Pascual-Leone, 2001; Robertson et al., 2001). They observed that sequence learning was enhanced in a condition with congruent cues (i.e., location and color) relative to single cue conditions. Why, then, did sequence learning not benefit from combined visual and tactile stimuli in the current study? One could argue that the visual/tactile combination did not enable sufficient integration of the two sources because of the spatial disparity between cued locations. In other words, it could be that participants were unable to effectively divide their attention across both the visual and tactile stimulus locations, therefore strategically selecting the visual stimuli to focus on (due to visual dominance). This can explain why sequence learning in the typical visual setting did not benefit from the addition of tactile stimuli, as well as accounting for the differential findings of Robertson and colleagues. However, we believe that some notions need consideration in light of this possibility.

Tactile stimuli were presented directly to the fingers, nearby the response locations. It seems hard to believe that attention was not focused on these locations. Moreover, tactile stimuli are highly pregnant, and therefore unlikely to be fully ignored. More importantly, Cock, Berry & Buchner (2002) simultaneously presented two stimuli at different locations of a horizontally outlined array, only one of which was task-relevant (indicated by the color). Presentation of both stimuli followed independent sequences. Despite the spatial disparity of stimuli, participants learned the sequence of locations of the task-irrelevant stimulus (as indicated by negative priming effects when this stimulus was made task-relevant in a transfer phase). This indicates either that spatial attention is not a strict prerequisite for sequence learning, or that spatial attention can be effectively divided across different locations. Finally, because of their high temporal synchrony, one could expect the visual and tactile stimuli to become integrated as one percept, regardless of their spatial disparity. This may very well enable sufficient processing of both stimuli. Indeed, it is known from simple detection RT tasks that integration of stimuli can occur on the sole base of temporal synchrony (e.g., Murray et al., 2005). So, even though spatial disparity may be a logical and fertile issue to explore in future research, we would like to postulate two additional explanations for the absence of any benefit of the addition of tactile stimuli.

First, it may be that the tactile stimuli are so strongly S-R compatible (i.e., they are presented directly to the finger to respond with) that they need no elaborated processing on the level of stimulus features (including stimulus location). Hence, they may only produce substantial processing at response-based stages that are shared with the S-R processing for the visual stimuli, and not at any stages related to sequence learning that are not already engaged by the visual stimuli.

Second, it may be that visual and tactile sequence learning (partly) develop in different sensory modules of information processing, that independently enable speeding up of responses. If that is the case, then the relative speed of processing within each module becomes relevant: if one of the modules is much slower than the other, than little or no benefit can be taken in addition to a much faster working module. Clearly, in the current study that may have been the case, as tactile stimuli by themselves generally produced much larger response latencies than the visual stimuli. This notion would be in line with a recent race model proposed for sequence learning in the DSP task (Verwey, 2003), in which it is indeed proposed that different modules exist for sequence learning that all race each other in producing the next response. So, whereas the current study provides a start in exploring the effects of congruent bimodal stimuli on sequence learning, further research is needed to determine the underlying mechanisms in more detail.

The current findings also relate to some other issues that deserve to be discussed here briefly. It was observed that sequence performance for the visual only and the tactile only training groups was more or less similar when compared under same stimulus conditions in the visual and tactile transfer tests (see below for a possible explanation on why this was not the case in the bimodal transfer test). Thus, in contrast to the claim by Abrahamse et al. (2008) that visual stimuli produce better sequence learning than tactile stimuli (as appeared to be the case also in the training phase of the current study), the current study seems to indicate that the smaller sequence effect for the tactile stimuli mainly reflects impaired sequence performance, rather than sequence learning (for similar ideas, see Deroost et al., 2009; Frensch et al., 1998; Hoffmann & Koch, 1997). In other words, sequence learning is expressed differentially with visual and tactile stimuli. This may be explained by taking into consideration a short-cut model of sequence performance. It has been suggested that sequence knowledge may work to (partly) circumvent or facilitate processing stages by priming the next response. More specifically, a clear candidate would be the response selection stage (e.g., Clegg, 2005; Pashler & Bayliss, 1991). As tactile stimuli in the current study were more S-R compatible than visual stimuli (the latter needing a more demanding spatial translation, as the former are directly mapped to the fingers to respond with), they may require less demanding response selection processing than their visual counterparts. Thus, if sequence knowledge serves (among others) to circumvent or facilitate response selection, more benefit can be taken of this sequence knowledge with visual than tactile stimuli. This would explain the performance differences observed in the current study.

Another observation from Abrahamse et al. (2008) that was tested here in a more elaborate transfer design was the seemingly partial transfer from visual to tactile stimuli, and the perfect transfer the other way around. These findings were replicated in the current study, but the interpretation may need some consideration. Abrahamse et al. claimed that the partial transfer from visual to tactile stimuli indicated a modality-specific component of sequence learning in the typical visual SRT task. Of course this remains a solid interpretation, thereby strengthening the notion from Abrahamse et al. (2008) that sequence learning cannot easily be explained by pure response location learning (i.e., Willingham et al., 2000) and that stimulus information has a role, too. However, in line with the idea discussed above that the benefit of sequence knowledge may be larger for visual than tactile stimuli (due to the differences in S-R compatibility), the lower sequence effect of the visual only training group in the transfer test with the tactile stimuli than in the transfer test with the visual stimuli could also just be performance differences. This issue motivates further research.

We believe it is important to note here that, in line with earlier studies (e.g., Deroost et al., 2009; Frensch et al., 1998), the current study indicates that sequence effects can not always readily be taken as a clean index for the amount of sequence learning, but rather reflects a combination of the amount of sequence learning and the task-dependent constraints for expressing this knowledge. Therefore, comparing sequence learning across different task-variations should be taken with the necessary caution.

Finally, it was observed that the tactile only training group could not transfer its sequence knowledge to the bimodal transfer test as well as the visual only and bimodal training groups. This probably does not reflect differences in the amount of sequence learning, as sequence learning was comparable between the training groups on the two further transfer tests (i.e., the visual and bimodal transfer tests). Therefore, it seems that the participants who trained with tactile stimuli were unable to fully express their sequence knowledge in the bimodal stimulus condition. This might be due to a conflict in selective attentional processing. Typically, the visual stimuli are easier to process than the tactile stimuli, and therefore probably preferentially selected by naïve participants. However, during training the tactile only training group became highly familiar with responding to the tactile stimuli, thereby producing a selection conflict in the bimodal transfer test. It has been suggested before that certain task changes may affect participants' sense of control, causing them to (temporarily) suspend all ongoing automatic processes (e.g., Abrahamse & Verwey, 2008). The conflict arising in the bimodal transfer test, then, may have drawn participants from the tactile training group to partly suspend implicit learning effects, and return to controlled stimulus-response processing. However, we agree that this issue needs more exploration.

Overall, the current study is another step in moving towards an ecologically more valid approach of the SRT task, in line with other recent studies (e.g., Chambaron, Ginhac, Ferrel-Chapus & Perruchet, 2006; Jiménez & Vázquez, 2008; Witt & Willingham, 2006). Comparing between visual stimuli only, tactile stimuli only, and a combination of congruent tactile and visual stimuli, it partly replicated and extended earlier findings from Abrahamse et al. (2008). Most importantly, it showed that a combination of congruent tactile and visual stimuli does not produce better sequence awareness, sequence learning or sequence performance than single visual stimuli. Additionally, opposed to what was claimed by Abrahamse et al. (2008), rather than sequence learning it seems the expression of sequence learning that is impaired with single tactile stimuli compared to single visual stimuli.

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NOTES

1. Throughout the current paper, modality will be used to refer to sensory modality, and not to response modality.
2. One may argue that comparing all training groups on only a single stimulus condition (as opposed to all three stimulus conditions) in the transfer phase should suffice with regard to this issue. However, seeing that different training conditions could produce differential constraints on the expression of sequence knowledge, comparing across all three stimulus conditions at transfer provides a more accurate overview.

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Chapter 6 Sensory redundancy in the serial RT task

Abstract

In daily life we encounter multiple sources of sensory information at any given moment. This prompts the question how these multiple sources combine to affect human cognition and behavior. Whereas this issue has been extensively explored for simple and choice reaction time tasks, few studies explored it with respect to learning a sequence of actions across trials. In one of our previous studies we observed no sequence learning benefits from adding congruent tactile response cues to the typical visual serial reaction time task (Abrahamse, Van der Lubbe & Verwey, 2009). However, that may be explained by the spatial disparity between visual (presented at a screen) and tactile stimuli (presented to the fingers), preventing successful integration. In the current study, we explored the effect of congruent, spatially coinciding position and color cues on sequence learning in a design similar to our previous study. Results show that combining these cues does not facilitate sequence learning in comparison to conditions with either position or color cues. Moreover, reliable transfer was observed between cue conditions in all directions. These findings are surprising in the sense that empirical support is mounting for the notion that sensory information plays an important role in sequence learning.

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INTRODUCTION

Implicit learning refers to the phenomenon that people are able to acquire skilled behavior, or structured knowledge about their environment in a seemingly automatic and unconscious fashion. One of the most productive tools over the last decades in the investigation of implicit learning has been the serial reaction time (SRT) task (e.g., Nissen & Bullemer, 1987; for an overview see Clegg, DiGirolamo & Keele, 1998). In this task participants are required to respond fast and accurately to the location of successively presented stimuli. Unknown to the participants, stimulus presentation is structured, thereby allowing learning of the sequential order of trials across training. To differentiate sequence learning from general practice effects, a block of (pseudo-)randomly selected stimuli is inserted near the end of the practice phase. The cost in RT and/or accuracy of this random block relative to its surrounding sequence blocks serves as an index for sequence learning. Typically, with training a dissociation develops between sequence awareness and behavioural measures (i.e., reaction times and accuracy): relatively small increases in the former are accompanied by substantial increases in response speed and accuracy. Learning is therefore said to be (partly) implicit.

In recent years attempts have been made by various authors to build the SRT task into an ecologically more valid context by moving away from the typical simple key-presses in response to simple, single cues on the screen (e.g., Abrahamse, Van der Lubbe & Verwey, 2008; Abrahamse, Van der Lubbe & Verwey. 2009; Chambaron, Ginhac, Ferrel-Chapus & Perruchet, 2006; Jiménez & Vázquez, 2008; Robertson & Pascual-Leone, 2001; Witt & Willingham, 2006). For example, one may argue that in real life we regularly encounter multiple sources of sensory information simultaneously. This raises the question how these multiple sensory sources combine to affect human cognition and behavior.

The effect of congruent and temporally synchronized response cues has been explored extensively for simple and choice RT tasks (e.g., Miller & Ulrich, 2003; Teder-Sälejärvi, Di Russo, McDonald & Hillyard, 2005), but only a few previous studies aimed at exploring their impact on sequence learning. Abrahamse et al. (2009) did not find that the addition of congruent tactile cues (presented directly to the fingers) to a typical visual SRT task affected the amount of sequence learning. This may indicate that sequence learning in an SRT task does not benefit from multiple cues. However, as noted in Abrahamse et al. (2009), there is an alternative explanation in terms of spatial disparity that deserves to be explored before such a conclusion can be made. In the study by Abrahamse et al. (2009), the visual cues were presented on the screen, while the tactile cues were presented directly to the fingers; this may have rendered integration of both cues very difficult. Indeed, spatial correspondence is typically understood to be an important determinant of sensory integration (e.g., Driver & Spence, 2000; Radeau, 1994; Stein & Stanford, 2008).

Exploring the effect of congruent, spatial-temporally coinciding cues on sequence learning in the SRT task can be achieved by using position and color cues; i.e., each response is mapped exclusively onto a stimulus with a specific color that appears at a specific position, so that the correct response is simultaneously signaled both through the position and the color of the stimulus. In fact, Robertson and Pascual-Leone (2001) have explored sequence learning in a design just like this. They reported augmented sequence learning in a condition with congruent position and color cues in comparison to either single cue condition. Hence, this seems to indicate that sequence learning can benefit from redundant response cues, and that the absence of such a benefit in the study by Abrahamse et al. (2009) was probably due to the spatial disparity between visual and tactile cues. However, if one takes a detailed look at the study of Robertson and Pascual-Leone (2001), then some problems and/or eccentricities seem to surface that question the conclusiveness of their findings.

When considering absolute RTs in the study by Robertson and Pascual-Leone (2001), sequence learning in the combined condition (the absolute difference in mean RTs between sequence and random blocks amounting to 176 ms) is not better than in their color only condition (the absolute difference in mean RTs between sequence and random blocks amounting to 186 ms). However, Robertson and Pascual-Leone (2001) chose to analyze Z-transformed scores instead of absolute differences in RT in order to normalize baseline differences. This is a rather unusual method of analysis throughout the literature on the SRT task, and seems to build upon some implicit assumptions regarding the processes involved (across conditions with color, position or combined cues). Most importantly in this respect, it builds from the assumption that sequence learning is better expressed in a task with a larger baseline RT than in a task with a smaller baseline RT: taking baseline RT into account by performing a normalization, then, would compensate for these assumed differences in the expression of sequence learning. We believe that the claim of differential expression across their training groups is difficult to justify on the base of existing literature. Instead of comparing sequence learning across tasks by taking into account baseline differences, an alternative and probably more conclusive method could be comparing sequence learning in a transfer phase under identical task conditions (see Abrahamse et al., 2009), thereby minimizing baseline differences as much as possible and largely circumventing the problem.

Additionally, in our experience, baseline performance on the SRT task is characterized by substantial differences between participants even when performing the precise same task. Thus, by taking into account baseline differences, the sequence effect (i.e., the performance difference between sequential and random blocks) becomes sensitive to these accidental individual differences; especially so with the relatively small number of participants employed in the study of Robertson and Pascual-Leone (2001)[1]. Finally, even though Robertson and Pascual-Leone (2001) seemed to have analyzed the data at the trial level (and not at the typical aggregate level of individual participants), thereby apparently creating sufficient power, one may still wonder about the reliability and generazibility of their findings on the basis of merely four participants per condition.

Overall, then, it remains unclear whether the absence of sequence learning benefits in a setting with redundant visual and tactile cues (Abrahamse et al., 2009) can be contributed to the spatial disparity between these cues, and the issue needs further exploration. The aim of the current study was to reexamine the effect of redundant spatial-temporally overlapping position and color cues in a training-transfer design similar to the one employed by Abrahamse et al. (2009). Task parameters were attempted to resemble more or less those used by Robertson and Pascual-Leone (2001), though some changes were adopted (see Table 1). In the present study, participants were trained in an SRT task either while responding to position cues (*position training group*), to color cues (*color training group*), or to a combination of these (*combined training group*). After the training phase, all participants were tested in all three cue conditions (the order of which was counterbalanced across participants) in a transfer phase: a position transfer test, a color transfer test and a combined transfer test. Hence, it included a test of transfer to the initial training cue condition, thereby providing a clean baseline condition for transfer. Overall, this transfer phase allowed us to compare performances between training groups when tested on identical tasks. Finally, participants were tested for their awareness of the practiced sequence through the process dissociation procedure (PDP; Destrebecqz & Cleeremans, 2001) task, arguably providing a stronger measure of awareness than the free recall method employed in Robertson and Pascual-Leone (2001). The PDP consisted of two free generation tasks of 96 key presses, first under inclusion instructions (i.e. participants were required to reproduce as much of the experimental sequence as possible), and subsequently under exclusion instructions (i.e. participants were required to avoid the experimental sequence as much as possible). In the latter task, participants received the additional instruction that no strategy was allowed to facilitate performance (such as constantly repeating a small and unfamiliar set of key presses).

Table 1 Overview on the differences and similarities between the current study and that of Robertson and Pasual-Leone (2001). RSI: response-to-stimulus-interval.

a. Pure randomization has been shown to produce more reversals than a regular training sequence. This possibly artificially inflated the RTs on the random block, as reversals produce longer response latencies than regular trials (i.e. Vaquero et al. 2006). Therefore, for the test blocks we chose to employ a pseudo-random trial order in which the frequency of reversals was similar as in sequential blocks.

	Robertson & Pascual-Leone (2001)	Current study
Identical		
fingers to respond with	4 fingers of the dominant hand	
placeholders	Equally spaced horizontal array	
RSI	400 ms	
target	circle (diameter of 3.5 cm)	
Different		
awareness test	free recall	PDP task
Color cues in color task	blue, brown, green and red	blue, yellow, green and red
errors	stimulus remained until correct response	error message, next stimulus
random trials	purely random	pseudo-random[a]
response board	4-button response pad	QWERTY keyboard
Total number of training trials	450	864
training sequence	4321342312 (10-item ambiguous)	242134123143 (12-item second order conditional)
transfer tests	non-training cue conditions (between-subject)	all cue conditions (within-subject)

METHOD

Participants

Fifty-three undergraduates (42 women, mean age of 20 years, three left-handed) from the University of Finance and Management (Warsaw, Poland) gave their informed consent to participate in the experiment in exchange of course credit. They had normal or corrected to normal visual acuity.

Stimuli and apparatus

Stimulus presentation, timing, and data collection were achieved using the Presentation 10.1 experimental software package on a standard Pentium© IV class PC. Stimuli were presented on a 22 inch Mitsubishi Diamond Pro 2070SB display running at 1024 by 768 pixel resolution in 32 bit color, with a refresh rate of 120 Hz. Viewing distance was approximately 60 cm (not strictly controlled). Depending on the specific experimental group, placeholders consisted either of a) an horizontally outlined array containing four grey-lined squares (3 x 3 cm) filled with white, continuously presented on a black background, or b) a single grey-lined square (3 x 3 cm) filled with white presented on a black background. Stimuli consisted of the appearance in one of the square placeholders of a circle (with 2.5 cm diameter) that was colored purple, red, blue, green or yellow, depending on the specific experimental group.

Procedure

Participants were randomly assigned to one of three experimental groups for the training phase, in which an SRT task was performed: the position training group (18 participants), the color training group (16 participants), or the combined training group (19 participants). In the position training group participants were instructed to respond to the position of a purple colored circle appearing at one of the four positions of an array, with positions from left to right corresponding to the c, v, b, and n keys (standard QWERTY keyboard), respectively. In the color training group participants were instructed to respond to the color of a circle presented in a centrally located square, with colors red, blue, yellow and green corresponding to the c, v, b, and n keys, respectively. In the combined training group each of the four colored (i.e. red, blue, green and yellow) circles was uniquely presented at one of the four array positions, so that participants could respond to either the position or the color of the circle, or to both. The circle remained visible on the screen until responding, but with a maximum latency of 1500 ms. After that, the next stimulus would appear with a response-to-stimulus-interval (RSI) of 400 ms. Erroneous responses were signaled to the participants by presenting the word *Źle* (Polish for "error"), after which the next stimulus was presented at a 1-sec interval. Participants were always responding with the index, middle, ring and little fingers of their dominant hand.

During the training phase participants performed 10 blocks of 108 trials each. Block 1 and 9 were always pseudo-randomly structured; i.e. they consisted of a series of 9 randomly selected different 12-element second order conditional (SOC) sequences, with no element and sequence repetitions allowed. Pseudo-random blocks were never repeated for the same participant. In blocks 2-8 and block 10 a 12-element SOC sequence (242134123143; with numbers denoting either stimulus positions from left to right, or the colors red, blue, green and yellow respectively) was repeated 9 times. Short 30-sec breaks were provided in between blocks.

After this training phase all participants were tested in a fully within-subject design for transfer to each of the three cue conditions, i.e. a transfer test with just position cues, a transfer test with just color cues, and a transfer test with combined position and color cues. The order of these three transfer tests was counterbalanced across participants. For each transfer test, three blocks of stimuli were presented: a pseudo-random block, a sequence block, and another pseudo-random block. The sequence block in every transfer test involved 4 repetitions of the same 12-item sequence as practiced in the training phase, for a total of 48 trials (less trials were used than in the training phase to reduce sequence learning in the transfer phase as much as possible). The pseudo-random blocks in each transfer test now consisted of a series of four randomly picked SOC sequences, with no element and sequence repetitions allowed. Again, pseudo-random blocks were never repeated for the same participant. In all other aspects the transfer phase was identical to the training phase. Finally, participants performed the PDP task with the same cues as in their training phase.

RESULTS

For each participant and each block, erroneous key presses and correct responses with RTs three standard deviations above the mean RT of the block were excluded from further analyses. This eliminated less than 5% of the data in both the acquisition and the test phases. Then, for all participants, mean RTs and error percentages (PEs) were calculated for each block in both the training and transfer phases on the basis of the remaining data. Additionally, awareness scores were calculated for both the PDP inclusion and exclusion tasks by counting the number of correctly produced 3-element chunks (which constitute the basis of an SOC sequence) and dividing this number by the maximum number of correctly produced chunks of three (which is 94), in order to create an awareness index ranging from zero to one.

Awareness

A mixed ANOVA was performed on awareness scores for the PDP, with Task (2; inclusion versus exclusion) as within-subject variable, and Group (3; position training group, color training group and combined training group) as between-subject variable. This produced a reliable Task main effect, $F(1,50)=6.5$, $p<0.05$, $\eta^2=0.12$, indicating more correctly produced chunks of three sequence elements in the inclusion (mean awareness score = 0.42) than the exclusion task (mean awareness score = 0.38). The Task x Group interaction was not significant ($p=0.44$), showing that PDP awareness scores did not reliably differ between the different training groups. Then, we compared the inclusion and exclusion scores (collapsed across groups as there were no reliable group differences) to chance level (0.33), demonstrating that both inclusion, $t(52)=5.7$, $p<0.001$, and exclusion scores, $t(52)=4.8$, $p<0.001$, exceeded chance level. Thus, overall, there seem to be indications of both explicit (i.e. the inclusion score exceeding the exclusion score) and implicit (both inclusion and exclusion scores exceeding chance level) sequence learning, but the most important finding is that the different cue conditions did not produce reliable differences in awareness scores.

Training

Blocks 2 to 8

Mean RTs were analyzed for blocks 2 to 8 (see Figure 1) in a mixed ANOVA with Block (7; blocks 2 to 8) as within-subject variable and Group (3; position training group, color training group and combined training group) as between-subjects variable. This indicated reliable main effects for both Block, $F(6,300)=34.8$, $p<0.001$, $\eta^2=0.41$, and for Group, $F(2,50)=31.2$, $p<0.001$, $\eta^2=0.56$. Also, there was an almost reliable Block x Group interaction ($p=0.07$), indicating a tendency for the color training group to show better performance improvement over training than the other two training groups. The main effect of Block confirmed learning during training. Then, separate mixed ANOVAs were performed for each pair of training groups to further investigate the Group main effect. This showed that the color training group responded slower in general than both the position training group, $F(1,32)=35.6$, $p<0.001$,

$\eta^2=0.53$, and the combined training group, $F(1,33)=33.9$, $p<0.001$, $\eta^2=0.51$, but there was no reliable difference between the position training group and the combined training group ($p=0.44$). Similar analyses on PEs did not indicate any reliable effects.

In conclusion, the time course of learning appeared more or less the same for the different training groups, even though the color training group showed a tendency for better RT improvement over training than the other two training groups. The latter may be explained by taking into consideration the arbitrary color to response mapping, the learning of which accelerated responses more with practice than the highly compatible position to response mapping. Furthermore, participants in the color training group were generally slower in responding than the position and combined training groups.

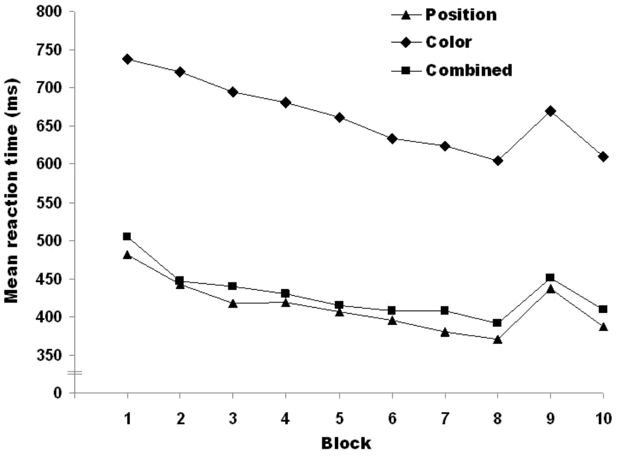

Figure 1. Mean reaction times (ms) for the position, color, and combined training groups in the training phase.

Blocks 8 to 10

The critical comparison with respect to sequence learning is the difference between the mean of Block 8 and 10, and Block 9 (see Figure 1; position training group: 58 ms; color training group: 61 ms; combined training group: 51 ms). A mixed ANOVA was performed with Block (2; mean of Block 8 and 10, versus Block 9) as within-subject variable and Group (3; position training group, color training group and combined training group) as between-subject variable. Reliable main effects were found for Block, $F(1,50)=114.0$, $p<0.001$, $\eta^2=0.70$, indicating sequence learning across blocks, and for Group, $F(2,50)=30.4$, $p<0.001$, $\eta^2=0.55$. The main effect of Group was rooted in reliably slower responding in general for the color training group than both the position training, $F(1,32)=35.8$, $p<0.001$, $\eta^2=0.53$, and the combined training groups, $F(1,33)=32.7$, $p<0.001$, $\eta^2=0.50$. Importantly, the Block by Group interaction was not significant ($p=0.67$), suggesting that sequence learning was not reliably different between training groups.

A similar mixed ANOVA on PEs resulted in a reliable Block main effect, $F(1,50)=11.7$, $p<0.01$, $\eta^2=0.19$, indicating reliable sequence learning. Again, sequence learning did not reliably differ between training groups ($p=0.70$).

Transfer

Transfer scores (see Figures 2 and 3) were calculated for each participant and for each transfer test (i.e., position transfer, color transfer and combined transfer) by taking the differences in RT and PE between the sequence block and its two surrounding pseudo-random blocks. The order of performing the three transfer tests did not affect performance in any way, and will not be included in the analyses reported below.

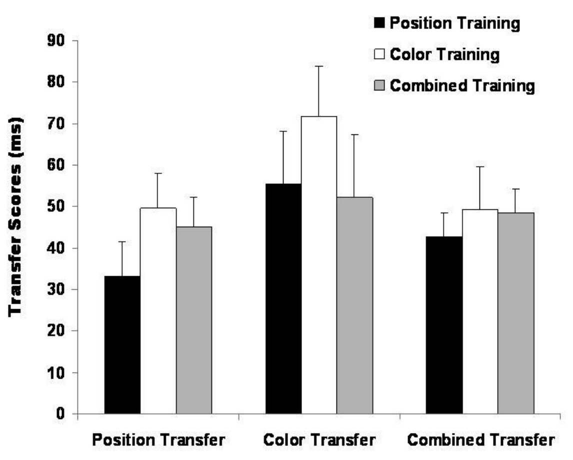

Figure 2. Mean transfer scores (ms) for the different training groups across transfer tests. Error bars depict standard errors.

First, we performed one-sample *t*-tests (test-value = 0) for all transfer tests, separately for each group, to determine in which directions reliable transfer occurred. This showed reliable and positive transfer to all three cue conditions for the position training group[2], $t(17)>4.3$, $p<0.01$, the color training group, $t(15)>4.8$, $p<0.001$, and the combined training group, $t(18)>3.4$, $p<0.01$. The same analyses on PEs are not reported for the sake of brevity, but reliable transfer on PEs was always in the same direction as the corresponding transfer on RTs.

Then, to explore performance of the three training groups measured on identical tasks, separate MANOVAs for RTs and PEs were performed with the three transfer scores (position transfer, color transfer and combined transfer) as different dependent measures, and with Group (3; position training group, color training group and combined training group) as a fixed factor.

The effect of Group was not significant for transfer scores on RTs (p=0.78; separate univariate tests all demonstrated ps>0.30), but there was a reliable effect of Group for the transfer scores on PEs, $F(6,98)=3.0$, $p<0.01$, $\eta^2=0.16$, that was rooted in a reliable Group effect on the PEs of the color transfer test (which becomes immediately clear from Figure 3), $F(2,50)=6.9$, $p<0.01$, $\eta^2=0.22$, but not on the position or combined transfer test (ps>0.30). Specifically, this reliable Group effect on the color transfer test for PEs originated from reliable differences in transfer between the position training group (mean transfer score = 0.039) and the color training group (mean transfer score = -0.004), $t(32)=3.1$, $p<0.01$; between the position training group and the combined training group (mean transfer score = 0.012), $t(35)=2.2$, $p<0.05$; and between the color training group and the combined training group, $t(33)=2.1$, $p<0.05$. Please note, however, that the transfer effect on PEs of the color training group to the color transfer test may have been affected by the relatively large (though not significantly so; see Figure 2) transfer on RTs, possibly indicating some trade-off between transfer on RTs and PEs.

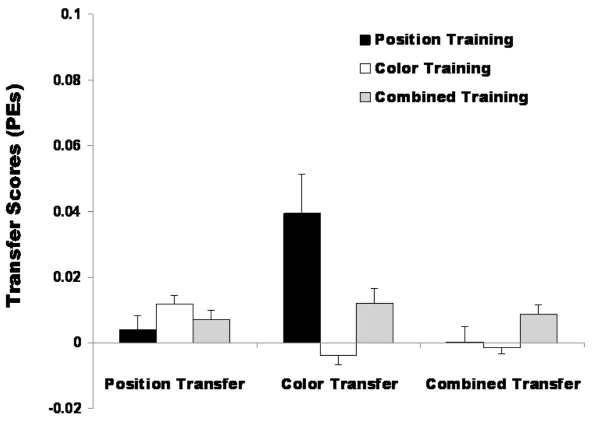

Figure 3. Mean transfer scores (PEs) for the different training groups across transfer tests. Error bars depict standard errors.

Even though we succeeded in minimizing differences in baseline RT, by comparing sequence performance across different training groups on identical tasks in the transfer phase (differences in baseline RT never exceeded 50 ms), we decided to run the same analysis on proportional sequence effects to control for possible influences of baseline differences that may still exist. Proportional sequence effects were calculated for each participant and each transfer task through dividing the sequence effect (i.e., the difference in RT between sequential and random blocks) by the mean of the two (pseudo-)random blocks (which was considered as an index for baseline RT). Then a MANOVA was performed on the proportional sequence effects, with the three transfer tasks (position transfer, color transfer and combined transfer) as different dependent measures, and with Group (3; position training group, color training group and combined training group) as a fixed factor. In line with the MANOVA on absolute sequence effects, the effect of Group was not significant (p=0.73), and separate univariate tests all demonstrated ps>0.40.

Thus, overall, transfer was similar for all three training groups on all transfer tests for RTs, and almost all the transfer tests for PEs. This strengthens the findings from the training phase that sequence learning was not modulated by cue condition during training.

DISCUSSION

In the current study we aimed at exploring the effect of redundant cues on sequence learning in an SRT task. This issue is particularly interesting as in daily life we typically encounter multiple sources of sensory information concurrently. Specifically, we employed a training condition in which both the position and the color of the stimuli signaled the correct response, and compared sequence performance to that under single cue (i.e., position or color) training conditions. Subsequently, for all participants we assessed the transfer of sequence knowledge to all three cue conditions. The main result of this study is that we did not observe any indications that sequence learning benefited from training with combined position and color cues. In the training phase, participants training with either position, color, or combined cues all showed comparable amounts of sequence learning on both RT and accuracy measures. The transfer tests strengthened this notion as sequence learning was still highly comparable between training groups when performing the task under identical cue conditions[3], with the only exception to this being the accuracy measure on the color transfer test. This latter finding will be briefly discussed below, but, in anticipation of this discussion, it may be stressed here already that it indicates that the redundant color cues in the combined training group were not fully ignored.[4]

The findings of the current study are in line with those of Abrahamse et al. (2009) in that congruent and temporally synchronized cues do not facilitate sequence learning. Abrahamse et al. (2009) employed redundant visual and tactile cues, with the latter being presented directly to the fingers. Whereas the absence of better sequence learning with redundant cues in that study may have been explained by the spatial disparity of both cues (thereby preventing successful integration), the current study employed temporally synchronized cues that were presented from the same location (i.e., the color and the position of the stimulus) and still sequence learning was unaffected by cue redundancy. It seems, then, that sequence learning in the SRT task does not actually benefit from multiple sensory cues.

The role of sensory information in sequence learning is one of the major issues of debate within SRT literature. Even though response-based sequence learning has been the dominant view since a set of studies by Willingham and colleagues (i.e., Bischoff-Grethe, Goedert, Willingham & Grafton, 2004; Willingham, 1999; Willingham, Wells, Farrell & Stemwedel, 2000), over the last decades support is mounting for a role of sensory information in sequence learning as well: perceptual (e.g., Remillard, 2003; Deroost & Soetens, 2006) and response-effect learning (Ziessler & Nattkemper, 2001). Then why would sequence learning be unaffected by the use of multiple congruent cues? Below we will consider three explanations; the former two build upon the assumption that no stimulus-based sequence learning developed with respect to the redundant cues in the combined training group; this would go against the notion that implicit learning is unselective, taking all available regularity into account (e.g., Keele, Ivry, Mayr, Hazeltine & Heuer, 2003; Reber, 1993). The latter explanation does not exclude the possibility of additional stimulus-based sequence learning, but rather stresses its (absence of) effects on performance.

First, the simplest explanation may be that sequence learning in the current study was predominantly response-based (i.e., based on a series of response locations; Willingham et al., 2000), and that learning based on stimulus features did not develop substantially in this specific study. In fact, this account is supported by the reliable transfer in all directions (i.e., all three training groups were able to use the sequence knowledge acquired during training in all three transfer conditions) in the current study, indicating that sequence knowledge could be applied independent of the cues employed. From the notion that stimulus information is involved in sequence learning at least under some conditions (e.g., Abrahamse & Verwey, 2008; Clegg, 2005; Remillard, 2003; Ziessler & Nattkemper, 2001), this perspective triggers the question about what is determining the relative weights of response and stimulus features as the building blocks of sequence representations across different studies. In other words, instead of arguing whether sequence learning in general is based on a sequence of stimulus locations (e.g., Remillard, 2003), response-effects (e.g., Ziessler & Nattkemper, 2001) or response locations (e.g., Willingham et al., 2000), interest should shift to the question what factors determine the precise nature of the representation underlying sequence learning. One may think, for instance, about the role of different task sets and/or individual differences.

A second potential explanation for the current findings is that stimulus-based learning is contingent upon attentional selection. It has been shown that stimulus features need to be attentionally selected to become associated (Jiménez & Méndez, 1999). Specifically, Jiménez and Méndez (1999) employed a design in which on each trial one of four different shapes was presented at one of four locations. Participants were responding to sequence of stimulus locations, but, in addition, there was a contingency between the shape of the stimulus and the next stimulus location. It was observed that the latter contingency was learned only when the shape feature was made task-relevant by a secondary counting task. This notion could imply that redundant sensory cues in general do not improve sequence learning, as only one specific feature is used to base action on. However, even though the color cues probably were not selected to guide the responses in the combined training group of the current study[4], below we will briefly elaborate on some tentative evidence that these cues were not fully ignored as well.

Finally, and again from the notion that different kinds of learning can develop, the current findings can also be interpreted in terms of a race model. Recently, Verwey (2003) proposed a race model for sequence learning in the discrete sequence production (DSP) task, a task that seems highly related to the SRT task. Specifically, it was proposed that different systems of sequence learning develop in parallel during sequence training (cf. Keele et al., 2003), and that all these systems are racing each other in producing the next response. In line with this model, it may be argued that multiple (sensory-specific and motor) learning systems are involved in sequence learning in the SRT task that are racing each other. The absence of any benefit from congruent cues can be explained, then, by assuming that one of the (sensory-specific) systems is much slower in producing the next response than the other(s); in both the study of Abrahamse et al. (2009) and the current study, indeed one of the single cue conditions (i.e., tactile and color cues, respectively) was much slower in general than the other single cue condition (i.e., the position of a visual stimulus). This would explain why redundant cues do not affect sequence performance as compared to single cue designs. Future research will have to further explore the precise mechanism underlying the role of sensory information in sequence learning.

Another finding of the current study deserves to be briefly elaborated on here. We observed clear and more or less similar transfer between cue conditions in all directions. As noted above, the only exception to this was with respect to PEs for the color transfer test: the position training group showed a higher transfer to color cues than the combined training group, whereas transfer of both was higher than that of the color training group. This probably does not reflect differences in amounts of sequence learning between groups, as across all other transfer tests (RTs and PEs) there were no reliable differences. We believe these differences in transfer rather reflect the amount of experience with the color cues and their arbitrary mapping to responses. Obviously, the color training group already learned very well the arbitrary mapping between colors and responses before entering the color transfer test, and could perform this transfer test without much effort (i.e., producing few errors). On the other hand, the position training group had no experience whatsoever with the color to response mapping during the training phase. Moreover, whereas this group could use their sequence knowledge in the sequence block of the transfer test to circumvent this mapping, they had to fully rely on this mapping during the random blocks of the transfer test. This can possibly explain the relatively large difference between sequence and random blocks on PEs for the position training group. Most interestingly, from this reasoning it seems that the participants from the combined training group gained some benefit from their exposure to the color cues during their training session, in that they learned the mapping between colors and responses already to some extent. Thus, it seems that even though the color cues were not facilitating baseline response latencies or sequence learning (possibly because the color cues were not selected for action), the color cues were not completely ignored as well in the combined training condition.

To summarize, in line with our previous study (i.e., Abrahamse et al., 2009) we observed that sequence learning in a typical SRT task does not benefit from cue redundancy. Furthermore, reliable transfer was observed between all cue conditions. These findings are somewhat surprising as sensory information has been shown to have a role in sequence learning by various studies. Future research will have to determine how and when sensory information is precisely involved in sequence learning.

ACKNOWLEDGEMENTS

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NOTES

1. Robertson and Pascual-Leone (2001) observed a difference in baseline RTs between the position task and the combined (position and color) task of over a hundred ms. In our opinion it is rather surprising that participants in the combined task were so much faster in general, and we believe that this probably reflects accidental differences rather than task-specific differences. For example, in the current study, the group training with position cues was responding slightly (though not significantly so) faster in general than the group training with combined position and color cues.
2. Robertson and Pascual-Leone (2001) observed an absence of transfer from position to color cues, and explained this by claiming that "a coupling between color and response is a prerequisite for skill within the color task" (page 342). Thus, because participants training with the position cues did not yet master the arbitrary color-to-response mapping, they were unable to express their sequence knowledge in the transfer task with color cues. It could be argued that in our fully counterbalanced within-subject design, some participants that were trained with position cues were able to transfer to the transfer task with color cues because they first performed the combined transfer task from which they could master the color-to-response mapping. To control for this possibility, we analyzed from the position training group only those participants who performed the color transfer task *before* the combined transfer task. Still we observed reliable transfer from position to color cues both on RT, $t(9)=2.8$, $p<.05$, and error percentages, $t(9)=2.9$, $p<.05$.
3. The coherence in results (i.e., similar sequence learning across training groups) in the present study between the training phase (with relatively large differences in baseline RTs) and the transfer phase (with relatively small differences in baseline RTs), indicates that differences in baseline RT did not affect the expression of sequence learning in the training phase. Hence, the choice of normalizing baseline scores as reported in the study by Robertson and Pascual-Leone (2001) may indeed have distorted the amount of sequence learning as expressed through RT differences between random and sequential order.
4. We assume here that the position cues were employed as the primary cues in the combined training group, as these are more S-R compatible than the color cues that were arbitrarily mapped onto the responses.

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Chapter 7

Controlled response selection benefits explicit, but not implicit sequence learning

Abstract

In two experiments with the serial reaction time task the effect of response selection processes on sequence learning was examined by manipulating stimulus-response compatibility between training groups. In Experiment 1 participants were first trained with either compatible or incompatible stimulus-response mapping. Then, to dissociate effects on sequence learning versus sequence performance, transfer across stimulus-response compatibilities was measured in order to allow comparison of sequence learning under similar conditions. Surprisingly, the data from the training phase showed that sequence learning was better with compatible than incompatible stimulus-response mapping. The divergent nature of this finding from those observed in previous studies (e.g., Deroost & Soetens, 2006b; Koch, 2007) was hypothesized to indicate that explicit but not implicit sequence learning is affected by stimulus-response compatibility. Experiment 2 supported this notion as stimulus-response compatibility did not affect sequence learning while employing a complex probabilistic sequence, known to produce very limited explicit sequence knowledge.

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INTRODUCTION

Sequential structure is a fundamental characteristic both of our behavior and of the events that surround us, as they typically do not occur in a random order but entail some sort of inherent structure. Both are relevant to goal directed behavior, as it benefits from acquiring the skill of appropriately sequencing one's actions, as well as from learning the structure underlying external events, thereby allowing anticipation. Sequence learning has been widely studied through the serial reaction time (SRT) task (Nissen & Bullemer, 1987), a paradigm that has been very productive over the last two decades, and has become one of the major tools in the investigation of implicit learning; for reviews, see Clegg, DiGirolamo and Keele (1998) and Shanks (2005). In its basic form, the SRT task is a continuous four choice reaction time task, in which subjects have to respond to the location of a stimulus. Unknown to them, however, stimulus locations (and hence the corresponding responses) are sequentially structured. Following practice subjects learn and use this structure, as indexed by shorter response latencies to the sequenced items than to a series of random locations. Additionally, many subjects are apparently unaware of any regularity during the training phase, or are aware of experiencing regularity but cannot clearly describe its nature. Since performance benefits still occur for participants with limited awareness, learning within this paradigm is typically regarded as mainly implicit (e.g., Seger, 1994).

One of the main issues within SRT research concerns the nature of implicit sequence learning; i.e. what exactly is learned in this task? In investigating the mechanism underlying implicit sequence learning, seemingly equivocal findings have been reported across literature. Specifically, in the debate about whether implicit sequence learning is based on stimulus or response features, support has been found for the involvement of both. On the one hand, Willingham and colleagues provided compelling evidence for implicit sequence learning being predominantly based on learning a series of successive response locations (Willingham, 1999; Willingham, Wells, Farrell, & Stemwedel, 2000). Their findings at the same time offered no evidence of any substantial role for stimulus information. On the other hand, however, over time sufficient evidence has accumulated that offers support for the role of stimulus information in implicit sequence learning (e.g., Abrahamse, Van der Lubbe & Verwey, 2008; Clegg, 2005; Deroost & Soetens, 2006a; Remillard, 2003; Ziessler & Nattkemper, 2000).

To accommodate this range of findings there seems to be an emerging consensus that sequence learning must be a distributed, multi-level phenomenon, as it can probably develop from multiple associations both within (i.e., response-based and/or perceptual learning) and between (i.e., response-effect learning; Ziessler & Nattkemper, 2000) stimulus and response features. However, response-based learning is still much better documented in the literature than stimulus-based learning or any multi-level approach, and it still seems to be the prevailing theory of implicit sequence learning for many authors (e.g., Bischoff-Grethe, Goedert & Willingham, 2004; Grafton, Hazeltine & Ivry, 1995; Nattkemper & Prinz, 1997; Rüsseler & Rösler, 2000; Willingham, 1999), also strengthened by the observation that implicit sequence learning is typically impaired in patient groups with movement disorders such as Parkinson's and Huntington's disease (see Doyon, 2008 for a review).

The simple dichotomy between stimulus- and response-based learning does not cover the whole range of possibilities (see Clegg et al., 1998). One of the less discussed levels in the literature concerns intermediate stages of information processing, such as the response selection stage: Can implicit sequence learning be based on a series of stimulus-response (S-R) associations? Initially, this was proposed by Willingham et al. (1989), but the idea was abandoned after it did not match with some of their later findings (Willingham, 1999; Willingham et al., 2000). Furthermore, Hoffman and Koch (1997) found that changes to S-R compatibility do not affect sequence learning, whereas Kinder, Rolfs and Kliegl (2008) showed reliable sequence learning in a case of maximal S-R compatibility (i.e. subjects were responding by merely looking at the target).

Recently, the interest in the involvement of S-R associations in sequence learning was renewed through two lines of research. First, it was observed that spatial sequence learning relies on many of the same brain areas as spatial response selection (Schwarb & Schumacher, 2008). Second, the sequence effect (i.e. the difference in response times and/or accuracy between a random test block intermitted at the end of training, and its surrounding sequence blocks) was found to be larger for spatially incompatible than for spatially compatible S-R mappings (Deroost & Soetens, 2006b; Koch, 2007). Even though these findings do not directly require that implicit sequence learning is actually based on S-R associations, these observations have been taken by some authors to suggest that the response selection stage has a mediating influence on implicit sequence learning (e.g., Deroost & Soetens, 2006b; Schwarb & Schumacher, 2008), and is thus actively involved in sequence learning. This will be referred to as the learning hypothesis.

The claim that S-R compatibility affects implicit sequence learning, however, is somewhat premature as it may rather be the expression of sequence learning that is manipulated by employing different S-R mappings. In other words, it may be that S-R compatibility does not affect implicit sequence learning itself, but rather only the benefits possible from within sequence performance. The problem of distinguishing effects on sequence performance from the effects on sequence learning is not an unfamiliar issue; seen previously for example in the effects of a dual task design on sequence learning. Frensch and colleagues (e.g., Frensch, 1998; Frensch, Wenke & Rünger, 1999) revealed how distraction by a second task can partly suppress the expression of sequence learning in an SRT task, rather than affecting learning itself[1]. Such an alternative account of the results of Deroost and Soetens (2006b) and Koch (2007) in terms of effects on performance will be referred to here as the performance hypothesis.

The obvious way to test this alternative hypothesis is by comparing performance on identical S-R mappings in a transfer phase. Thus, in Experiment 1 of the current study participants were trained with either compatible (i.e. the compatible training group) or incompatible S-R mapping (i.e. the incompatible training group), in line with earlier studies (e.g., Deroost & Soetens, 2006b; Koch, 2007). After training, they were presented with short transfer sessions (the order of which was counterbalanced across participants) that involved either the familiar S-R mapping or the alternative S-R mapping. The learning hypothesis can be understood to claim that sequence performance reflects the amount of acquired knowledge, and is independent from the specific S-R mapping employed at transfer. Conversely, the performance hypothesis implies that the benefit of sequence learning is dependent on the S-R mapping employed at transfer. It has to be noted that in the unfamiliar S-R mapping session, the response (location) sequence from training was always maintained, implicating a changed stimulus sequence on the screen. As response location learning (e.g. Willingham et al., 2000) is still widely accepted to be the dominant level of sequence learning, one could expect reliable transfer between S-R mappings.

EXPERIMENT 1

In Experiment 1 S-R compatibility was manipulated between training groups, and transfer to both compatible and incompatible S-R mappings was assessed for each training group. In order to reduce the effects of increased task difficulty when participants trained with compatible mapping were transferred to an incompatible mapping, all participants performed four blocks of pre-training with the incompatible mapping in which they had to respond to randomly structured trials. After this phase, participants were first trained in the corresponding condition, and learning was then tested in both compatible and incompatible mapping conditions.

According to the learning hypothesis, learning is determined during the training phase and, once established, it will be expressed independently of the S-R mapping employed. Hence, in accordance with previous results (Deroost & Soetens, 2006b; Koch, 2007), the incompatible training group would be expected to consistently show a larger sequence effect than the compatible training group for both the training and transfer phase. Conversely, if the smaller sequence effect for participants trained with a compatible as compared to an incompatible S-R mapping (Deroost and Soetens, 2006b; Koch, 2007) reflects an expression deficit instead of a real difference in sequence learning (i.e., performance hypothesis), then over the training phase we would still expect a larger sequence effect for the incompatible compared to the compatible training group. However, for both groups the sequence effect would be larger over the transfer task with incompatible rather than when compatible S-R mapping. Moreover, we would expect no differences in sequence effects to arise when both training groups are compared on matching S-R mappings over the transfer phase.

Method

Participants

Informed consent was obtained from 40 students (25 men) from the University of Twente, who participated in the experiment in exchange for course credits. They were aged between 18 and 28 (mean age 21.5), had no hand or vision problems, and were naïve as to the purpose of the study. The study was approved by the ethics committee of the Faculty of Behavioral Sciences from the University of Twente.

Apparatus and stimuli

Stimulus presentation, timing, and data collection were achieved using the E-prime© 1.1 experimental software package on a standard Pentium© IV class PC. Stimuli were presented on a 17 inch Philips 107T5 CRT display running at 1,024 x 768 pixel resolution in 32 bit color, and with a refresh rate of 85 Hz. The viewing distance was approximately 50 cm, but not strictly controlled. Stimuli consisted of four horizontally outlined rectangles (yellow lining and light-grey filling color) presented at a black background. From a viewing distance of 50 cm these rectangles measured 2.3° x 2.0°. The comparative stimulus consisted of the filling in red of one of the four rectangles.

Procedure

Participants were placed in front of a computer and received all instructions written on the screen. The task consisted of a typical SRT task, in which we manipulated S-R compatibility. For the compatible S-R mapping, stimuli from left to right on the screen were mapped on the c, v, b and n keys respectively. For the incompatible S-R mapping, stimuli from left to right on the screen were mapped on the n, b, v and c keys, respectively. All participants started with a pre-training phase in which an incompatible S-R mapping was employed in four blocks of pseudo-randomly ordered trials. The pseudo-random blocks in the pre-training phase consisted of a series of eight 12-element second-order conditional (SOC; sequence in which the next stimulus and response are perfectly predictable on the base of the two preceding trials, whereas the preceding trial by itself gives no information) sequences that were randomly picked from a pool of fifteen, with no element and sequence repetitions allowed. The pre-training phase was intended especially for the compatible training group, to prevent as much as possible strong influences of task difficulty when encountering the incompatible S-R mapping at transfer.

After the pre-training phase, half of the participants continued with the incompatible S-R mapping in the training phase (the incompatible training group), whereas the other half changed to the compatible S-R mapping (the compatible training group). In this training phase, all participants were performing a total of 13 blocks of 96 trials each; each block repeated the same 12-element SOC sequence eight times, except for blocks 5 and 16 in which the order was pseudo-random using the same procedure as explained above. The incompatible and compatible training groups were performing the same response sequence during sequence blocks, indicating that the sequence of stimuli on the screen were different between these groups. For all sequence blocks, the first trial was picked randomly, with the constraint of not producing a repetition with the second trial.

Finally, all participants entered the transfer phase in which they performed four blocks with the compatible S-R mapping, and four blocks with the incompatible S-R mapping. The order of S-R mapping was counterbalanced across participants. For both series of four blocks only the third one was sequential, with the other blocks being pseudo-random (again following the procedure explained above). In this transfer phase, during the unfamiliar S-R mapping (i.e. the one not used during training) the response sequence was maintained as response location learning is considered to be predominant in implicit sequence learning (e.g., Willingham et al., 2000), indicating a mirror sequence of stimuli on the screen.

Participants were instructed to respond as quickly and accurately as possible to the location of each stimulus, using the middle and index fingers of both hands to press the c, v, b, and n keys on the keyboard. A correct response was defined as the participant pressing the appropriate key within a 2-sec time limit. Erroneous responses were signaled to the participants, after which the next stimulus was presented after a 2-sec interval. This relatively long interval was intended to motivate the participant to prevent errors. Short 30-sec breaks were provided in between blocks. With numbers denoting stimulus location from left to right, half of the participants of both the compatible and the incompatible training groups trained with the SOC sequence 342312143241, and the other half of participants of both groups trained with the SOC sequence 213243412314. Response-to-stimulus-interval (RSI) was always 50 msec.

After the computer tasks, participants performed a free generation task to examine the extent to which they were aware of the order of the sequence elements. This involved telling them that there had been a 12-element fixed order and then having them write down the complete 12-element sequence that according to them had been repeated during the experiment (e.g., Witt & Willingham, 2006; Abrahamse & Verwey, 2008).

Results

Reaction time (RT) analyses excluded both erroneous key presses and RTs exceeding the criterion of mean plus 3 standard deviations (calculated per block). This eliminated less than 5% of the data in the acquisition and transfer phase. Mean reaction times and accuracy scores were calculated for each block, for each participant. For two participants the data for Block 1 of the pre-training phase was not registered due to technical malfunction. Analyses on the pre-training were therefore performed on the remaining 38 participants. Greenhouse-Geisser correction was applied where appropriate.

To obtain awareness scores we counted the number of correctly reproduced chunks of three elements (as the training involved SOC sequences each next stimulus can be predicted on the basis of the two previous stimuli, whereas the previous stimulus by itself provides no predictive information).

Awareness

An independent t-test performed on awareness scores between the compatible (M=3.8) and the incompatible training group (M=3.4) did not indicate a reliable difference (*p*>.35). Furthermore, considering a post-hoc split-group variable on awareness scores in all analyses reported below did not produce reliable interactions. Therefore, awareness will not be included in further analyses.

Pre-training phase

In the pre-training phase, all participants performed 4 pseudo-random blocks with an incompatible S-R mapping. An ANOVA on mean RTs and mean error percentages (PEs) was performed with Block (4; Block 1 to 4) as a within-subject variable and Group (2; compatible versus incompatible training group[2]) as between-subject variable. This resulted in reliable main effects for Block on both RTs, *F*(3,108)=21.4, *p*<.05, partial η^2 = .37, and PEs, *F*(3.108)=12.4, *p*<.05, partial η^2 = .26. Both indicated improved performance with practice. There were no other significant effects.

Training phase

Figure 1 shows the mean RTs for the training phase. An ANOVA on RTs was performed with Block (10; Block 6 to 15) as a within-subject variable and Group (2; incompatible versus compatible training group) as a between-subject variable. This resulted in reliable main effects for both Block, *F*(9,342)=32.8, *p*<.05, partial η^2 = .46, and Group, *F*(1,38)=39.6, *p*<.05, partial η^2 = .51. Moreover, a reliable Block x Group interaction, *F*(9,342)=2.8, *p*<.05, partial η^2 = .07, was found, indicating superior performance improvements across training for the incompatible training group. A similar ANOVA on PEs resulted in a reliable Group main effect, *F*(1,38)=3.1, *p*<.05 (one-sided), partial η^2 = .07, indicating more errors on average for the incompatible than for the compatible training group.

To explore sequence learning, a second ANOVA was performed on RTs with Block (2; Block 16, versus the mean of Blocks 15 and 17) as a within-subject variable, and Group (2; compatible versus incompatible training group) as a between-subject variable.

This resulted in reliable main effects for Block, $F(1,38)=78.0$, $p<.05$, partial $\eta^2 = .67$, and Group, $F(1,38)=32.7$, $p<.05$, partial $\eta^2 = .46$, and, more importantly, a reliable Block x Group interaction, $F(1,38)=6.7$, $p<.05$, partial $\eta^2 = .15$. In contrast with expectations based on earlier work (e.g. Deroost & Soetens, 2006b), and thus with the predictions of both theoretical hypotheses being tested, the latter indicated a larger sequence effect for the compatible (67 ms) than for the incompatible training group (37 ms). A similar ANOVA on PEs resulted only in a reliable Block main effect, $F(1,38)=13.9$, $p<.05$, partial $\eta^2 = .27$.

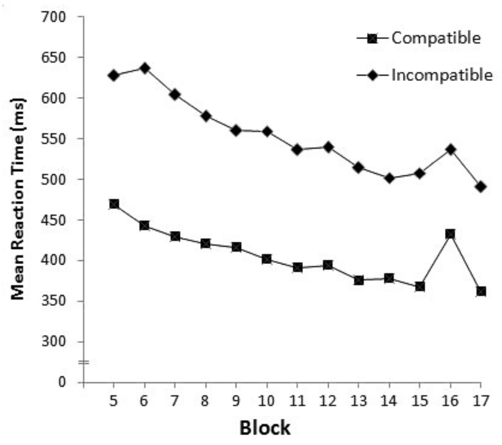

Figure 1. Mean reaction times for the training phase of Experiment 1, with Blocks 5 and 16 pseudo-random. Please note that the pre-training phase (Block 1-4) is not depicted here.

Transfer phase

Figures 2 and 3 show the sequence effects on both RTs as well as PEs for the transfer tasks of both the compatible and incompatible training groups. Sequence effects were calculated separately for the compatible and incompatible transfer tasks from the difference in mean RTs and PEs between the sequence block and the average of its immediately surrounding pseudo-random control blocks. Then, to see whether transfer varied as a function of prior training, an ANOVA on RTs with Transfer (2; compatible versus incompatible mapping) as within-subject variable, and Group (2; compatible versus incompatible training group) as between-subject variable was performed on these difference scores. This resulted in a reliable main effect for Transfer, $F(1,38)=10.3$, $p<.05$, partial $\eta^2 = .21$, and a reliable Transfer x Group interaction, $F(1,38)=38.8$, $p<.05$, partial $\eta^2 = .51$. A similar ANOVA on PEs resulted in a reliable Transfer x Group interaction, $F(1,38)=6.9$, $p<.05$, partial $\eta^2 = .16$. More detailed analyses indicated reliable differences between groups (compatible versus incompatible training group) in both the compatible, $t(38)=5.0$, $p<.05$, d=1.58, and the incompatible S-R mapping transfer, $t(38)=3.3$, $p<.05$, d=1.57, on RTs. There were no reliable differences on

PEs, though there was a near reliable difference in PEs between compatible and incompatible training groups on the incompatible S-R mapping transfer session (*p*=.07).

Finally, for each training group we performed one-sample t-tests (test value = 0; adjusted critical p-value = .0125) for each transfer task on both RTs and PEs. For the compatible training group positive transfer was observed to the compatible transfer task on both RTs, *t*(19)=8.0, *p*<.0125, and PEs, *t*(19)=5.2, *p*<.0125. No transfer was found for this group to the incompatible transfer task on either RTs or PEs (*p*s>.6). Note that response locations, which are thought to constitute the major base of implicit sequence learning, remained unchanged at transfer. For the incompatible training group positive transfer was found to the incompatible transfer task on both RTs, *t*(19)=5.4, *p*<.0125, and PEs, *t*(19)=2.8, *p*<.0125, as well as to the compatible transfer task on both RTs, *t*(19)=4.8, *p*<.0125, and PEs, *t*(19)=2.8, *p*<.0125.

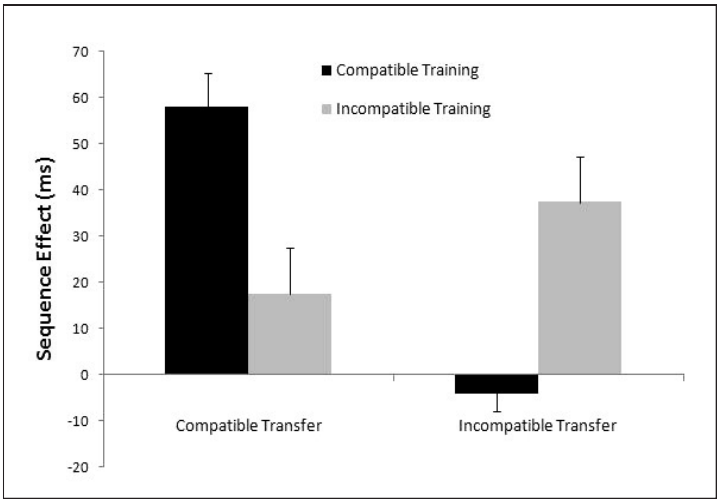

Figure 2. Mean sequence effects (i.e. the difference in scores on sequence versus pseudo-random blocks) for the reaction times (ms) of the transfer phase of Experiment 1.

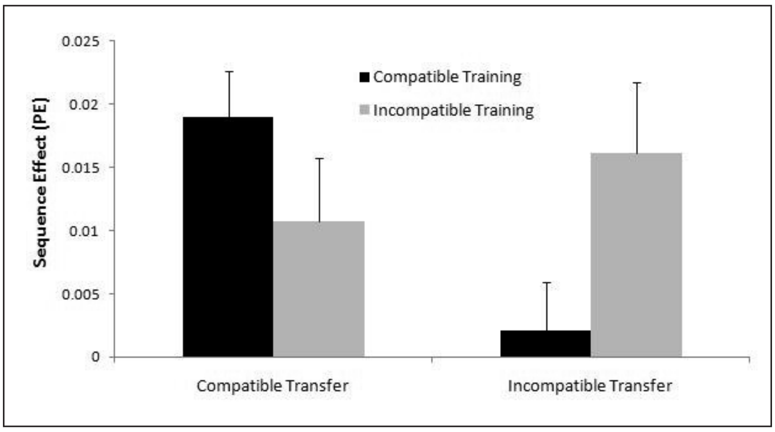

Figure 3. Mean sequence effects (i.e. the difference in scores on sequence versus pseudo-random blocks) for the error percentages of the transfer phase of Experiment 1.

Discussion

Experiment 1 aimed at testing whether the increased effects of sequence learning observed in previous studies by arranging lower levels of S-R compatibility could be attributed either to differences in the acquisition or in the expression of learning. Both learning and performance hypotheses produced clear predictions regarding training and transfer (see above). However, our results were not in accordance with any of the above stated predictions. Indeed, whereas positive transfer in both directions was expected as the response locations were maintained from training to transfer, we observed zero transfer from compatible to incompatible S-R mapping, and only a reduced transfer from the incompatible to the compatible conditions. Furthermore, the training phase also produced a surprising result, as the difference between groups over the training phase was reversed from what we had expected: In contrast with earlier studies that manipulated spatial S-R compatibility (i.e. Deroost & Soetens, 2006b; Koch, 2007; Experiment 1), a larger sequence effect was observed for the group that was trained with compatible S-R mapping than for the group that was trained with incompatible S-R mapping.

The data of Experiment 1 do not provide support for either the learning or the performance hypothesis. Even though the two transfer tests of the incompatible training group would be in line with the performance hypothesis as sequence performance was better with incompatible than compatible S-R mapping, the data from both the training phase (see below) as well as the transfer tests of the compatible training group are not compatible with either the learning or performance hypothesis. Although response locations remained unchanged, we observed no transfer from compatible to incompatible S-R mapping. The asymmetrical performance on the transfer tests between the incompatible and compatible training groups may be interpreted in various ways. It could be that transfer is affected by task difficulty, with better transfer obtained from a difficult to an easy task than vice versa. Alternatively, it may be that transfer is affected by control demands, so that those tasks requiring an increase in control demands, such as performing an incompatible mapping after being trained with a compatible mapping, would automatically inhibit the flow of implicit knowledge. Finally, one may argue that different S-R mappings during SRT training lead to qualitatively different sequence representations, with the compatible S-R mapping inducing a more stimulus-based, and the incompatible S-R mapping inducing a more response-location based sequence representation. The former two are hard to disentangle empirically, as a change in task difficulty typically is accompanied by a change in control demands. The latter would provide further support against the unconditional dominance of response location learning in the SRT task, as we observed zero or only partial transfer between two conditions that imposed the exact same response demands. We will elaborate on all these possibilities below in the General Discussion section.

The results from the training phase are no less surprising than those obtained over the transfer phase: contrary to earlier studies we observed a larger sequence effect for the compatible than the incompatible training group. This does not fit with either the performance or the learning hypotheses. First, we believe that the training phase invalidated the performance hypothesis. As noted above, the only significant difference in design between Experiment 1 of the current study and the study of Deroost and Soetens (2006b) concerns the pre-training phase. This clearly did not change the fact that S-R selection processes in the incompatible training group were more time demanding than those in the compatible training group (i.e. baseline RTs were reliably higher in the former group). Then, if the difference in sequence effect between compatible and incompatible training groups in earlier studies indeed reflected only performance differences caused by a more time demanding S-R selection process, a similar pattern as found in earlier studies (i.e. a larger sequence effect for the incompatible training group) should have been observed here. However, this was not the case as the sequence effect was reliably larger for the compatible training group.

Second, concerning the learning hypothesis, one could argue that in line with this hypothesis, the pre-training phase may have caused the incompatible S-R mapping to become significantly more automated as compared to Deroost and Soetens (2006b). This would render response selection less demanding during the subsequent training blocks, causing the response selection stage to mediate sequence learning to a lesser extent (i.e. more similar to a condition with compatible S-R mapping). However, if that were the case, then one could expect to observe similar sequence effects between the two training groups in Experiment 1, at most, but never a lower sequence effect for the incompatible training group. Hence, the current findings from the training phase cannot be easily explained in line with the learning hypothesis.

Overall, then, one is left looking outside of the two previously proposed hypotheses for a mechanism to account for the entire pattern of data. One possibility in trying to account for the reversed finding in the training phase involves taking into consideration the role of sequence awareness. Indeed, Deroost and Soetens (2006b) did not consider the issue of awareness, and Koch (2007; Experiment 1), reported that higher scores were obtained for the incompatible than for the compatible training group, even though this difference was not significant. It has been noted before that explicit knowledge may exist, even when it is not reliably shown through subsequent awareness tests (e.g., Shanks, 2003). Furthermore, in studies exploring non-spatial or task-irrelevant spatial S-R incompatibility it has been shown that explicit knowledge may serve to overcome the conflict of an incompatible S-R mapping at the response selection stage, whereas implicit sequence knowledge would be far less useful in this regard (i.e. Koch, 2007; Experiment 2 and 3; Hoffmann & Koch, 1997).

Thus, it is possible that in the studies of Deroost and Soetens (2006b) and Koch (2007; Experiment 1) higher awareness for participants that trained with incompatible S-R mapping in fact caused the larger sequence effect compared to those that trained with compatible S-R mapping, but that this increased awareness went undetected for a variety of reasons, including the lack of process-pureness of awareness tests. Put differently, it could be that more controlled response selection did not affect implicit but explicit sequence learning. It is not hard to imagine that participants who train with more demanding S-R mappings, could be more highly motivated to actively search for regularity, because that may help them to overcome conflict, and thereby decrease task demands. Furthermore, earlier work has shown that higher RSIs tend to induce higher awareness (e.g. Destrebecqz & Cleeremans, 2001), presumably as participants are able to use this time for explicitly searching for regularity. It may be that the extra time it costs to select a response with incompatible S-R mappings can also (partly) be used for this purpose.

The pre-training phase with random stimuli that was introduced in our Experiment 1 may have been sufficient to have participants abandoning any search strategy for regularity before the training phase even started, as they did not find any regularity during the first four pre-training blocks. This could explain the discrepancy between our data and the findings of Deroost and Soetens (2006b). Indeed, in Experiment 1 of the current study, the compatible training group showed a larger sequence effect, as well as higher (though not significantly) scores on the awareness test.

With SOC sequences and with relatively easy probabilistic sequences as used by Deroost and Soetens (2006b)[3], sequence learning has a high probability of ending up being a mix of implicit and explicit effects. As noted above, trying to control for explicit learning with post-hoc awareness tests is a tricky mission, as none of the existing awareness tests have been proven to be fully process-pure.

An alternative way to tackle the problem may be to prevent explicit sequence learning as much as possible. It has been shown that some probabilistic SOC sequences produce little if any sequence awareness within participants (e.g., Stefaniak, Willems, Adam & Meulemans, 2008). Therefore, in Experiment 2 we manipulated S-R compatibility between groups that trained with probabilistic 12-element SOC sequences. If awareness was responsible for the larger sequence effect in participants trained with incompatible S-R mapping in Deroost and Soetens (2006b) and Koch (2007), then employing probabilistic SOC sequences should eliminate the difference between S-R mapping groups.

EXPERIMENT 2

Method

Participants

Informed consent was obtained from 43 (14 men; ages between 18 and 22; mean age 18.5) undergraduates from Colorado State University. They participated in the experiment in exchange of partial, optional course credit.

Apparatus and stimuli

The same equipment and stimulus materials were employed as in Experiment 1.

Procedure

Experiment 2 was very similar to the training phase of Experiment 1 (i.e. there is no pre-training or transfer phase involved in Experiment 2). The only differences are the number of blocks, the number of trials per block, the sequential structure across blocks, and the awareness test employed after the SRT task. Specifically, in Experiment 2 participants (23 with compatible S-R mapping, and 20 with incompatible S-R mapping) performed a total of 14 sequence blocks containing 120 trials each. Most importantly, rather than the fixed SOC sequences of Experiment 1, in Experiment 2 a probabilistic sequence was employed in a design similar to Schvaneveldt and Gomez (1998). The two 12-element SOC sequences (121432413423 and 323412431421, with numbers denoting stimulus locations from left to right) that were used to generate both training (i.e., probable) and control (i.e., improbable) trials for each block were adopted from Jiménez and Vázquez (2005), and are matched for the number of reversals (e.g. one in both sequence), and are maximally discriminative between sequences (i.e. they do not share a run of three elements). For each block, 120 trials were produced on the base of these two sequences by selecting 80% of the trials according to the training sequence, and generating the remaining 20% according to the control sequence. Each of the two sequences was used as the training sequence for half of the participants, and thus served as the control sequence for the other half. It should be noted that all blocks were sequential, as with probabilistic sequences it is possible to measure sequence learning online, and thus no random test is required.

After performing the 14 training blocks, participants performed a process dissociation procedure (PDP) as described in Destrebecqz and Cleeremans (2001) to measure awareness of the training sequence. This task may provide a stronger measure of awareness than the forced free recall questionnaire employed in Experiment 1. The PDP consisted of two free generation tasks of 96 key presses, first under inclusion instructions (i.e. participants were required to reproduce as much of the experimental sequence as possible), and subsequently under exclusion instructions (i.e. participants were required to avoid the experimental sequence as much as possible). In the latter task, participants received the additional instructions that a) no repetitions were involved in the experimental sequence, and b) no strategy was allowed to facilitate performance at the PDP task (e.g., constantly repeating a small and unfamiliar set of key presses in the exclusion task).

Results

RT analyses excluded erroneous key presses. Mean reaction times and accuracy scores were calculated for both training and control trials, for each block of each participant. PDP scores were calculated for both the inclusion and exclusion task by counting for each participant the number of correctly reproduced chunks of three elements from the training sequence. With 96 key-presses, the maximum number correct is 94 chunks of three elements. Moreover, with the explicit instruction that no repetitions were involved in the experiment, chance level of correctly reproduced chunks of three elements is 31.33 (i.e. after every two elements, three possibilities remain for the third element; one of which is correct).

Awareness

An ANOVA was performed on PDP scores with Task (2; inclusion versus exclusion) as within-subject variable, and Group (2; compatible versus incompatible training group) as between-subject variable. This produced no reliable main effects or interaction. Then both the PDP inclusion (M=37.0) and PDP exclusion (M=34.2) scores (collapsed across all participants) were compared to chance level with one-sample t-tests (one-sided; test value = 31.33). This showed that both the PDP inclusion, $t(42)=2.8$, $p<.01$, and the PDP exclusion scores, $t(42)=1.9$, $p<.05$, exceeded chance level. Overall, this indicates that there was very little explicit knowledge, which is in line with expectations with complex probabilistic sequences.

Response times

Figure 4 shows the mean RTs for the compatible and incompatible S-R mapping groups for the training phase of Experiment 2. An ANOVA was performed on RTs with Block (14; Block 1 to 14) and Trial (2; training versus control) as within-subject variables, and Group (2; compatible versus incompatible training group) as between-subject variable. This resulted in the expected reliable main effects of Trial, $F(1,41)=110.8$, $p<.05$, partial $\eta^2 = .73$, Block, $F(13,533)=20.5$, $p<.05$, partial $\eta^2 = .33$, and Group, $F(1,41)=67.2$, $p<.05$, partial $\eta^2 = .62$. Furthermore, there were reliable interactions between Block x Group, $F(13,533)=7.9$, $p<.05$, partial $\eta^2 = .16$, and Trial x Block, $F(13,533)=3.0$, $p<.05$, partial $\eta^2 =.07$. The former interaction indicates superior overall performance improvement across training for the incompatible training group. The latter interaction indicates reliable sequence learning, as the difference in RTs for training and control trials increases across training. Importantly, the three-way interaction between Block x Trial x Group was far from significant (*p*=.33, partial $\eta^2 = .03$), indicating that sequence learning did not differ between training groups.

To further explore whether any potential differences between the compatible and incompatible training groups may have existed, additional analyses were performed on various subsets of the training blocks to seek differences early or late in training. The same analysis as above were performed for a) Block (6; block 1-3 and 12-14), b) Block (4; blocks 1, 2, 13, and 14), c) Block (3; blocks 12, 13 and 14), and d) Block (2; blocks 13 and 14). In all cases, critical results were analogous, with the three-way interaction being far from significant. The difference in absolute RT at the end of the training between training and control trials was always slightly larger (though not reliable) for the compatible than the incompatible training group, whether averaged solely over the final block (62 vs 43 ms), over the final two blocks (56 vs 46 ms), or over the final three blocks (55 vs 52 ms).

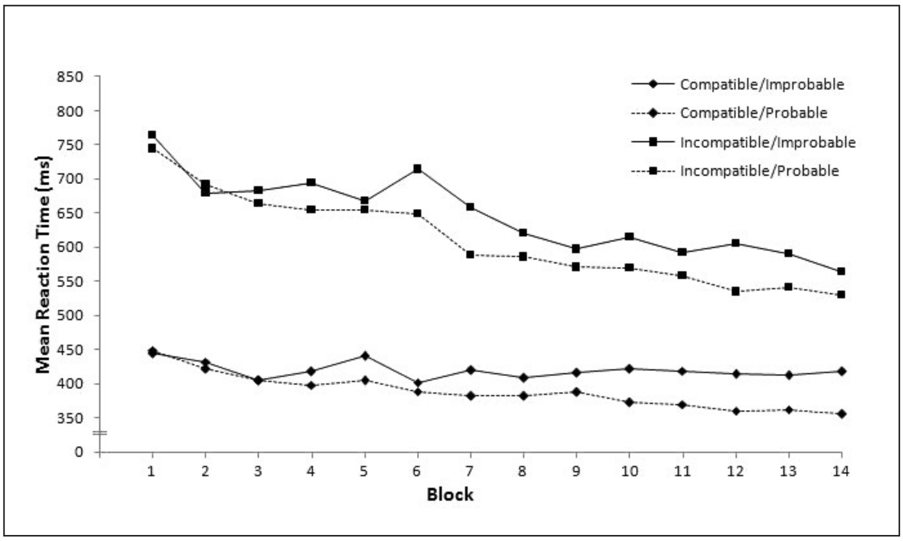

Figure 4. Mean reaction times (ms) for the <u>compatible</u> and <u>incompatible training groups</u> of Experiment 2 for both training (80% probable; dashed line) and control trials (20% probable; fixed line).

Error percentages

A same ANOVA as for RTs was performed on PEs. This resulted in reliable main effects for both Trial, $F(1,41)=43.6$, $p<.05$, partial $\eta^2 = .52$, and Block, $F(13,533)=2.0$, $p<.05$, partial $\eta^2 = .05$. Furthermore, reliable interactions were observed between Block x Group, $F(13,533)=2.6$, $p<.05$, partial $\eta^2 = .06$, and Trial x Block, $F(13,533)=3.2$, $p<.05$, partial $\eta^2 = .07$. The former interaction is mainly caused by relatively low PEs on the first and second block for the incompatible training group. The latter interaction reflects larger differences with practice between PEs on control versus training trials, indicative of sequence learning. Again, the three-way interaction was not significant ($p>.25$).

Discussion

Experiment 2 tested the hypothesis that the increased sequence effect in the SRT task as observed for participants training with spatially incompatible S-R mapping (Deroost & Soetens, 2006b; Koch, 2007; Experiment 1) could be related to superior explicit learning, and thus would not be obtained when the sequence is complex and probabilistic. The results were consistent with this idea as a difference in sequence effect between compatible and incompatible S-R mapping was not observed with probabilistic SOC sequences, which are known to result in little explicit knowledge.

It is always dangerous to be looking for the absence of effects, as such an absence may be due to a lack of sufficient power to detect such variations in learning. Therefore, a) we performed the analysis on different combinations of blocks, always showing the absence of an interaction between Group, Block and Trial, and b) we showed that the sequence effect at the end of the training was always in favor of the compatible S-R mapping group. Finally, an a priori analysis of power suggested that to obtain a power of .95 we would need a sample of 44 participants (43 participants were included in Experiment 2), based on effect size = 0.2, $\alpha = .05$, correlation among repeated measures = .75, and nonsphericity correction (Buchner, Erdfelder, & Faul, 1997). Thus while we naturally cannot rule out such an explanation of a null effect, the current data would seem to imply that at the very least the size of any effect of response selection within probabilistic sequences is decidedly small.

GENERAL DISCUSSION

The current study explored the claim that more controlled response selection processes (as is presumably the case with incompatible S-R mappings) would benefit implicit sequence learning (Deroost & Soetens, 2006b). Two experiments presented here run counter to this claim. Specifically, contrary to earlier findings of Deroost and Soetens (2006b) and Koch (2007; Experiment 1), it was observed that sequence learning was not better for incompatible than compatible S-R mapping when a) four pseudorandom blocks with incompatible S-R mapping were presented before the actual training phase (Experiment 1), and b) a probabilistic sequence was employed (Experiment 2).

A mediating role of sequence awareness seems to be the most parsimonious explanation for this pattern of results. Participants employing an incompatible S-R mapping may be highly motivated to engage in an active search for regularity, as that helps them to overcome the relatively effortful response selection process. This led to improved (explicit) sequence learning in the studies of Deroost and Soetens (2006b) and Koch (2007; Experiment 1). However, in both experiments presented here, such a search was not immediately beneficial. First, the four pseudo-random blocks at the beginning of Experiment 1 may have discouraged further active search during the actual sequence training. Second, Experiment 2 employed a fairly complicated probabilistic sequential structure which is hard to figure out even when actively attempting to do so (e.g., Stefaniak et al., 2008). Thus, in line with suggestions in earlier work (Koch, 2007; Experiment 2 and 3) the current findings seem to suggest that not implicit, but explicit sequence learning is prompted by incompatible S-R mappings.

The current findings weaken the available support for an active role of the response selection process in implicit sequence learning (cf. Kinder, Rolfs & Kliegl, 2008). However, as stated above, it does not exclude the possibility that S-R associations constitute one of the building blocks of implicit sequence learning in terms of a multilevel account, alongside with, for instance, perceptual, response effect, and response location learning. Future research will be needed to explore this in more detail.

One concern remains, however, regarding the current findings: Why was sequence learning better for the compatible than the incompatible training group in Experiment 1, whereas no difference was observed in Experiment 2? Knowing that explicit sequence knowledge improves sequence performance with deterministic but not probabilistic SOC sequences (e.g., Stefaniak et al., 2008), this difference might also be tentatively explained by slightly higher levels of sequence awareness being obtained for the compatible as compared to the incompatible training group in Experiment 1. In fact, awareness scores were nominally higher for the compatible training group in this experiment, although no significantly so. This notion, at first glance, seems to be in contradiction with the claim that incompatible S-R mapping could induce an increase in explicit knowledge. However, one may argue that such an increase is only to be expected when an early search strategy results in the discovery of a regular structure, which could not be achieved in Experiment 1 because of the interposition of a relatively large number of initial random blocks. Without the aid of such an active strategy, one may speculate that only for a compatible mapping substantial explicit knowledge could be acquired, whereas the high cognitive demands required by incompatible S-R mapping prevented this.

As noted above, the transfer data from Experiment 1 are also somewhat surprising, especially the lack of transfer from compatible to incompatible mapping. Response location learning is usually considered a dominant form of implicit sequence learning, and in Experiment 1 the response location sequence did not change between training and transfer, so that one could expect sequence learning to have been transferred completely over these transfer task. Interestingly the evidence offered by Willingham (1999, Experiment 3) in defending his case for a response-based representation of sequence learning within the SRT, included only transfer from less compatible to more compatible responses, but not the reverse.

One explanation for the absence of transfer from a more compatible condition to a less compatible condition here might be that the current data are simply an anomaly. A very similar pattern, however, was reported by Clegg (1998; experiment 5), thus suggesting that the apparent asymmetry of transfer observed within Experiment 1 merits some more attention. Above we have mentioned three possible interpretations of these results. To close this article, we will elaborate a little bit more deeply on these possibilities.

First, it could be that task difficulty affects transfer of sequence knowledge. Specifically, going from a relatively easy to a more difficult task (i.e. from compatible to incompatible conditions) could increase the resources needed to perform the task, thereby leaving less resource to express the implicit sequence knowledge. The other way around (i.e. from incompatible to compatible conditions) could initially be experienced as a difficult task in that it requires a change in the S-R rules, but this initial experience would be almost immediately overcome as the S-R processes are easier over transfer. This would explain the partial but reliable transfer observed in this direction. However, this reasoning relying on the idea that applying implicit sequence learning requires cognitive resources is not completely consistent with the fact that, in Experiment 2, we observed no differences in learning between compatible and incompatible training groups throughout the whole experiment.

A second, closely related but fundamentally different explanation has to do with control processes. It could be argued that when the control demands of the task at hand change, this affects all automatic processing not because they require resources unavailable, but because the system is able to actively suspend many of its ongoing automatisms. Thus, when response selection becomes more demanding over an incompatible S-R transfer, the whole S-R process comes under direct control, thereby suspending all automatic processes related to responding; including implicit sequence effects. In contrast, when response selection becomes less demanding over a compatible transfer, controlled processing could take over just briefly over the transition, but the automatisms will soon be restored, thereby explaining the observed partial transfer. This account can be linked to the growing discussion on the existence of truly automatic processes, and on a host of phenomena showing that seemingly “automatic” processes often allow for some sort of control operations as well (e.g., Stroop interference; Tzelgov, Henik & Berger, 1992).

Finally, from a multiple level model of sequence learning, it could be argued that the compatible and incompatible training groups developed qualitatively different sequence representations. Multiple forms of implicit sequence learning have been identified in the literature so far (e.g., stimulus-based learning, response location learning, response-effect learning). It could be that the brain somehow tailors the representation of the sequence to the requirements of the task at hand, implying possibly different representations for different variations of the SRT task. Indeed, it has been argued (see Clegg, 1998) that a more compatible training group results in a more stimulus-based representation that can not transfer when the stimulus sequence is changed, whereas an incompatible training group results in a representation that is dominated by response (location) information. This would explain the pattern of transfer data from Experiment 1.

Furthermore, this latter view would be consistent with a selective attention argument. In compatible conditions, the most important dimension to be processed is the location of the stimulus, because responses are obvious after locating each stimulus. In incompatible conditions, however, participants may learn about the series of stimuli, but more emphasis is made on the location of responses which is no longer obvious for each stimulus. Further research is needed to explore this in more detail, as these are all post-hoc explanations of a complex set of results.

To summarize, the current study indicates that an increase of demands at the response selection stage does not unconditionally improve sequence learning. In two experiments we observed less or equal sequence learning for incompatible compared to compatible S-R mapping. We proposed to explain these findings by claiming that more controlled response selection processes do not mediate implicit, but rather explicit sequence learning. Earlier studies supported this notion for non-spatial or task-irrelevant spatial S-R compatibility (i.e. Koch, 2007; Experiment 2 and 3), and the present findings extend this notion to task relevant, spatial S-R compatibility. Overall, this weakens the support for the view that S-R associations should be considered as one of the building blocks of implicit sequence learning, even though it does not directly focus this issue. Furthermore, it once again stresses the necessity to consider awareness as a significant factor in explaining SRT findings, even when post-hoc awareness measures do not directly indicate this concern.

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NOTES

1. Though it has to be noted that various other explanations implying a direct effect of a secondary task on sequence learning have received empirical support (e.g., Jiménez & Vázquez, 2005).
2. Please note that the Group variable in this analysis is artificial, as all participants performed an identical task.
3. The probabilistic sequence employed by Deroost and Soetens (2006) can be broken down into the following rule: "expect an extreme location (i.e. 1 or 4) after locations 1 or 2, and a central location (i.e. 2 or 3) after locations 3 or 4".

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Chapter 8

Designing training programs for perceptual-motor skills: Practical implications from the serial reaction time task

Abstract

Within various domains, such as sports and the military, training programs are being designed to effectively and efficiently guide perceptual-motor skill acquisition. Even though this notion is often underestimated, the design of such training programs may greatly benefit from findings and theories from basic cognitive psychology. One particular basic paradigm that speaks to this issue is the serial reaction time task. In the current article we take on the challenge to review this paradigm from an applied point of view. We highlight a range of themes that have been explored with this paradigm that could have a direct relevance for the process of optimizing training procedures for perceptual-motor skill acquisition.

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INTRODUCTION

Within the field of cognitive psychology, one might distinguish between basic and applied branches. Basic cognitive psychology is devoted to understanding into its elementary components the underlying mechanisms of (human) cognition and behavior. In contrast, applied cognitive psychology[1] is concerned with producing knowledge that is directly applicable in the overcoming of real-life problems, and promotes well-being. At first sight, these two approaches of cognitive psychology take on different, sometimes even conflicting ways of working. The former seeks in-depth knowledge of a particular scientific issue, whereas for the latter knowing the surface structure usually suffices (i.e., "Does it work or not?"). Nonetheless, they are intimately entangled, and have valuable information to offer to each other in what may be seen as a "back-to-back" relationship: basic research provides new insights that can be employed with respect to real life problems; and existing real life problems may prompt new questions for basic researchers (for similar ideas see Hutchins, 1995; Neisser, 1976; Parasuraman and Rizzo, 2008).

Research on serial skill in perceptual-motor tasks is typically approached from a basic experimental perspective. However, the potential impact of such research on real life themes and topics should not be ignored. For instance, the construction of training (or rehabilitation) methods and programs related to a variety of perceptual-motor skills may greatly benefit from building upon the concepts and findings from basic psychological research on skill acquisition. In this review, we aim to illustrate the relevance of the findings from a particular basic cognitive paradigm, called the serial reaction time (SRT) task (Nissen & Bullemer, 1987; see below), from an applied point of view. Our main claim is that training and transfer of serial perceptual-motor skills can be optimized by taking into account the findings and theories from basic cognitive paradigms such as the SRT task. To further develop this claim within an appropriate application domain, in some sections of this article we will elaborate on possible implications of basic findings with the SRT task for the use of technology in training, and VR technology in particular.

DESIGN OF TRAINING PROGRAMS

Every year a lot of time and resources are spent on training – both of intellectual (i.e., purposing a symbolic outcome) and (perceptual-)motor skills. Efforts made in education, industry, sports and the military are geared towards providing trainees with the relevant skills to successfully fulfill their professional goals and duties. In terms of reducing costs, important considerations are training efficiency, retention, and adequate transfer of training. Training efficiency is involved with the question of how to reach sufficient quality of acquired skills while expending a minimum of time and resources. Transfer adequacy refers to flexibility of a certain skill to be useful in situations other than the one in which the skill was initially acquired (i.e., the training context). Finally, skill retention refers to the extent that a learned skill is maintained over time. These concepts are highly relevant to skill training, and can typically be successfully approached from a basic perspective in order to obtain clean, reliable and interpretable measures.

The design of training programs does not need to be approached differently than any other product design. Wickens and Hollands (2000) presented a simple model of the iterative process of product design, in which a product is refined on the base of an evaluation by users. To render this evaluation cycle effective, it is important to gather the relevant information from the users. To this purpose, there are various methods (see Wickens and Hollands, 2000), including field studies, surveys, and laboratory experiments. Each of these has its strengths and weaknesses, and some methods are thus more appropriate in particular circumstances than others. Laboratory experiments, the focus of the current article, are possibly most useful in the early stages of the design process. They offer the potential to explore the effects of manipulating a particular variable in a highly controlled environment, hence preventing against confounding of variables that lay outside the range of interest. It must be noted, however, that eliminating variables one is not (directly) interested in, may also have a downside. Placing a particular task outside real life context arguably changes fundamental task aspects, rendering it difficult to justify the ecological validity of findings and implications. In other words, are we still investigating in the laboratory a mechanism that is present in real life human activities?

A major merit of controlled laboratory experiments is that it can gather information from users that would otherwise possibly remain concealed. Even though people’s metacognitive assessments may often match well with their actual performances (e.g., Hart, 1965), there are clear examples of situations in which people's evaluations were not reliable, or even negatively related to their own future performance (e.g., Baddeley & Longman, 1978; Benjamin, Bjork & Schwartz, 1998; Jacoby & Kelley, 1987). Basic cognitive research has shown that serial perceptual-motor skill acquisition is a clear example of a domain in which people develop new skills in the relative absence of awareness of this progress (e.g., Nissen & Bullemer, 1987; Clegg, DiGirolamo & Keele, 1998; Keele, Ivry, Mayr, Hazeltine & Heuer, 2003). Directly measuring performance (e.g., reaction times and error percentages) very precisely in a laboratory setting, then, may enable users to express learning-related information of which they are not precisely aware themselves.

Training of sequential perceptual-motor skills

Serial perceptual-motor skills refer to skills that involve learning a fixed pattern of goal-directed movements, while at the same time emphasizing the significant role of perceptual processing for these skills. These skills are essential for human activities. If one would perform a task-analysis on activities such as playing sports, playing a musical instrument, driving a car, walking down the stairs, or picking up a cup of tea, one major aspect would concern the sequencing of information and/or action. In order to study serial perceptual-motor skills in a controlled laboratory setting, various paradigms have been developed that are all more or less related to each other, such as the discrete sequence production (DSP) task (e.g., Verwey, 1996; 2003), the 2x5 task (e.g., Hikosaka, Sakai, Miyauchi, Takino, Sasaki & Putz, 1996), and the SRT task (e.g., Nissen & Bullemer, 1987). The latter task is the most frequently used of these, and by now firmly grounded in a vast literature.

In a basic SRT task, participants are seated behind a regular desktop computer. They are asked to rest four designated fingers (e.g., the middle and index fingers of both the left and right hand) on specific keys of a regular keyboard (e.g., the c, v, b and n keys on a regular QWERTY keyboard). Four possible stimulus locations (i.e., placeholders) are presented on the screen and remain there throughout the experiment. Participants are required to respond as fast and accurately as possible to the locations of a series of stimuli that are successively presented on the screen. A response is made by pressing the single key (spatially) corresponding to the location of the stimulus. After a response is given the next stimulus will appear after a fixed response-to-stimulus-interval (RSI). Participants are required to work through a number of blocks, usually containing between 50 and 100 trials.

Unbeknownst to the participants, stimulus presentation is pre-structured during most of the blocks (i.e., sequence blocks), either on the base of a fixed deterministic (i.e., noiseless) sequence, a probabilistic (i.e., noisy) version of a deterministic sequence, or a probabilistic finite-state grammar (see Cleeremans & McClelland, 1991). Decreasing response times and/or error rates are typically observed with training, indicating that learning has occurred. To differentiate serial skill from general practice effects, a random block of stimuli is inserted to the end of the practice phase: the cost in RT and/or accuracy for this random block relative to its surrounding sequence blocks serves as an index for serial skill, and is sometimes referred to as the sequence effect. Serial skill can be understood to indicate that the participant has formed a representation of the spatial-temporal structure that allows anticipation for future trials.

Importantly, the task captures the implicit feature of learning and performing that is typically involved in real life examples of perceptual-motor learning: Often, participants show clear learning in this task through the direct learning measures (RT and accuracy), while this goes unaccompanied by the ability to present a clear description of what was learned exactly (i.e., implicit learning; e.g., Seger, 1994).

Approaching a scientific issue from a controlled, experimental perspective inherently produces a cost in ecological validity. We believe, however, that the SRT task is a particularly strong experimental tool in a back-to-back approach of serial perceptual-motor learning. The task offers a simple and highly controllable laboratory tool, with its relatively fast acquisition and relatively objective index of serial skill. This makes it possible to separate out the effects of the variable of interest uncontaminated by unwanted variables. At the same time, the SRT task touches upon a large range of aspects of human cognition, such as memory, learning, motor control, consciousness, perception, and attention, that are also jointly in play during most real life activities. Additionally, in recent years, increasing attempts have been made to explore the SRT task within more ecologically valid settings, mostly confirming the reliable development of serial skill. For instance, serial perceptual-motor learning develops in settings that involve more complex motor tasks than the simple key-presses (e.g., Shea, Wulf, Whitacre & Park, 2001; Witt & Willingham, 2006), and in settings that provide perceptually richer environments (e.g., Jiménez & Vázquez, 2008). Finally, the SRT task offers an easy tool to explore the potential limitations concerning transfer of knowledge, a crucial element of training procedures.

Transfer of sequential perceptual-motor skills

A well known phenomenon related to skill acquisition is transfer asymmetry, which denotes a failure of transfer between different uses of what appears to be the same underlying knowledge (e.g., Rosenbaum, Carlson & Gilmore, 2001). This has been shown for intellectual skills (e.g., Fendrich, Healy Bourne, 1993; McKendree & Anderson, 1987), but also applies to the perceptual-motor domain (for a review, see Schmidt & Lee, 1999). For example, Proteau, Marteniuk & Lévesque (1992) trained participants on a manual aiming task (i.e., hitting a target as quickly and accurately as possible) without visual feedback of their performance. When visual feedback was provided in a subsequent transfer test, performance was impaired. As transfer of skill is a key criterion in evaluating the usefulness of training, determining the aspects of a task that allow for, or prevent reliable transfer is highly relevant for the construction of training methods and/or programs. In the SRT task it is relatively easy to determine the transfer of serial skill to new settings, by measuring performance near the end of a training phase, and compare it with performance measures from a subsequent transfer phase. Learning in this task typically develops relatively fast, and the comparison between sequential and (pseudo-)random blocks provides a relatively objective index of serial learning and transfer. The SRT task, then, provides a useful tool in studying transfer of skill. Some examples of this will be shown below.

Technology-aided training of sequential perceptual-motor skills

To exemplify the applied implications that emerge from basic cognitive paradigms such as the SRT task, we want to stress the strong link that exists between technology and training. Technologies such as virtual reality (VR; including surgical, driving and flight simulators) are increasingly recognized as embodying many characteristics of an ideal training medium (e.g., Berkley, Turkiyyah, Berg, Ganter & Weghorst, 2004; Ishii, Hatayama, Seki, Kobayashi, Murakoshi & Hashimoto, 2005; Kampiotis & Theodorakou, 2003; Pantelidis, 1993; Waxberg, Goodell, Avgerinos, Schwaitzberg & Cao, 2004), especially in cases when training in real life situations is dangerous, unduly expensive, or logistically difficult. VR has long been approached mainly from a technological perspective: how to optimize its realism? Over the last decades this has led to substantial progress, with the building of many high-tech semi- and fully immersive systems. However, the next step is taking into use these technologies. Though virtual environments have already found their use in various fields ranging from product design to training programs, the value of basic research for VR application is often underestimated. Users are interacting with the virtual, computer-simulated environment, and optimizing this interaction requires an evaluation from a psychological point of view: Basic psychological research can be used to provide information a) on specific abilities and limitations that the user brings into the world of VR, and b) on the specific requirements of VR technology to optimize its use. At the same time, VR may offer to basic research a tool that extends the possibilities of research (e.g., Loomis, Blascovich & Beall, 1999). Therefore, bridging the gap between basic psychology and the application of VR may be of great benefit to both.

With the advancement of virtual reality (VR) techniques, and the simultaneous drop in costs of these systems, the idea of using VR technology in the training of perceptual-motor skills is an inviting one. This development is also visible in the interest in VR shown by the scientific community. The possible merits of VR are increasingly investigated within the field of cognitive ergonomics. For example, research has shown that flight simulators can effectively improve pilot performance related to landing skills (Hays, Jacobs, Prince, & Salas, 1992a, b) and instrument and flight control abilities (Pfeiffer, Horey, & Butrimas, 1991). Additionally, skill training using virtual environments has been demonstrated to improve user performance in wayfinding (i.e., the ability to navigate through a space; Sebrechts, 2000). However, the limitations of the use of VR are also clear: performance after training on the basis of VR technology is typically better than after no training at all, but almost never reaches the level of performance after real life training (e.g., Hamblin, 2005; Kenyon & Afenya, 1995; Kozak, Hancock, Arthur & Chrysler, 1993; Waxberg et al., 2004). In gaining better in-depth knowledge about the precise mechanism underlying this finding, basic research may provide useful tools, as will be shown below.

OVERVIEW

In this article, the challenge is undertaken to approach the SRT task from an applied perspective. Over the last decade, findings across a wide range of themes have been reported within the SRT literature that may be of direct relevance to the process of designing training programs in the domain of perceptual-motor skills. Below we will elaborate on a number of such themes, which are summarized in Table 1. Based on these SRT studies, general recommendations can be provided for optimizing training programs.

Table 1. Overview of research topics in the SRT literature that are related to the optimization of training programs for perceptual-motor skills.

Theme	Major question(s)	References
Context dependence	Why can a perceptual-motor skill sometimes not be (fully) applied outside the training context?	Abrahamse & Verwey (2008) Wright & Shea (1991)
Offline learning	What variables affect the effectiveness of offline learning in perceptual-motor skill acquisition?	Robertson et al. (2004a) Robertson, 2004 Cohen et al. (2005) Robertson et al. (2004b)
Sensory modalities	Can perceptual-motor skill acquisition be guided by different modalities? Does sensory redundancy benefit perceptual-motor skill acquisition?	Abrahamse et al. (2008) Abrahamse et al. (2009a) Abrahamse et al. (2009b)
Observational learning	Can perceptual-motor skill acquisition be based on observation?	Howard et al. (1992) Song et al. (2008)
Movement disorder	Can a basic research paradigm like the serial RT task be of use in the process of diagnosing and/or treating movement disorders?	Doyon (2008) Ghilardi et al. (2003) Siegert et al. (2006) Vandenbossche et al. (2009)
Choking-under-pressure	Does the serial RT task provide a tool in exploring the mechanisms underlying the well-known phenomenon of choking-under-pressure?	—

EFFECTS OF CONTEXT

Usually, simulators are built with high face validity (they should look good), and designers hope this will yield substantial transfer of training to the operational environment. This is an expensive procedure, yet it does not guarantee high transfer of training. Successful transfer may not require high-fidelity simulators. Druckman and Bjork (1994) note that multiple studies show no training advantage for real equipment or realistic simulators over cheap mock-ups and drawings (see also Kozak et al., 1993; Lathan, Tracey, Sebrechts, Clawson & Higgins, 2002; Schneider, 1985). When stimulus similarities are greater than response similarities, and inappropriate response tendencies have to be suppressed, high similarity may even be detrimental and transfer negatively (Holding, 1976; also see Anderson, 1983;

Osgood, 1949; Schmidt & Young, 1986). Despite the present technical capabilities of VR systems, there are still many differences between simulated tasks and real-world tasks, and it is currently not clear which of these differences are responsible for the sometimes very limited amount of transfer from simulator to operational environment (i.e., real-world). As Lathan et al. (2002) put it “it is still not clear what exactly should be simulated” (p.410). Furthermore, learning may be counteracted because additional attention is required for interacting with VR systems, for example, because it has a narrow field of view, poor visual resolution, or no or incorrect haptic feedback.

From the perspective of cognitive psychology, there are different potential explanations for the sometimes rather low transfer of skill between virtual and real world. As noted above, this may have to do with the suppression of response tendencies, or with the high attentional demands of interacting with VR systems. Moreover, it could simply be that virtual training addresses skills that are not directly required in the operational environment. However, there is another account available that is somewhat overlooked. It may be that somehow irrelevant features from the virtual context are integrated in the skill representation that is being formed during practice, rendering this representation less accessible when being transferred to a new context in which these features are absent.

Context dependent skill acquisition

Skill-based behavior is assumed to be highly stimulus driven and therefore susceptible to the presence of information in the environment that was available during practice (e.g., Anderson, Wright & Immink, 1998; Greeno et al., 1993; Wright & Shea, 1991). For example, performance may reduce when irrelevant information like the room, the experimenter, or the background music is changed (e.g., Anderson et al., 1998; Smith, 1985; Smith & Vela, 2001). Context-dependence of skills is related to findings in memory research showing that information retrieval from memory can be facilitated (i.e., ‘primed’) by presentation of information that is either perceptually or semantically related, or that happened to be present during practice (e.g., Dibbets, Maes & Vossen, 2002; for an overview see Davies and Thompson, 1988). Studies have shown that such priming can be impaired by changes in contextual features like the preceding task, the mood of participants, and superordinate goals of participants. Interestingly, similar effects can occur on the base of changing seemingly superficial properties of the task context, like the font of a word, the stimulus modality, and the stimulus location (e.g., Tenpenny, 1995). In line with this, research with VR training systems showed that learners use contextual but irrelevant cues to support and mediate their actions (Lathan et al., 2002; Stanney, Mourant & Kennedy, 1998).

Serial perceptual-motor learning

Being a concept originating from verbal memory literature, the context dependencies that may exist in sequential perceptual-motor learning have been explored first by Wright and Shea (1991; see also Shea & Wright, 1995) in a key-press task. In their study, participants viewed an order of four successive key presses for 400-800 ms, and then, after removal of the instruction, they rapidly typed the sequence on a keyboard. Three sequences were practiced in this fashion for 36 trials each, while the intentional stimulus for each sequence was accompanied by a combination of three context features (i.e., display colour, tone, placeholder shape). When in a subsequent test phase these contextual cues were changed, error rate increased.

In their model of context dependent serial learning, Wright and Shea (1991) distinguished between intentional and incidental cues. The importance of intentional cues is usually easily recognized because they are essential to perform the task. Changing their format will reduce performance because they have to be processed differently and low-level associations can no longer be used to trigger the appropriate response (e.g., Hommel, 1998; Pashler & Baylis, 1991). Incidental cues are the context features of a task that are not directly required to perform the task. Because they do not provide essential information to the task, their importance for training is likely to be underestimated. Incidental cues may become associated with specific actions because of selective presence in the training situation and not because the individual is testing hypotheses and is aware of them; changing these, then, may still impact performance. Though not explicitly mentioned in the Wright and Shea (1991) model, we propose that incidental cues should be further sub-divided into (a) cues that co-vary with the imperative stimulus (e.g. primes, eye movements), and (b) cues that are fixed (i.e., static context); like room, music, background color (cf. Dibbets et al., 2002).

Static context and learning

Training in virtual environments is often beneficial to performance in real life situations when compared to no training; however, it almost never reaches the effectiveness of real life training itself. How can this be? One explanation could be that the trained skill becomes sensitive to the specific training context in VR. As noted above, Wright and Shea (1991) have shown that this specificity can be developed when seemingly task-irrelevant cues from the environment co-vary with the task-relevant information (thus rendering these cues to be more or less task-relevant in an indirect manner). This clearly suggests that performance can be impaired when such cues are removed at a transfer stage, providing an important issue to consider in putting together a training method/program. However, this leaves open the question if this specificity can also apply to context features that are more or less static, i.e. those that do not co-vary with the task-relevant information.

The potential impact of such static context features may be understood by referring to a concept from the literature that is highly related to context dependent learning, the procedural reinstatement principle. According to this principle, transfer of procedural skill is dependent on the extent to which the memory representations developed during training are reinstated at the time of transfer: high levels of retention / transfer are predicted for tasks that use the same procedures (i.e., motoric, perceptual and cognitive operations) at test as those used during training (Healy, Wohldmann & Bourne, 2005; Clawson, Healy, Ericsson & Bourne, 2001).

Abrahamse and Verwey (2008) addressed the impact of static context on perceptual-motor performance in an SRT task, and observed performance to deteriorate when static features are changed at transfer. Specifically, they trained one group of participants on a series of blocks that contained a fixed sequence, whereas another group of participants were trained solely on random blocks. At the end of the training phase, both groups were tested in a different "static context" in which the shape of the placeholders marking the possible stimulus locations was changed. Both groups showed impaired performance (i.e., larger response times) on this test block, but more so for the group trained on sequence blocks. This indicates that processes specific to the serial skill were affected by this change of (seemingly task-irrelevant) context.

This sensitivity may also be operating in more complicated contexts. For example, stylistic features of the heads-up display may be integrated within the task representation during training in a driving simulator. Afterward, then, transfer to the real world could be impaired when such features are somehow changed[2]. Future research may be aimed at exploring ways to prevent the development of such context dependencies in skill acquisition. One may think of training participants in a more frequently changing context, as to avoid irrelevant information to become integrated with the to-be-acquired skill representation.

The study of Abrahamse and Verwey (2008) shows that changing seemingly task-irrelevant, static features from a particular context can influence performance, but the effects are rather small (i.e., in the range of 50 ms). One may wonder how these effects translate to more complex serial action, such as in dancing, sports, or music production. We believe that VR could be a particularly useful tool in this sense, because VR potentially highlights and leverages the role of perception in learning. It gives the opportunity to immerse the participant in a particular task context while performing a complicated (set of) action(s), and still work from a highly controlled setting. This may enable an ecologically more valid extension to the study of Abrahamse and Verwey (2008).

Contextual interference

Before we close this section, we want to briefly address a phenomenon referred to as contextual interference (CI). CI has its roots in the verbal learning literature (e.g., Battig; 1972, 1979), and was later successfully applied to motor skill training (for a review see Magill and Hall, 1990). It refers to the observation that under some conditions retention or transfer of knowledge or skills eventually benefits from randomly employing different task variations during practice, even though performance during practice itself is depressed. In experimental settings learners are typically asked to practice a number of related tasks or task variations, and the training schedule is systematically varied to maximize or minimize interference. Presenting task variations in a random order is thought to produce high contextual interference, while blocked presentation (i.e., the completion of training on one task variation before continuing with the next) should minimize interference. It has repeatedly been observed that performance in a delayed retention phase is better after training with high contextual interference. This is explained by the more elaborate and distinctive processing of the material to be learned (e.g., Shea & Morgan, 1979). Please note that CI may be easily confused with the phenomenon of context dependent skill acquisition discussed in the section above. However, in contrast to that, CI refers solely to manipulations of task-relevant (i.e., intentional) features.

The CI effect has been shown in sequencing tasks (e.g., Shea & Morgan, 1979; Immink & Wright, 1998) other than the SRT task. For instance, Shea and Morgan (1979) had people perform a barrier knock-down task. There were three different fixed orders in which the barriers had to be knocked down, and these three versions were either practiced in a random (high interference) or blocked order (low interference). Retention after a 10-day delay was better for the high than the low interference condition. However, CI has not been explored in an implicit sequence learning task as the SRT task. This may be a missed chance; CI-like effects can be expected under some conditions in the SRT task, and this may offer interesting extensions to what is known on CI. For instance, it would be interesting to explore if CI occurs both with implicit and explicit serial perceptual-motor skill acquisition.

Overall, the effects of the task context on performance are far from fully understood. Opposed to intentional task features (for which the impact on performance is intuitive and clear), the potential impact of incidental, seemingly irrelevant features is often underestimated. Indeed, basic research has shown that such incidental features from the task context can play a role in determining performance, mainly in the transfer to a new context (e.g., the real world). This notion should be considered in constructing training programs for both intellectual (e.g., Smith & Vela, 2001) as well as perceptual-motor skills (Abrahamse & Verwey, 2008; Wright & Shea, 1991).

OFFLINE LEARNING

Everyone knows that practice is crucial in the acquisition of a new skill. However, less intuitive is the finding that information processing related to the skill often continues even when practice has stopped (i.e., offline processing). After practice, changes take place that strengthen (and possibly modify) the new skill. These findings have been summarized by the concept of consolidation, and have introduced a whole new field of research within the domain of motor learning (for a review see Robertson, Pascual-Leone & Miall, 2004).

Consolidation thus refers to the offline (i.e., in between training sessions) process of turning a fragile memory representation into a more stable and longer-lasting one. The preservation of motor memory (i.e., preventing performance from deteriorating), however, is only one aspect of offline processing in motor training. In addition, it has repeatedly been shown that, under some conditions, sleep following physical practice and memory consolidation can even result in additional enhancements of motor performance (e.g., Blischke & Erlacher, 2007); this may be called offline learning.

The effects of sleep on motor learning have been studied mostly while using mirrow drawing or sequence production as the criterion task (e.g., Blischke & Erlacher, 2007). Recent work in the domain of serial perceptual-motor skill comes from Robertson and colleagues (e.g., Robertson, Pascual-Leone & Miall, 2004; Robertson, 2004; Cohen, Pascual-Leone, Press & Robertson, 2005; Robertson, Pascual-Leone & Press, 2004). They have reported some interesting findings that refine the overall conclusion that sleep is beneficial in the consolidation of serial perceptual-motor skills. In addition, both age and overall cognitive abilities have been identified as important population characteristics that modulate the effectiveness of offline processing (i.e., Brown, Robertson & Press, 2009; see also Yan, Abernethy & Li, 2009).

Sequence learning in the SRT task can be both explicit and implicit, and may even sometimes end up being a mix of both (e.g., Willingham, 1999). Robertson, Pascual-Leone and Press (2004) have shown that these two types of learning are affected differentially by sleep. Specifically, it was observed that the benefits taken from offline processing are dependent on sleep for explicitly, but not for implicitly learned serial skills in the SRT task. Implicit serial skill was solely dependent on the passage of sufficient time, irrespective of sleep.

In another study, Robertson and colleagues (Cohen, Pascual-Leone, Press & Robertson, 2005) showed that distinct consolidation processes exist for the separate movement and goal components of serial skill acquisition. They explored the effect of a 12-h consolidation interval with or without sleep on the execution of a trained sequence in a test phase with the untrained hand. Maintaining the sequence of response keys in the test phase left intact the goal of the movement, while changing the exact finger movements. In contrast, maintaining the sequence of (homologous) finger movements left intact the finger movement sequence while changing the goal of the movement. A double dissociation was observed in which only the movement component improved over the day, and only the goal component benefited from sleep.

Finally, support is growing for the notion that age may be an important factor in modulating the precise workings of offline processing during sleep (i.e., Yan et al., 2009). Specifically, Yan et al. (2009) observed performance improvements for younger adults both through online and offline processing, whereas older adults (with normal cognitive capacities) only seemed to learn through an online processing mode. Recent work has provided further support for this notion in the domain of serial perceptual-motor learning. Using a typical SRT task, Brown, Robertson and Press (2009) trained and tested younger and older participants across two sessions with a 24-h interval. The younger participants showed clear serial skill improvements at session two compared the first session the day before, indicative of offline learning (but see Rickard, Cai, Rieth, Jones & Ard, 2008). However, no such contribution of offline processing was observed for the older participants.

Overall, these studies seem to indicate that different forms (e.g., implicit versus explicit skills) or components (e.g., goal or movement) of to-be-acquired serial skills, as well as different target populations (e.g., different age groups, populations with cognitive impairments) may require a different approach in emphasizing offline processing during sleep as part of the optimal training program.

SENSORY MODALITIES

Cross-modality

An important finding in the literature on sensory modalities is the existence of robust crossmodal links in spatial attention, for instance between vision and touch (see Spence & Driver, 2004, for a review). Butter, Buchtel, and Santucci (1989) demonstrated that the presentation of spatially-predictive vibrotactile cues to either the left or right hand leads to a shift of visual attention to the cued side (or hand). Following this vibrotactile cue, participants detected visual targets on the cued side 14 ms faster than when the targets appeared on the uncued side. Similar cross-modal links have been reported for audio-visual (e.g., Van der Lubbe & Postma, 2005) and audio-tactile (Van der Lubbe, Van Mierlo & Postma, 2009) combinations. From an applied perspective, the existence of such cross-modal links is particularly interesting as it suggests that spatial information can be effectively signaled through other modalities than the task-dependent primary modality – in order to prevent modality overload[3].

Modality overload

Users of modern interfaces more and more report becoming victim of modality overload in carrying out their duties (e.g., Sorkin, 1987; Zlotnik, 1988), which may be catastrophic in critical moments of decision making when the perceptual and/or cognitive loads are already substantial. Being the primary sensory modality involved in most tasks, it is typically the visual modality that suffers from this overload. Therefore, it may be worthwhile to search for alternatives to the visual domain. One strong candidate is the tactile domain. The tactile modality is typically underused in the processing of task-relevant information, and therefore not as sensitive to (effects of) overload as the visual modality.

In recent years, a range of potential uses has been identified for tactile stimulation, such as in providing directional information (e.g., Van Veen, Spapé & van Erp, 2004), haptic feedback in virtual reality (e.g., Wood, 1998), and increasing orientation awareness in complex environments (e.g., Rupert, 2000; Van Erp & Van Veen, 2003, 2001). In addition, Ho and colleagues (e.g., Ho, Reed & Spence, 2006; Ho, Tan & Spence, 2005) have shown the efficacy of using vibrotactile warning signals in providing spatial information to car drivers. For instance, this information could be used to facilitate a driver's response to situations of potential front-to-rear-end collisions. By presenting this information through the tactile domain, increased processing demands are prevented in the already highly engaged visual modality.

Perceptual-motor skill acquisition

The use of the tactile modality is not common in Human Computer Interaction. Visual and auditory domains are dominating the field. However, this may be a missed chance. In many situations the tactile modality may be an interesting alternative, because the visual and/or auditory modalities are not available, not adequate for the task at hand (i.e., limited scope of view), or overloaded (e.g., driving in an unknown area). Various relevant uses of tactile cues can be identified, such as being a tool for communication, providing geometric information, or providing warning signals (e.g., van Veen & van Erp, 2001). However, with respect to training programs, tactile cues could possibly also serve additional use.

In the studies of Abrahamse, Van der Lubbe and Verwey (2008, 2009a) it was shown tactile stimuli can be effectively used to guide serial perceptual-motor skill acquisition. Specifically, serial skill in a tactile SRT task was more or less similar to that in a typical visual SRT task (even though the expression of serial skill may be better with visual than tactile stimuli; Abrahamse et al., 2009a). In addition, the transfer of sequence skill from tactile to visual stimuli was near perfect, indicating good flexibility in applying the acquired skill in new, visual contexts. This flexibility indicates that tactile stimuli can be effectively used to train skills that eventually need to be applied to visual contexts.

One major development in recent years is the design of virtual teaching systems: a "virtual teacher" is a device or agent that supplements an environment in order to facilitate skill acquisition. This may apply both to intellectual (e.g., web-based learning) and perceptual-motor skill (e.g., Gillespie, O'modhrain, Tang, Zaretzky & Pham, 1997). Having shown that multiple modalities can be successfully employed in guiding skill acquisition (e.g., Abrahamse et al., 2008; 2009a), implementation of this notion may of benefit to the impact of such virtual teaching systems.

Multimodality in perceptual-motor skill acquisition

In real life we are typically bombarded with sensory information, rendering perception of the world an inherently multisensory experience. The brain integrates information from the different sensory modalities to better interact with the environment, motivating the question of how this affects human behavior and cognition. In simple detection and choice RT tasks it has been repeatedly shown that multiple, congruent stimuli from different modalities have a positive impact on performance, as response times and error percentages typically decrease. However, not many studies have explored the effect of such redundant stimulus pairs for serial perceptual-motor learning.

Over the last decades, evidence is mounting that perceptual information plays an important role in serial perceptual-motor learning (e.g., Abrahamse, Jiménez, Verwey & Clegg, in preparation; Clegg, 2005; Remillard, 2003; Ziessler & Nattkemper, 2001). From the notion that serial perceptual-motor learning can be guided by various sources of sensory information (e.g., Abrahamse et al., 2008; Willingham, 1999), this may imply that serial perceptual-motor learning can benefit from sensory redundancy. This may be especially predicted for the implicit component of serial perceptual-motor learning: implicit learning is thought to be unselective and automatic (e.g., Keele, Ivry, Hazeltine, Mayr & Heuer, 2003; Reber, 1993), detecting and utilizing all regularity available.

This hypothesis on possible benefits of sensory redundancy has recently been explored in two SRT studies (i.e., Abrahamse et al., 2009a; Abrahamse, Van der Lubbe, Verwey & Jaśkowski, 2009b). Abrahamse et al. (2009a) employed an SRT task in which congruent visual and tactile stimuli were presented, both of which had separately been shown to reliably enable sequence skill acquisition in a previous study (i.e., Abrahamse et al., 2008). In addition, Abrahamse et al. (2009b) created sensory redundancy within the visual domain as both the position and the color feature of each stimulus signaled the correct response. Somewhat surprisingly, both studies showed no indications for serial learning benefits in conditions with redundant sensory cues as compared to single cues conditions (for details and possible explanations see Abrahamse et al., 2009a; 2009b).

Regardless of possible explanations for these results, here it suffices to note that employing redundant sensory information in guiding serial perceptual-motor performance is not necessarily beneficial to training; even though VR technology may be sufficiently developed to implement it. From a cost-related point of view, similar caution may be appropriate with respect to the implementation of high-tech feats into training systems in general: even though the implementation may be feasible from a technological perspective, it may not be necessarily beneficial to the desired outcomes.

OBSERVATIONAL LEARNING

The transfer of information from instructor to learner is crucial for effective skill acquisition. While (perceptual-)motor learning typically involves performing the to-be-learned task, it has been shown that such learning can also be achieved by mere observation. In fact, a number of experiments have indicated not only that observational learning of (perceptual-)motor tasks occurs, but that performing a task confers no special advantage over simply watching someone else performing it (Blandin, Proteau, & Alain, 1994; Vogt, 1995; see McCullagh, Weiss, & Ross, 1989, for a review).

The role of observational learning has been extensively explored in the SRT task (e.g., Bird & Heyes, 2005; Howard, Mutter & Howard, 1992; Kelly & Burton, 2001; Song, Howard & Howard, 2008; Willingham, 1999). While the incentive for this exploration typically concerns the basic question if serial learning has a perceptual component that is independent of responding, these studies clearly speak to more applied issues as well. In these studies participants typically go through a training phase in which they merely watch sequences of stimuli on a screen (or a model that is responding to sequences of stimuli; e.g., Bird & Heyes, 2005), and then they are tested while responding to the same sequence of stimuli. Observational sequence learning reliable develops, as responding to the sequence of stimuli is faster and/or more accurate than responding to a (pseudo-)random or new sequence (e.g., Howard, Mutter & Howard, 1992; Kelly & Burton, 2001; Song, Howard & Howard, 2008; Willingham, 1999). However, it has been discussed whether this learning is solely explicit (e.g., Kelly & Burton, 2001; Willingham, 1999), or can also be implicit (e.g., Song et al., 2008). Song et al. (2008) observed serial learning through observation of stimuli that were structured according to probabilistic sequences, which are known to prevent the spontaneous development of explicit awareness. This finding seems to indicate that, under the correct conditions, mere observation may also benefit the implicit component underlying serial skill.

Additionally, it has been shown that serial learning by observation can be effector-specific. Bird and Heyes (2005) employed a training phase in which participants were watching a model respond to a sequence of stimuli. At a subsequent test phase, the participants were required to respond themselves to the same sequence of stimuli, and, in line with the studies mentioned above, they found indications that the participants had acquired sequence knowledge during the training phase. Importantly, these indications of serial learning were only observed when the test phase was performed with the same hand as the model had been using during the observational learning phase. Hence, under these conditions, the serial skill resulting from observational training is effector-specific, which is often thought to reflect the learning of motor dynamics (e.g., Hikosaka, Nakamura, Sakai, & Nakahara, 2002; but see Verwey, Abrahamse & Jiménez, 2009 for an alternative explanation). In line with research on the human "mirror system" (Rizolatti & Craighero, 2004; Rizzolatti, Fogassi, & Gallese, 2001) and the electrophysiological evidence of motor facilitation during action observation (Aziz-Zadeh, Maeda, Zaidel, Mazziotta, & Iacoboni, 2002; Maeda, Kleiner-Fisman, & Pascual-Leone, 2002; Strafella & Paus, 2000), the study by Bird and Heyes (2005) indicates that even motor processes can be learned by mere observation.

Overall, training by mere observation has been shown to be effective for (perceptual-) motor skill acquisition, at least under some conditions. This could go beyond the single example that a trainer may provide to its trainees before letting them engage in active training; training could benefit from complete sessions that involve mere observation. This may provide a number of advantages for training procedures. For instance, it would enable a collective session for a large group of trainees (e.g., dancers, sportsmen, etc.) during the early stages of training, in which an instructional video may provide training on (some aspects of) a (perceptual-)motor task. This would be advantageous in terms of time and costs. Furthermore, for tasks in which errors are very costly (one may think of training the procedure for sky-diving), it may provide a way of gaining experience before actually performing the task, thereby decreasing the chance of layman errors. Finally, observational training may be useful in situations of temporary motor deficits, such as with repetitive strain injury (RSI).

MOVEMENT DISORDERS AND REHABILITATION

There exists a growing literature that describes performance of clinical populations on the SRT task. The nature of serial learning in the SRT task is an important issue because it is thought to reflect a fundamental aspect of human cognition. Furthermore, studying its underlying mechanism may reveal better insight into the nature of various disorders. Obviously, there is a pitfall to the use of basic cognitive paradigms in the study of various disorders: If the basic mechanisms underlying serial learning are not yet sufficiently understood, what does it tell us that one or another population is impaired on performance in the SRT task? Fortunately, progress has been made over the last decade in unraveling the processes and brain areas at work in the SRT task.

Some studies have reported impaired serial skill in patients suffering from schizophrenia (e.g., Pedersen, Siegmund, Ohrmann, Rist, Rothermundt, Suslow & Arolt, 2008) and dyslexia (e.g., de Kleine & Verwey, 2009; Menghini, Hagberg, Caltagirone, Pertrosini & Vicari, 2006). However, most studies have focused on the serial skills of patients with movement disorders (for a review, see Doyon, 2008), sometimes by comparing their performance on the SRT task with controls (typically matched on factors like age, sex and education). This is theoretically motivated by the assumption that the SRT task is basically a serial perceptual-motor task, and by the presumed involvement of the basal ganglia both in most movement disorders as well as in implicit serial learning (e.g., Deroost, Kerckhofs, Coene, Wijnants, & Soetens, 2006; Kim, Reading, Brashers-Krug, Calhoun, Ross, & Pearlson, 2004; Knopman & Nissen, 1991; Wilkinson, Kahn & Jahanshahi, 2009).

Siegert, Taylor, Weatherall & Abernethy (2006) performed a meta-analysis on a set of studies that explored (implicit) serial learning in populations of Parkinson's disease (PD) patients. This meta-analysis showed that serial learning is impaired in PD patients, a notion that was further supported by the recent studies of Vandenbossche, Deroost, Soetens & Kerckhofs (2009) and Wilkinson, Khan and Jahanshahi (2009). Moreover, recent findings support similar conclusions with respect to other movement disorders, such as stuttering (e.g., Smits-Bandstra & Nil, 2007), Huntington's disease (e.g., Kim et al., 2004; Knopman & Nissen, 1991), or dystonia (e.g., Carbon, Ghilardi, Argyelan, Dhawan, Bressman & Eidelberg, 2008; Ghilardi, Carbon, Silvestri, Dhawan, Tagliati, Bressman, Ghez & Eidelberg, 2003). These advances have major implications, not only for optimizing ways to learn new skilled behaviors in real-life situations, but also for guiding therapeutic approaches in patients with movement disorders.

This seems like a very strong back-to-back approach: basic models and theories are employed to explore the mechanisms that underlie specific problems of clinical populations, whereas previous knowledge about such populations can be used to further sophisticate the theories that underlie a particular paradigm. However, whereas many studies have by now shown that (implicit) serial learning in the SRT task is impaired across a range of movement disorders, further development seems to progress slowly. Having outlined the intimate relationship between movement disorders and performance on a particular task, the aim for future research should be to accurately predict the evolution of the different movement disorders, and to explore the potential recovery processes. One way to go, for example, would be to put more effort into the use of basic cognitive paradigms, such as the SRT task, for testing the effectiveness of potential forms of treatment for the various forms of movement disorder.

CHOKING UNDER PRESSURE

To close the current article, we want to briefly speculate on the potential that the SRT task may offer in exploring "choking under pressure". In the context of sports, choking is a slang concept that denotes the inability to perform up to a former standard under more demanding or stressful conditions (e.g., Baumeister & Showers, 1986). An example may be a tennis player who misses an easy shot, and immediately produces a double fault on the serve following her miss, or an athlete who is overly concerned about what others (coach, teammates, or audience) might think about his/her performance. Even more dreadful would be a football player who misses a penalty in the penalty shootout of an important final, even though his penalty skills are almost flawless during training sessions. It has been investigated whether certain types of personalities are more prone to choke than others, or whether the occurrence of choking is to some extent dependent on the task performed. However, the precise processes and/or mechanisms involved have barely been explored, possibly due to the lack of appropriate laboratory tools.

Here we would like to speculate that some findings in the SRT task with regard to transfer between different conditions may be relevant to the topic. Specifically, it is often observed that serial skill acquired during training does not transfer to a new situation (e.g., Abrahamse & Verwey, 2008; Abrahamse et al., 2008; Abrahamse, Jiménez, Deroost, Van den Broek & Clegg, in preparation; Jiménez, Vaquero & Lupiánez, 2006; Willingham et al., 2000). For instance, Abrahamse and Verwey (2008) observed that serial performance was reduced in a condition that only deflected from the training context on seemingly task-irrelevant features (i.e., the shape of placeholders). Similarly, Abrahamse et al. (in preparation) observed that transfer from a spatially compatible to a spatially incompatible stimulus-response (S-R) mapping is fully absent, even though the sequence of key-presses was maintained at transfer. In addition, Willingham et al. (2000) showed that participants trained on an SRT task with a particular response board configuration could not transfer their serial knowledge to a different response board configuration.

Transfer tasks are typically employed as the main tool in studying the contents of the representation underlying serial learning (Clegg, DiGirolamo & Keele, 1998); the idea is that transfer will occur to the extent that the information that was included in the sequence representation during training is being maintained at transfer. However, besides such a “direct” impact of changing task features, (partial) absence of transfer may also be explained in a more indirect manner. It may be that increasing task difficulty by changing the (context of the) task (e.g., switching from the relatively easy compatible S-R mapping to a more difficult incompatible S-R mapping; switching to a new response board configuration) causes the participants to switch from a (relatively) uncontrolled to a (relatively) controlled information processing mode. In the latter mode, all implicit learning effects may be suspended, and thus leave performance unaffected by previous implicit learning experiences. Such an explanation comes close to an explanation of “choking” as an attentional phenomenon: Performance on critical moments switches from implicit (and successful) to explicit (and slow, error prone) ways of performing a task (e.g., Erhlenspiel, 2006; Schmidt & Wrisberg, 2008). The SRT task may thus be an experimental paradigm that allows for more rigorous investigations into the mechanisms underlying this phenomenon. However, future research is needed to explore the viability of such an interpretation of partial or absent transfer in the SRT task.

DISCUSSION & CONCLUSIONS

As noted above, one major issue in cognitive psychology research concerns the ecological validity of the paradigms used. Ideally, these paradigms are stripped down versions of real life scenarios, leaving intact the basic mechanisms at work. Yet, this may not always be the case. For instance, Wulf and Shea (2002) seriously question the validity of some principles on motor learning that are derived from highly controlled laboratory settings. For example, consider the contextual interference effect. Wulf and Shea (2002) review available evidence in favor of or against the benefit of random versus blocked practice, and conclude that this well documented effect only contributes to the learning of simple skills and does not transfer to complex skill learning; yet see, for instance, Hall, Domingues and Cavazos (1994) who observed a clear CI effect in the complex sport setting of playing baseball. The reason for the absence of CI effects in complex skill training may be related to the increased memory and processing demands for complex motor skills, which could cause short-term memory to become overloaded in case of random practice. Similar questions can be raised to the other themes discussed in the current article. However, though it may not always be straightforward, the field of cognitive psychology should not abandon all attempts to bridge the gap between basic and applied branches of research.

Basic cognitive research can be valuable for the applied branch in providing hypotheses that are derived from its findings and can be (re-)tested in more applied settings. This is mainly dependent on basic researchers asking the right questions, thus letting themselves be inspired by practical themes and problems (e.g., Broadbent, 1980). In this context, basic paradigms provide a strong tool for testing the feasibility of particular ideas early in the design process of, for example, training programs for perceptual-motor skills. In the current article we explored this potential for the SRT task. The SRT task is typically conceived of as a basic cognitive paradigm. However, with the development of increasingly sophisticated theories and findings, the merit of the paradigm from an applied point of view should not be ignored.

In the current article we showed that findings from this paradigm across a wide range of themes are of direct relevance to the improvement of training procedures for serial perceptual-motor skills. In sum:

- Context dependent learning may play an important role in reaching optimal transfer between artificial training environments and real world. Based on previous findings (i.e., Abrahamse & Verwey, 2008) we claim that also static context features should be considered in this regard, even though common sense would deem them task irrelevant.
- Offline serial perceptual-motor learning has been clearly observed, but various refinements exist with regard to its optimal workings. For instance, it seems to be modulated by age, skill awareness, and precise skill components. Therefore, the optimal implementation of offline learning in training programs requires consideration of these aspects.
- Guiding serial perceptual-motor learning is not solely dependent on cues in the visual domain; tactile cues can do the trick as well. This allows for dividing the informational input to users in training environments across multiple modalities, in order to prevent users from potential overload in the visual domain.
- More is not always better. Redundant perceptual information in the guiding of performance is not necessarily beneficial in the acquisition of serial perceptual-motor skills. Hence, the costly implementation of such techniques in, for example, virtual teaching systems should be carefully considered.

- Perceptual-motor skill acquisition benefits from observational learning. This provides a useful method in terms of safety and cost-reduction.

Additionally, we have also made some suggestions for extending the use of the SRT task for the future investigation of real world phenomena. For instance, we believe that the SRT task potentially provides a useful tool in the exploration of the mechanism underlying "choking under pressure", for which extensive investigation is currently lacking. Furthermore, with the increasing support for the notion that performance in the SRT task is impaired for patient with movement disorders, we believe that the SRT task provides a useful tool in exploring the success of potential therapeutic approaches, treatments and rehabilitation programs.

Overall, then, we aimed to illustrate that basic cognitive psychology employs various paradigms that can be employed as tools in the direct investigation of more applied issues. In line with the current article on the SRT task, we believe that similar attempts should be made to clarify this role for various other basic cognitive paradigms.

NOTES

1. A debate about the correct terminology for applied cognitive psychology is beyond the scope of this article (see for instance Proctor and Van Zandt, 2008).
2. Please note that we do not claim that transfer is necessarily absent between simulator and real world from the notion of context dependent skill acquisition; just that it may not be optimal.
3. It should be noted that some caution should be taken in the employment of different modalities to present information without careful testing, as information is not always perceived congruently by the different senses. First, many interactions may exist between information processing in different modalities. A good example is the well documented finding that discrepant visual speech alters the auditory speech percept (i.e., the McGurk effect; e.g., McGurk & MacDonald, 1976). Second, modalities may dominate each other. For instance, in the spatial domain it has been shown that vision dominates touch, whereas touch dominates audition (van Erp, 2001).

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Summary and conclusions

Perceptual-motor skills are essential for efficient goal-directed behavior, and typically involve the sequencing of actions and information. Since its introduction by Nissen and Bullemer (1987), the serial reaction time (SRT) task has become one of the major tools in exploring sequence learning. For each trial of this task, a stimulus is presented at one of several locations, and participants are instructed to press the key assigned to that location as fast as possible. At a fixed interval after the key-press, the next trial begins with the presentation of a new stimulus, and this usually continues up to around one thousand trials. The critical manipulation in the SRT task entails the implementation of regularity within the series of stimuli; for example, stimuli could be presented according to a fixed, repeating sequence. Although participants are not informed about the presence of regularity (and often remain unaware of its precise contents), performance typically improves over the course of task execution on the basis of this regularity.

The central theme of this dissertation concerns the nature of the representations that underlie perceptual-motor sequence learning as studied in the SRT task. This issue has triggered a vast amount of debate over the last two decades; for reviews see Abrahamse, Jiménez, Verwey and Clegg (submitted; chapter 2) and Clegg, DiGirolamo and Keele (1998). Some authors have proposed that sequence learning can be based on associations at the response selection stage (e.g., Deroost & Soetens, 2006; Koch, 2007), or at some abstract level that is independent from stimulus and response features (e.g., Golschke & Bolte, 2007). However, these two accounts are not well-documented, and strong empirical support for it is missing. More convincing support exists for three further levels: perceptual learning (S-S associations), response-based learning (R-R associations) and response-effect learning (R-S associations). In fact, the strong evidence for these multiple forms of sequence learning has gradually caused a shift away from a long held oppositional view, towards the notion that sequence learning can be represented at different levels of information processing.

In Chapter 2 of the current dissertation, it was attempted to make explicit this multiple level notion by reviewing the relevant literature, and link the notion to an existing framework for sequence learning that is referred to as the dual system model (Keele, Ivry, Mayr, Hazeltine & Heuer, 2003). Specifically, it was proposed to refine the concept of a dimension, which lies at the core of the framework, by having it refer to features from ongoing stimulus-response processing. In doing so, the model automatically generates the three main forms of sequence learning from the SRT literature (i.e., S-S, R-R and R-S associations). This offers a solid framework from which to integrate these different forms of sequence learning, while at the same time grounding the framework into a rich literature on the nature of sequence learning. Moreover, this integration makes solid predictions for future research, with some concrete research ideas already described in Chapter 2.

Most of the empirical chapters (i.e., Chapters 3-6) were based upon the notion that sequence learning develops also at the stimulus level, either through perceptual (S-S) or response-effect (R-S) associations. In Chapter 3, the effect on sequence performance of changing seemingly task-irrelevant features of the visual display was explored, in order to determine possible context dependencies in sequence learning. In addition, it was explored whether sequence learning can be guided by tactile as opposed to typical visual stimuli (i.e., Chapters 4 and 5), and whether sequence learning benefits from the availability of multiple, congruent response cues (i.e., Chapters 5 and 6). In Chapter 7, the final empirical chapter, the focus was shifted from the stimulus to the response selection level of information processing. Through manipulating the stimulus-to-response (S-R) mapping, it aimed at further exploring the involvement of the response selection stage in (implicit) sequence learning. Finally, in Chapter 8 it was explored to what extent findings on the SRT task may provide practical recommendations for the optimization of training programs for perceptual-motor skills.

Here the empirical chapters will be briefly reviewed, while adding some critical remarks and discussing alternative interpretations that were not extensively addressed.

Review of the main empirical findings

Chapter 3 of this dissertation aimed to investigate whether perceptual-motor skills can become sensitive to changes in seemingly irrelevant features of the task context. Participants were trained in a typical SRT task, either with structured (i.e., sequential) or unstructured (i.e., pseudo-random) trial order. Three static, incidental features from the training phase were changed in a transfer block: the display color (i.e., white vs. dark-grey), the placeholder positions (i.e., top vs. bottom of the screen), and the placeholder shape (i.e., rectangular vs. triangular). Importantly, the trial order remained unchanged for the structured training group. It was observed that changing the placeholder shape significantly impaired performance for both the structured and unstructured training groups, but more so for the structured training group. Hence, both sequence-specific and -unspecific learning were affected by the change of this seemingly task-irrelevant feature, with the former indicating that incidental features can become integrated within a global sequence representation. In terms of the framework depicted in Chapter 2, the findings presented in Chapter 3 strongly indicate the involvement of the perceptual level in sequence learning. This notion may also be relevant to more practical training settings for perceptual-motor skill, such as with sports or driving a car: Optimal transfer to new contexts (e.g., from simulator to real world) possibly requires taking into consideration also the task-irrelevant, incidental features of the training context. Future research should aim at further exploring the veracity of this claim, and at determining possible ways to circumvent the development of context-dependent skill (e.g., changing the context regularly during training).

To further explore the involvement of the perceptual level in sequence learning, a new version of the SRT task was designed in which stimuli were presented tactilely to the fingers (i.e., Chapters 4 and 5). In Chapter 4 performance was compared between this tactile SRT task and its typical, visual counterpart in a between-subject training phase, and cross-modal transfer was measured in a subsequent test-phase. It was observed that the sequence effect (i.e., the performance difference between random and sequential blocks to the end of the training phase) was larger for the visual than the tactile SRT task. In addition, whereas transfer seemed to be perfect from tactile to visual stimuli, it was only partial the other way around, suggesting a stimulus- or modality-specific component for the visual SRT task in addition to typical response-based learning. This indicates once more that the perceptual level is involved in sequence learning. Overall, these findings suggest that tactile stimuli can be reliably employed to guide perceptual-motor skill acquisition. This may be relevant for practical training settings in which the visual modality is inadequate or at risk for overload (see Chapter 8 for elaboration).

In Chapter 5 it was attempted to replicate and extent the findings from Chapter 4 by exploring sequence performance for groups of participants that trained either with tactile (i.e., tactile only training group), visual (i.e., visual only training group), or combined (and congruent) tactile and visual stimuli (i.e., bimodal training group). In addition, transfer was measured in all directions: in the transfer phase, each participant was tested on all three stimulus conditions (thus including the initial training condition in order to establish a reliable baseline for transfer). First, and most importantly, no indications were found that the bimodal training group benefited from the addition of the tactile stimuli: both during training and transfer, performance in this group was very similar to the visual only training group. In line with Chapter 4, it was observed that the tactile only training group produced a smaller sequence effect during training than the visual only and bimodal training groups; however, results from the transfer phase indicated that this probably reflects differential expression, but not sequence learning, for the tactile only training group. Specifically, no differences between training groups were observed in the transfer phase when performance was tested under visual only or tactile only stimulus conditions (the bimodal transfer test did not yield similar findings; see chapter 5 for elaboration).

The absence of sequence learning benefits for the bimodal training group in Chapter 5 could possibly be explained by the spatial disparity between the visual stimuli (presented on the screen) and tactile stimuli (presented directly to the fingers). Indeed, successful integration between stimuli has been found to depend heavily on both temporal and spatial proximity. Therefore, a similar design as in Chapter 5 was employed in Chapter 6, but with both the color and location features of stimuli serving as the response cues. Hence, participants trained either with only centrally presented color cues, with location cues, or with a combination of these (i.e., stimuli were presented with a unique color for each location). Again, no sequence learning benefits were observed for participants trained with combined color and location response cues; in fact, no differences were observed at all between response cue conditions, both during training and transfer. Together, Chapters 5 and 6 seem to indicate that sequence learning does not benefit from having available multiple congruent response cues. This may also be relevant from an applied point of view (see also Chapter 8). For instance, virtual teaching systems are increasingly explored for their usefulness in perceptual-motor skill acquisition (e.g., Gillespie, O'Modhrain, Tang, Zaretzky & Pham, 1997), and the current results suggest that (the costly implementation of) redundant sensory information is not necessarily beneficial in this respect (even though technology would be sufficiently developed to achieve this).

The results of Chapters 5 and 6 may well be explained by the notion of selective attention. Stimuli or stimulus features may need to be attentionally selected in order to be involved in sequence learning (cf. Jiménez & Méndez, 1999), and, with the current design, the task could be successfully performed on the base of one particular stimulus or stimulus feature. Most probably, participants in the combined response cue conditions (i.e., visual-tactile and color-location) strategically selected the least demanding cue to respond to. Hence, in order to fully justify the claim that sequence learning does not benefit from redundant response cues, a design should be tested in which participants somehow use both the available response cues. Practically, however, it seems difficult to find two stimulus dimensions or stimulus types that have the same stimulus-response compatibility and similar salience.

As noted above, in Chapter 7 the focus was shifted from perceptual processing to processing at the response selection stage. A few previous studies had shown that increasing demands at the response selection stage (by manipulating the S-R mapping between groups of participants) positively affected sequence learning (Deroost & Soetens, 2006; Koch, 2007).

From these findings, it was suggested that sequence learning may be (partly) based on learning a series of successive response selections. To further explore this notion, the study by Deroost and Soetens (2006) was repeated and extended in the two experiments of Chapter 7. Results indicated that probably not implicit, but mainly explicit sequence knowledge benefited from employing incompatible S-R mappings. For instance, the benefit of employing an incompatible S-R mapping was absent when probabilistic sequences were used (Experiment 2), which are known to hinder the development of explicit knowledge.

The idea that the impact of differences in S-R compatibility occurs at the level of explicit learning is intuitively easy to understand: as the incompatible S-R mapping is more demanding, participants in this condition may have been motivated stronger to explicitly search for regularity in order to circumvent the S-R mapping. However, more data is needed to support this claim. Specifically, in addition to the data presented in Chapter 7, it needs to be shown within a single experiment that manipulating the S-R compatibility impacts sequence learning with a deterministic but not a probabilistic sequence. Ideally this would go accompanied by increased sequence awareness (as measured by, for example, the process dissociation procedure) in the incompatible S-R mapping condition for the deterministic, but not the probabilistic sequences.

Overall, in the current dissertation we have explored the representations underlying sequence learning in the SRT task. The results mostly fit well with a dynamic approach on implicit sequence learning that comprises associations a) between successive stimulus features (i.e., perceptual learning), b) between successive response features, and c) between successive response-to-stimulus compounds (i.e., response-effect learning). This may be extended by the notion that attentional selection plays a crucial role in stimulus-related learning (i.e., perceptual and response-effect learning; cf. Jiménez & Méndez, 1999), thereby explaining the absence of any sequence learning benefits from sensory redundancy. Such an approach was extensively elaborated on in the review that is presented in Chapter 2.

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Nederlandstalige samenvatting

Perceptueel-motorische vaardigheden zijn een even belangrijk als gecompliceerd onderdeel van de menselijke cognitie. Zonder deze vaardigheden zou het leven bestaan uit series op zichzelf staande acties, en zouden onze mentale bronnen al snel uitgeput raken in het bereiken van de doelen die we ons stellen. Om op gecontroleerde wijze onderzoek te doen naar perceptueel-motorische vaardigheden als dansen, sporten, autorijden of het bespelen van een muziekinstrument, zijn een aantal laboratoriumtaken ontwikkeld die elk één of meerdere processen onder de loep nemen van hun “grote broers” in het echte leven. De seriële reactietijd (SRT) taak, bijvoorbeeld, wordt gebruikt in het onderzoek naar het impliciet (i.e. niet-intentioneel, onbewust) aanleren van een vaste volgorde van acties.

In een typische setting van de SRT taak wordt iemand gevraagd plaats te nemen achter een computer. Op het beeldscherm worden gedurende de taakuitvoering vier (horizontaal uitgelijnde) locaties gemarkeerd waarop een stimulus kan worden aangeboden. Deze worden vanaf hier “placeholders” genoemd. Elk van deze locaties correspondeert met één specifieke toets op het toetsenbord. De instructie is het zo snel mogelijk indrukken van de toets behorende bij de locatie waarop een stimulus verschijnt, waarbij de volgende stimulus steeds wordt aangeboden op een vast interval na de laatste respons. De taak bestaat meestal uit om en nabij de duizend trials (waarbij één trial refereert aan één stimulusaanbieding en één toetsdruk), verdeeld over een aantal blokken met daartussen een korte pauze. Zonder dat dit bekend wordt gemaakt voor aanvang van de taak, worden de stimuli in een vaste volgorde (bv. met een lengte van twaalf elementen) aangeboden over de vier mogelijke locaties; dit impliceert dat ook de responsen een vaste volgorde doorlopen. Het aanleren van deze volgorde (i.e. sequentieel leren) maakt het mogelijk om te anticiperen op wat komen gaat, en dit wordt zichtbaar in de snelheid en accuratesse van reageren: naargelang er meer wordt geoefend, reageert men sneller en meer accuraat. Tegen het einde van de taak wordt de vaste volgorde van stimuli tijdelijk vervangen door een onvoorspelbare reeks stimuli, en de hierdoor veroorzaakte terugval in prestatie wordt gebruikt om het sequentieel leren te kunnen indexeren. Belangrijk is de observatie dat dit sequentieel leren vaak plaats heeft in de absentie van enig vermogen om de vaste volgorde te beschrijven, en zelfs in sommige gevallen zonder een besef van de aanwezigheid van enige structuur.

Een omvangrijk thema in de literatuur over de SRT taak betreft de precieze aard van het leren: welke soort informatie ligt er ten grondslag aan de representaties die zich vormen aan de hand van oefening? Dit vraagstuk staat centraal binnen het huidige proefschrift. Lange tijd werd het gekenmerkt door een streng oppositioneel denken, waarbij sommigen een verklaring op perceptueel niveau aanhingen (i.e. leren van de vaste volgorde van stimuli), en anderen juist een grote rol toedichtten aan responsgerelateerde informatie (bijvoorbeeld het leren van een vaste volgorde van respons locaties). Meer en meer ontstaat er tegenwoordig het besef dat er voor beide verklaringen zeer sterke ondersteuning is gerapporteerd in de literatuur, en dat een rol van betekenis voor beide niet langer kan worden ontkend. Daarnaast is er ook nog een derde, goed ondersteunde verklaring in omloop onder de noemer van respons-effect leren, waarbij zowel perceptuele als responsgerelateerde informatie belangrijk zijn. Namelijk, een gepresenteerde stimulus wordt beschouwd als een direct effect van de er aan voorafgaande respons, en het sequentieel leren vindt plaats op grond van een samenstelling van informatie van beide.

Aangezien er voor drie verklaringen van sequentieel leren goede ondersteuning bestaat in de literatuur, kan een goed model voor sequentieel leren niet langer gericht zijn op één specifieke verklaring, maar zal een structuur moeten hebben bestaande uit meerdere niveaus. In hoofdstuk 2 wordt voorgesteld om dit te bewerkstelligen op basis van een bestaand model van Keele en collegae (2003), dat bekend staat als het *dual system model*. Dit model gaat kortweg uit van een uni- en een multidimensionaal systeem voor sequentieel leren. Echter, een duidelijke uitleg betreffende het kernbegrip “dimensie” is tot op heden uitgebleven. Door nu dit begrip te relateren aan (representaties van) stimulus- en responseigenschappen uit het doorlopende informatieverwerkingsproces, brengt dit model bijna vanzelf de drie belangrijke vormen van sequentieel leren voort: het multidimensionale systeem is verantwoordelijk voor associaties tussen zowel a) achtereenvolgende stimuluseigenschappen (S-S of perceptueel leren), b) achtereenvolgende responseigenschappen (R-R of responsgerelateerd leren), als c) achtereenvolgende respons-stimulus samenstellingen (i.e., R-S of respons-effect leren). Het unidimensionale system, daarentegen, is alleen verantwoordelijk voor S-S en R-R associaties, en niet voor associaties tussen R-S samenstellingen omdat dit meerdere dimensies betreft. Deze voorgestelde synthese heeft wederzijdse voordelen. Aan de ene kant wordt het *dual system model* expliciet en direct gerelateerd aan een rijke literatuur over de aard van sequentieel leren (waardoor ook nieuwe voorspellingen aan het licht komen). Aan de andere biedt het *dual system model* een reeds uitgewerkt raamwerk waarbinnen de verscheidene vormen van sequentieel leren kunnen worden geïntegreerd.

Een belangrijk deel van dit proefschrift (met uitzondering van hoofdstuk 7) is gebaseerd op de gedachte dat een stimulusgerelateerd leren (i.e., perceptueel en respons-effect leren) een belangrijke rol speelt in de SRT taak, waarvoor toenemende ondersteuning bestaat. In hoofdstuk 3 is gekeken naar de mogelijke ontwikkeling van contextafhankelijk perceptueel-motorisch leren, waarbij het begrip context refereert aan ogenschijnlijk taakirrelevante (i.e., incidentele) informatie uit de taakomgeving. Dit fenomeen is bekend uit de (verbale) geheugen literatuur, maar binnen het domein van perceptueel-motorische vaardigheden echter nog amper onderzocht. In een SRT taak werd tussen trainings- en transferfase een verandering aangebracht in de achtergrondkleur (wit versus donkergrijs), de locatie op het scherm van de placeholders (onder versus boven), of de vorm van de placeholders (driehoekig versus rechthoekig). Belangrijk is dat de taak buiten deze contextuele veranderingen geheel hetzelfde bleef; dus inclusief het behoud van de sequentie. In het geval van verandering van de vorm van de placeholders bleek de prestatie te verminderen wat betreft reactietijden en foutenpercentages; er werd langzamer en minder accuraat gereageerd in de transferfase dan in de voorafgaande trainingsfase. In aanvulling hierop werd gevonden dat de prestatie op de taak weliswaar negatief werd beïnvloed wanneer de hele taak (training en transfer) werd uitgevoerd met enkel een pseudorandom volgorde van trials, maar in mindere mate dan in het geval van één vaste sequentie van trials. Dit laatste is belangrijk omdat het aantoont dat het negatieve effect van de verandering van placeholders op de prestatie gedeeltelijk sequentiespecifiek is.

In het vierde en vijfde hoofdstuk worden studies beschreven met onder meer een nieuwe versie van de SRT taak, waarbij niet de gebruikelijke visuele stimuli worden gebruikt, maar tactiele stimuli die direct op de vingers worden aangeboden. De resultaten van hoofdstuk vier impliceren a) dat sequentieel leren zich ook ontwikkelt met tactiele stimuli, b) dat sequentieel leren zich beter kan ontwikkelen met visuele dan tactiele stimuli, c) dat de transfer van tactiele naar visuele stimuli goed verloopt, en d) dat de transfer van visuele naar tactiele stimuli slechts gedeeltelijk plaatsvindt. In het vijfde hoofdstuk werden deze bevindingen nader bekeken in een uitgebreidere transferfase, en werd er eveneens een nieuwe hoofdvraag opgeworpen: heeft sequentieel leren voordeel bij redundante stimulusaanbieding (e.g., gecombineerde visuele en tactiele stimuli) ten opzichte van enkele stimuli? Dit laatste bleek niet het geval te zijn; sequentieel leren was zeer vergelijkbaar tussen condities met enkel visuele of tactiele stimuli, en een conditie met temporeel gesynchroniseerde, congruente visuele en tactiele stimuli wanneer werd vergeleken binnen identieke stimulus condities in een transferfase. Dit betekent ook dat er tegenbewijs werd gevonden voor één van de hoofdbevindingen uit hoofdstuk vier, namelijk dat sequentieel leren beter is met visuele dan tactiele stimuli. In hoofdstuk 5 bleek dat dit verschil meer te maken heeft met een betere expressie van het geleerde, dan met een daadwerkelijk verschil in sequentieel leren.

Hoofdstuk zes was eveneens gericht op de invloed van redundante stimuli op het sequentieleer proces. In hoofdstuk vijf werd een combinatie gebruikt van visuele en tactiele stimuli, en dit leidde niet tot enig voordeel voor het sequentieel leren. Een potentiële verklaring hiervoor is de fysieke afstand tussen de twee stimuli (i.e., tactiele stimuli op de vingers, visuele stimuli op het beeldscherm), terwijl spatiële congruentie (i.e., komend van dezelfde locatie), in aanvulling op temporele synchronisatie, een belangrijke determinant voor multisensorische integratie is. In hoofdstuk zes werd daarom gebruik gemaakt van de eigenschappen kleur en locatie van dezelfde stimulus om redundantie te scheppen. Met andere woorden, er werd een vergelijk gemaakt tussen a) een conditie waarbij alleen de locatie van de stimulus informatie over de te geven respons bevat, b) een conditie waarbij alleen de kleur van de stimulus informatie bevat over de te geven respons, en c) een conditie waarbij zowel de kleur als de locatie van de stimulus congruente informatie bevatten over de te geven respons. In overeenstemming met hoofdstuk vijf werd ook hier echter gevonden dat het sequentieel leren geen baat heeft bij redundante stimulusaanbieding.

Zoals aangegeven werd de focus in hoofdstuk zeven verschoven naar de rol van responsselectieprocessen bij impliciet sequentieel leren. Enkele eerdere studies hadden gerapporteerd dat impliciet sequentieel leren beter is bij een incompatibele dan een compatibele *mapping* tussen stimulus- en responsmogelijkheden (i.e., Deroost & Soetens, 2006; Koch, 2007). Omdat het manipuleren van deze *mapping* vooral het responsselectieproces wordt geacht te beïnvloeden, werd uit deze bevinding geconcludeerd dat impliciet sequentieel leren gedeeltelijk plaats heeft op het niveau van responsselectie. Om deze interpretatie verder te onderzoeken, werd in hoofdstuk zeven de studie van Deroost en Soetens (2006) twee keer overgedaan in settings die de ontwikkeling van het expliciete leren bemoeilijken. In deze settings verdween het eerder gevonden voordeel van een incompatibele *mapping*, wat suggereert dat niet het impliciete, maar juist het expliciete sequentieel leren baat heeft bij een incompatibele *mapping*. Dit zou begrijpelijk zijn vanuit de gedachte dat de incompatibele *mapping* meer moeite kost in de uitvoering, en dus meer motiveert tot het (expliciet) zoeken naar een manier om deze *mapping* (gedeeltelijk) te kunnen omzeilen, zoals regulariteit in de stimulus- en/of responsreeksen. Echter, om dit idee goed te kunnen ondersteunen, is een additionele studie nodig waar heel systematisch de interactie tussen *mapping* (i.e., compatibel versus incompatibel) en de aard van het leren (i.e., impliciet versus expliciet) wordt bekeken.

Over het algemeen vallen de empirische hoofdstukken goed binnen het raamwerk dat is voorgesteld in hoofdstuk twee van dit proefschrift, waarbij perceptueel leren, respons-effect leren en responsgerelateerd leren een dynamisch geheel vormen. Er komen aanwijzingen uit naar voren dat perceptuele informatie een rol speelt (i.e., hoofdstuk 3 en 4) bij sequentieel leren, maar eveneens dat niet het gehele leren gebonden is aan perceptuele informatie (en waarschijnlijk responsgerelateerd is). In aanvulling hierop weerspreken de resultaten uit hoofdstuk zeven het (indirecte) bewijs voor impliciet sequentieel leren op het responsselectieniveau zoals gerapporteerd door Deroost en Soetens (2006), waarmee het weglaten van deze vorm van sequentieel leren binnen het raamwerk zoals geposteerd in hoofdstuk 2 verder kan worden.gerechtvaardigd. Hoofdstuk vijf en zes laten ten slotte zien dat sequentieel leren geen baat heeft bij redundante stimulusaanbieding. Dit impliceert een rol voor attentionele selectie binnen het stimulusgerelateerde leren (i.e., perceptueel en respons-effect leren).

Tot slot van dit proefschrift wordt in hoofdstuk 8 geïllustreerd hoe verschillende bevindingen uit de SRT literatuur, inclusief enkele studies uit dit proefschrift, van waarde kunnen zijn voor toepassingsgericht onderzoek, in dit geval met betrekking tot ontwerpen van trainingsprocedures voor perceptueel-motorische vaardigheden.

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