Journal of Experimental Psychology: Learning, Memory, and Cognition

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Online First Publication, October 10, 2011. doi: 10.1037/a0025816

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0278-7393/11/$12.00 DOI: 10.1037/a0025816

Position–Item Associations Play a Role in the Acquisition of Order Knowledge in an Implicit Serial Reaction Time Task

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Knowledge of sequential regularities plays a key role in forms of explicit and implicit memory, such as working memory and motor skills. Despite important advances in the study of sequence knowledge in the past century, the theoretical development of implicit and explicit memory has occurred separately. Unlike the literature on implicit sequence learning, the explicit learning literature differentiates between 2 forms of representation of serial structure, chaining (*C* is the item following *B* in the sequence *A-B-C-D*) and ordinal position knowledge (*C* is the 3rd item). In 3 experiments, we demonstrate that these 2 forms of sequence knowledge can be acquired in implicit sequence learning. In Experiment 1, 2 trained sequences were recombined at transfer such that the strength of (a) associations between serial positions and sequence elements as well as (b) associations between successive sequence elements could be estimated. In Experiment 2, we compared sequence elements placed at the trained versus untrained serial position. Experiment 3 reduced cues that can be used to determine the start of a sequence within the stream of trials. Our results suggest that the discussion held in explicit memory research about different forms of representation of sequences knowledge also is relevant for implicit sequence learning.

Keywords: implicit sequence learning, serial order, SRT, chaining

The study of serial learning has a history that dates over a century (Ebbinghaus, 1885/1913; Nipher, 1878) and is commonly regarded as one of the most fundamental topics in the study of memory (Crowder, 1976; Lashley, 1951). Serial learning refers to the ability of animals to learn sequential information, supporting a successful reproduction of a sequence or anticipation of upcoming events such that responses can be prepared in advance (e.g., Cleeremans, 1993). The significance of this topic rests on the insight that much of human "memory power" derives from the order in which sequential input is stored. When one memorizes a telephone number, for instance, learning does not usually consist of establishing representations of numbers, but rather one learns that the numbers occur in a specific serial order. Two general ideas can be distinguished regarding the representation of serial order: It might consist of associations between successive numbers (i.e., for instance, 2 comes after 4) or as an association between serial positions in the sequence and the numbers (i.e., the second number to dial is a 4). In view of these two hypothesized forms of representations, memory researchers seek to understand the exact nature of serial learning (for reviews, Crowder, 1976; Marshuetz, 2005; Rhodes, Bullock, Verwey, Averbeck, & Page, 2004). In this article, we address fundamental issues regarding the implicit learning and memory of serial order representations—the first study to our knowledge that addresses this important topic.

To explicate the motivation of this research, we would like to advance two arguments. First, because the way knowledge is acquired is different in implicit and explicit memory tasks, it is conceivable that the acquired knowledge is different, too. Whereas in explicit learning tasks, participants have an explicit goal of acquiring knowledge, implicit learning tasks are characterized by the fact that learning is an unintended by-product of task processing (e.g., Frensch, 1998). Second, although some research has suggested that serial learning might be based on the same or similar mechanisms in different learning situations (Colombo & Frost, 2001; Mayr, 2009; Raanaas & Magnussen, 2006; Stadler, 1993), specific theories concerning the representation of order derived from explicit learning tasks have yet to be tested in implicit learning tasks. Furthermore, the representation of order information acquired in implicit sequence learning has not been thoroughly explored. The unquestioned view underlying work on

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Nicolas W. Schuck and Robert Gaschler were supported by a fellowship of the International Max Planck Research School "The Life Course: Evolutionary and Ontogenetic Dynamics" (LIFE; www.imprs-life.mpg.de). We thank Ulrich Mayr for an insightful discussion that led to Experiment 2. We are also grateful for helpful reviews by Iring Koch, Pierre Perruchet, Fergal Jones, and Stephen Monsell. Furthermore, we thank Tilo Strobach, Sabine Schwager, Valentin Umbach, and André Weinreich for valuable comments concerning earlier versions of the article and all members of Peter A. Frensch's laboratory who helped with manuscript editing (Kate Koennecke and Anika Hinz) and data acquisition.

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implicit sequence learning appears to be that the representation of serial order consists of associations between successive elements (see below). Yet, this is partly inconsistent with results on serial order representations in working memory tasks. We therefore believe that applying theoretical insights from explicit learning studies to understand implicit sequence learning can advance the understanding of order representation in implicit learning.

Specifically, we tackle the question of whether implicit learning of sequential regularities results in knowledge that a certain sequence element occupies a specific serial position (e.g., memory that the second digit of a phone number is 4). There is a lack of direct evidence for implicit learning in this context, but there is a strong case for such knowledge in explicit memory and animal research (e.g., Brown, Morin, & Lewandowsky, 2006; Farrell, 2008; Lee & Estes, 1981; Young, Hakes, & Hicks, 1967; for animal learning, see Chen, Swartz, & Terrace, 1997; Orlov, Amit, Yakovlev, Zohary, & Hochstein, 2006). This idea has mainly been supported by experiments using methodology uncommon in implicit sequence learning research—for instance, using multiple lists and studying transfer between lists (e.g., Melton & von Lackum, 1941). Here, we apply some of these principles (using multiple lists) to an implicit sequence learning setting in humans while also introducing novel methodology. As outlined below, this novelty consists of using previously unused "items" in the sequences during a test phase. We argue that this method enables us to draw clearer inferences about knowledge of serial positions from observable behavior.

Before we review theories on serial structure, it is necessary to define some terminology, which we use to describe statistical properties of sequences. At the heart of the theoretical issues that are discussed below is the term *serial position*, which refers to the position within a sequence with relation to the start of the sequence. That is, if we have a sequence with the elements/items *A-B-C-D*, presented in that order, the serial position of *C* would be 3 (note that in the verbal learning literature, the sequence elements/item are mostly words or syllables, but in our case, one "item" will be a target location on a screen in a visual search task). Hence, a repeated sequence exhibits a contingency between a serial position and a sequence item. We aim to investigate the representation of such contingencies, namely *serial position–item* associations. A second key feature of a sequence concerns *transition probabilities*, that is, the probabilities with which certain sequence items will follow other sequence items. Such transition probabilities can be represented as associations between items (*item–item associations*). Hence, sequences may differ with respect to their transition probabilities, contingencies between serial positions and items, and any other information that helps predict future items (e.g., knowledge that elements occur with equal frequency). Our goal is to determine the degree to which serial position contingencies and transition probabilities support implicit sequence learning.

In the remainder of this introduction, we first discuss existing evidence concerning the representation of order in implicit serial learning and, specifically, of serial position–item associations. Then, as the notion of serial position–item associations has been deployed mainly in working memory/verbal learning research, we delineate relevant theories in this literature.

Implicit Serial Learning and Representation of Order

Although most studies on implicit learning have been conducted using serial learning paradigms, the representation of serial order was not often the focus of research in this field. Implicit learning in general refers to the phenomenon of non-intentional, automatic acquisition of knowledge (Frensch, 1998), whereby it is broadly assumed that information about the structure of the stimulus environment is acquired (Cleeremans, 1993). One of the most common paradigms in implicit learning is the serial reaction time task (SRT). In the classical setup of the SRT task, participants are asked to respond to the screen location of a stimulus by pressing a spatially corresponding key (Nissen & Bullemer, 1987). In one condition, the screen locations of successive stimuli follow a repeated sequence. In this case, participants can in principle learn the serial structure (in the sense we defined above) of the reoccurring sequences. Participants are not informed about the sequential structure and the resulting possibility of learning the sequence. Learning can be inferred when participants respond faster to reoccurring sequences than to random sequences. At the same time, post-experimental interviews show that participants have no verbal knowledge of the sequences and are not aware that they learned anything at all (Willingham, Nissen, & Bullemer, 1989).

Research on implicit sequence learning has mainly focused on whether and to which degree sequential structure is learned implicitly, rather than on how that structure is represented. On the one hand, research has in many cases dealt with the question of *how much* implicit sequence knowledge can be acquired and detected depending on conditions such as neurological impairment (e.g., Nissen & Bullemer, 1987) or working memory/attentional load (e.g., Cohen, Ivry, & Keele, 1990; Frensch, Buchner, & Lin, 1994; Frensch & Miner, 1994; Schumacher & Schwarb, 2009). On the other hand, implicit sequence learning research focusing on sequence structure has generally not considered the possibility of serial position–item associations. For instance, Hoffmann and Koch (1998) summarized that "learning . . . takes conditional probabilities into account" (p. 183). In this sense, the study of implicit sequence learning has largely relied on the assumption that transition probabilities are learned and are represented as item–item associations. Cohen et al. (1990) noted in the context of an implicit SRT study that "[one] mechanism, which presumably can operate under distraction, forms associations between adjacent items" (p. 28).

Although the implicit sequence learning studies conducted with the SRT have focused on item–item associations (i.e., chaining), some reference to a potential role of associations between item and serial position for representation of sequential structure can be found in the literature on artificial grammar learning. Gomez and Schvaneveldt (1994), for example, found abstract (transferable) knowledge of an artificial grammar when participants were exposed to strings of letters but not when they were exposed only to pairs of letters (see also Dienes, Broadbent, & Berry, 1991; Gomez, Gerken, & Schvaneveldt, 2000; Mathews & Roussel, 1997; Pacton, Perruchet, Fayol, & Cleeremans, 2001; Tunney & Altman, 1999). Gomez and Schvaneveldt argued that the advantage of strings of letters over pairs of letters is derived from positional constraints about the frequency of letter pairs (so called bigrams). It is not only important to know which bigrams occur frequently, but also where within the sequence they occur, that is, at which serial position. In a similar vein, Pacton et al. (2001) demonstrated that children implicitly acquire knowledge about serial position–letter regularities in French orthography that are consistent with associations between a letter and its within-word position and cannot be attributed to letter-to-letter associations. More specifically, the children had learned that letter repetitions in their natural language may not occur at the beginning of words, which, as the authors argued, is not taught explicitly in school. It is likely that children implicitly extract ordinal position information about French morphology over the course of language acquisition.

Taken together, the existing literature on implicit serial learning (a) provides only few and indirect results from which acquisition of serial position–item associations can be derived and (b) includes only (artificial) grammar studies, not SRTs. The implicit acquisition of item–item associations, in contrast, is a well-established phenomenon.

Representation of Order in Explicit Memory Tasks

In explicit memory tasks, in contrast, the question of how serial order is represented has been addressed much more directly and thoroughly. For the purposes of this short review, we consider theories of explicit serial order memory that emphasize either of the two key statistical regularities of sequences that we introduced above: transition probabilities or serial position contingencies. The debate about the power of these classes of theories, chaining theories, and serial position theories, respectively, is a hotly contested issue in working memory research (Crowder, 1976; Marshuetz, 2005).

Figure 1A illustrates the principles of chaining. The common factor in *chaining theories* is that associations between items/elements of a sequence are assumed to be the means by which serial order is stored (e.g., Ebbinghaus, 1885/1913; Murdock, 1993; Young, 1968). In the classic Ebbinghaus (1885/1913) account, all items of a list (e.g., a sequence of nonsense syllables) become associated with all other items. Most importantly, serial order is achieved because (a) the strength of the associations between two items varies inversely with their remoteness in the list and (b) forward associations are stronger than backward associations. Therefore, when participants learn the list *A-B-C-D* (the letters can denote any sort of item/element), their learning would mainly involve the construction of associations between each two adjacent items in the forward direction, such as *A-B*, *B-C*, and so forth.[1] Consequently, the retrieval[2] of item *A* leads most likely to the retrieval of item *B*, as the strongest association is *A-B*. The retrieval of *B* then leads most likely to the retrieval of item *C* for the same reason, and in this fashion, the serial order of the memory content is explained. The ability of this mechanism to explain the variety of empirical reports has been debated intensely in the literature on verbal list learning/working memory (e.g., Marshuetz & Smith, 2006; for a review, see Crowder, 1976). Although the initial ideas have been applied successfully to a variety of empirical evidence and have inspired a number of related accounts that have shown even greater explanatory power (Botvinick & Plaut, 2006; Murdock, 1997), some data appear to be clearly incompatible with a chaining-based approach (Marshuetz, 2005). These incompatibilities concern the key prediction we outlined above, that is, that the retrieval of one sequence element should depend on the retrieval of the preceding sequence element. For the same reasons as the retrieval of item *C* is most likely after item *B*, it should be greatly affected if the retrieval of *B* is disturbed. Baddeley (1968) tested this idea by using lists of alternating phonological confusable and non-confusable words in an immediate serial recall task, in that *A* and *C* would be non-confusable and *B* and *D* confusable. From a chaining perspective, there is a clear prediction: If the retrieval of item *B* is hindered because it can be easily confused with another item, then the retrieval of item *C* should be less likely too—irrespective of its own confusability. In contrast to these predictions, however, it has been found that performance for item *C* (a non-confusable item) is as good as it was in a list of pure non-confusable items (Baddeley, 1968). This result clearly supports the notion that the retrieval of one item does not necessarily depend on the retrieval of the preceding item, as it is suggested by chaining theories.

The confusability effect finding supports alternative theories to chaining models of serial working memory, namely *serial position theories* (see Figure 1B). These theories usually entail two main components: (a) internal representations of serial position that

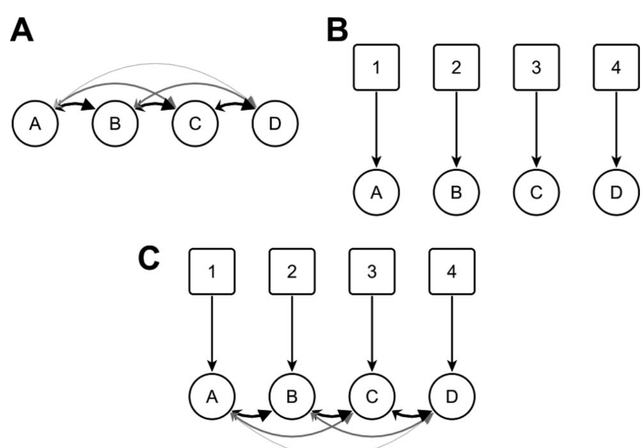

Figure 1. Theoretical approaches to storing sequential structures. (A) Stereotypical chaining approach, where the sequence elements A, B, C, and D are connected via associations between items. The strength of the associations is indicated by the respective arrow's color (black stronger than gray) and thickness. Larger arrowheads for forward than for backward transitions indicate weaker associations for the latter. See text and Footnote 1. (B) Stereotypical serial position approach. The rectangles indicate the internal representation of the serial position. Associations link the respective items with the serial position they occupied in the sequence during learning. (C) Combination of serial position and chaining approach, where both principles are combined. See text for explanations.

[1] Additionally, but to a greatly reduced extent, associations between *lag-2* adjacent items (*A-C*, *B-D*, etc.), and even (but again to a lesser extent) associations of a higher order (lags 3, 4 . . .), would be acquired. The second component in this account are backward associations (*B-A*, *C-B*, . . .) that are generally less strong than forward associations and follow the same principle, that is, their strength is inversely related to the remoteness of the items. For simplicity, we neglect these details here, as they do not change the overall predictions greatly.

[2] If the association originates from the production, the retrieval or the perception of the item is a question of its own that we do not address here, but see Slamecka (1977).

indicate the current position within the sequence and (b) associations between these representations and the current sequence element (e.g., Brown, Preece, & Hulme, 2000; N. Burgess & Hitch, 1999, 2006). The various accounts differ widely with respect to what exactly is meant by the internal representation of serial position, but for our present purposes, we can simply describe them as some representations that contain the generic information of the current serial position, irrespective of the sequence element (for more specific proposals of neural and computational instantiations, see Nieder, Diester, & Tudusciuc, 2006; Salinas, 2009). For the following illustrations, we denote such representations as [1st element], [2nd element], and so forth. The second component then involves associations of these serial position tags with the sequence elements that are currently learned. For instance, when a four-element sequence, again say *A-B-C-D*, is to be learned, serial position theories would posit that the following associations develop during learning: [1st element]—*A*, [2nd element]—*B*, [3rd element]—*C*, [4th element]—*D*. In this framework, the activation of the representation of [1st element] leads to the activation of *A*. Then [2nd element] has to be activated, which leads to *B*. We termed the associations between the serial position representation and the sequence elements *serial position–item* associations. We note that serial position representations are only possible in relation to an anchor that defines where a sequence starts and/or ends. Given the material we used in the present study, the start of a sequence is at the same time the end of the previous one. Therefore, we do not focus on the question of different roles of the start of a sequence and its end. Although we examine the role of an anchor in general in Experiment 3, we, for simplicity, conceptualize the anchor as the start of a sequence. We acknowledge, however, that an exclusive consideration of forward processing starting from start cues is, in the light of according studies on word segmentation (Perruchet & Desaulty, 2008), unwarranted.

In summary, two different classes of theories that aim to explain the knowledge of order are discussed most in the literature of explicit serial learning. In chaining accounts, retrieving memory contents in a learned order is achieved by associations between items. In serial position approaches, in contrast, such associations between sequence elements play a secondary role (or none at all), but associations between each sequence element and a representation of its corresponding serial position are the primary means by which serial order information is stored. Crucially, the theories differ in their predictions, particularly in situations where the retrieval of some items of a learned sequence is disturbed. Whereas in chaining theories the retrieval of one item depends on the correct retrieval of its preceding item, this is not the case in serial position theories. Accordingly, chaining theories predict performance losses for single elements from a learned sequence when the previous element was not recalled, whereas serial position theories do *not* predict performance losses as long as the sequence element is at the same serial position as it was during learning.

The Present Study

Although these theories have been discussed and tested extensively in the working memory literature, to date no reported study has been conducted in implicit sequence learning (see also, Schuck, Gaschler, & Frensch, in press). We conclude that some evidence from the implicit serial learning literature, on the one hand, and converging evidence from the working memory literature, on the other, supports the role of two types of knowledge in serial learning: item–item associations and serial position–item associations. In this study, we developed a serial learning task and transfer design that enabled us to assess the role of these two different representations of serial order in implicit memory. The argument advanced here is not that order information tied to serial position provides the *only* basis for implicit sequence learning. It is well known that humans form associations between (even remotely) successive items during sequential learning (Ebbinghaus, 1885/1913). Additionally, existing evidence suggests that probabilistic/statistical knowledge also plays a role in implicit learning (see Perruchet & Pacton, 2006). In fact, early researchers on sequential behavior proposed an integration of different sources of knowledge in one theoretical account, suggesting "position learning may not be adequate to account completely for serial learning" (Ebenholtz, 1963, p. 607). We strongly agree with this view, and the design of the present experiments reflects this belief. Figure 1C illustrates a combination of item–item associations and position–item associations.

We designed three experiments that test whether serial position information can be acquired in an implicit sequence learning task. We tested this general claim by rearranging learned sequences in Experiment 1. In Experiment 2, we tested the knowledge of serial position information more directly and ruled out that the results could be explained by knowledge of the overall frequency of items. In Experiment 3, we showed that consistent grouping by sequence segmentation anchors is necessary for serial position contingencies to be acquired.

Because our claim is directed at the case of *implicit* sequence learning, the assessment of explicit knowledge is important for the validity of our results. Following the argument of Rünger and Frensch (2008, 2010), we consider verbal recall as the best direct test of explicit sequence knowledge and used such procedures in all experiments. Although this is not the central issue of this work, we acknowledge the ongoing debate about tests for explicit knowledge and how they can affect outcomes (cf. Shanks & St. John, 1994). We therefore included an additional recognition test in Experiment 3. Furthermore, we used a conservative criterion for excluding participants based on their recall score.

Experiment 1

Experiment 1 tests whether serial position–item associations as well as item–item associations are implicitly acquired during an incidental sequence learning task.

Method

Participants. Twenty-seven participants took part in the experiment. Six were excluded due to partial explicit knowledge of the sequential regularities (see below). The remaining 21 participants (mean age = 26.6 years; seven men) were students at Humboldt-Universität (Berlin, Germany) and participated in exchange for course credit or a financial reward (6€). All participants had normal or corrected to normal vision.

Material and task. All experiments used the same basic methodology and design. For sequence learning, a visual search task was employed where the screen locations of successive targets followed different types of sequential regularities. We chose to use a serial visual search paradigm, as it offers specific advantages that are crucial for our design. In specific, for the here-used design, it is important to have many different sequences with non-overlapping items. In classical SRT paradigms, one item is always associated with one response (and has to be). In the following experiments, however, we needed 32 different "items," and in consequence a classical SRT setup (with, e.g., 32 screen positions as stimuli being mapped to 32 keys) was impractical. We discuss some of the implications of our choice below. Previous studies have already shown that in a paradigm similar to ours, sequences of target screen locations can be learned implicitly (e.g., Deroost & Soetens, 2006; Mayr, 1996; Remillard, 2003; Schuck et al., in press, Stadler, 1989; Ziessler, 1998). However, in these studies, the focus was not on testing the contribution of item–item associations and serial position–item associations to overall sequence knowledge. Please note that target screen locations describe the spatial *location* on the screen and are not to be confused with serial *positions* (i.e., "Where on the screen?" vs. "Where in the list of items?").

Participants were asked to search for a single target among distracters on the screen and to identify the tilt of the target. A "T" (tilted to the left or right) served as the target, and rotated "Ls" (same size) served as distracters (see Figure 2B). During each trial, the target appeared on the screen at one of 32 possible locations, and distracters occupied the remaining 31 locations. The stimulus locations formed a 6 × 6 (minus four because the corners were left empty) quadratic grid that was centrally presented. Each cell in the grid measured 96 × 96 pixels at a screen resolution of 1,024 × 768 pixels (17-in. [43.18-cm] screen). Participants were seated ~60 cm from the screen, resulting in a visual angle of ~3.01° for each target/distracter. If the "T" was tilted to the left, participants were to press the left key; the right key was to be pressed for a "T" tilted

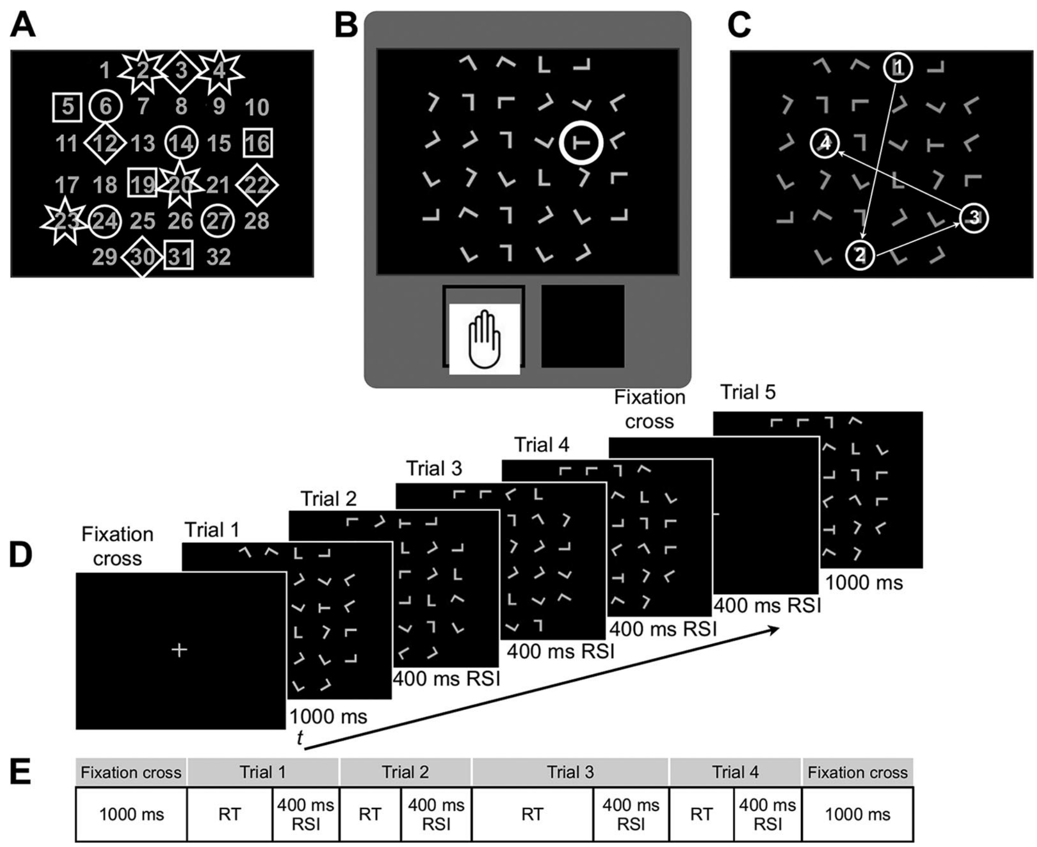

Figure 2. Serial visual search task. (A) Distribution of sets of target screen locations. For illustration purposes, the screen positions are numbered (the actual screen contained letters, see [B], [C], and [D]). Random and fixed sequences each consisted of four target screen locations. The actual sets of target screen locations used for the two random and fixed sequences were balanced across participants. The figure shows the four sets of locations that were used in Experiment 2 (the locations belonging to each set marked by a different shape, i.e., circles, squares, triangles, and stars). The different experiments used different location sets. (B) In each trial, participants saw 31 rotated Ls and one T on the screen. They were instructed to spot the target (the tilted T) and press a button corresponding to whether the T was tilted to the right or left. (C) Over successive trials, the target appeared on different locations on the screen. In most mini-blocks, the location where the target could be found followed a fixed, repeated sequence of locations. (D) The stream of trials was divided into mini-blocks by a fixation cross that appeared after each fourth trial and remained on the screen for 1,000 ms. Participants did not have to respond to the fixation cross. The regular response-stimulus interval (RSI) was 400 ms. (D) Because only the RSI and the duration of the fixation cross were fixed, but participants exhibited a variable reaction time (RT), the inter-stimulus interval was variable as well.

to the right. A fixation cross appeared after each fourth trial for 1,000 ms, dividing all trials into mini-blocks of four trials each (see Figure 2D, but note an exception in Experiment 3). Therefore, the target appeared successively at four different locations between two fixation crosses (see Figure 2C). The sequential regularities of consecutive target screen locations within such mini-blocks (four trials between two fixation crosses) differed between conditions. Errors were signaled by a tone. The response-stimulus interval (RSI) was set to 400 ms (i.e., after a response, the next stimulus appeared after a 400-ms pause).

Procedure and design. All experiments included a learning phase and a transfer phase. During learning, we employed two different sequence conditions. Each sequence condition concerned the sequence of four target screen locations within a mini-block and was implemented in two sequences. In the *fixed sequence* condition, successive target screen locations followed a fixed first-order sequence. In the *random sequence* condition, a given set of four locations was presented in random order without replacement. Consequently, the target screen location of each element of the fixed sequences had a serial position–item contingency (a given target screen location always occupied the same serial position) and deterministic transitions. The random sequences comprised probabilistic item–item transitions and no serial position contingencies. Previous implicit learning experiments have shown that participants can acquire such transition probabilities (for a review, see Perruchet & Pacton, 2006). The target screen locations of different sequences (random or fixed) did not overlap. The assignment of target screen locations to the random and fixed conditions was balanced between participants. Each fixed sequence principally allowed for the acquisition of item–item associations and serial position–item associations to be assessed separately in the transfer phase.

To ensure strong learning, the fixed sequences were presented twice as often as the random sequences. The learning phase consisted of 10 blocks of 96 trials each, totaling 960 trials/240 mini-blocks. Thus, all participants responded to each of the two fixed sequences 80 times during the learning phase and to each random sequence 40 times. All mini-blocks appeared in pseudo-random order, excluding the possibility of more than three consecutive mini-blocks with the same fixed sequence. Furthermore, sequences were constructed so that two consecutive target screen locations could not appear in neighboring positions on the screen and all four screen quadrants were used. Moreover, the mean distance of target screen locations from the fixed and random sequence conditions was balanced, as was the assignment of specific screen locations to the two conditions (counterbalanced between participants).

After the learning phase, we introduced an unannounced transfer block that constituted the last block of the experiment. The design of the transfer block entailed three types of transfer sequences and is illustrated in Figure 3. They targeted the two different types of sequence knowledge discussed: item–item associations and serial position–item associations. In any of the three versions of transfer sequences, *one* of the four serial positions was occupied with a target that had been trained on this serial position within one of the fixed sequences of the learning phase. This we call *test condition*. All serial positions in the fixed sequences were used with equal frequency. The three types of transfer sequences differed with respect to how the remaining three serial positions were filled (compare Figure 3; from now on: *background condition*).

Our main goal was to dissociate the learned serial position contingencies and transition probabilities. Consider the sequence *A-B-C-D*. The serial position contingency (the focus of serial position theories) reflects the fact that *C* appears as the third element. The transition probability (the focus of chaining theories) reflects the fact that *C* follows *B*. These two sequence properties were disentangled using the following kind of transfer sequence (which was common to all experiments). This sequence consisted of three target screen locations that had not been used in the learning phase (called *background condition*) and one that was part of a fixed sequence (*test condition*; see Figure 3A). The test item occupied the same serial position as in the fixed sequence (it conformed to the learned serial position–item contingency). A sequence *X-Y-C-Z* can serve as an example, where *X*, *Y*, and *Z* denote target screen locations that were not used during the learning phase, and *C* is the third item from one of the fixed sequences trained in the learning phase. Because *C* is not preceded by target screen location *B* (or *A*), chaining would not predict an RT advantage for finding the target *C* in the sequence, as the learned transition probabilities cannot be used. In contrast, a serial position theory would predict such an RT advantage because the target screen location remained at its trained serial position. Having acquired a serial position–item association therefore would lead to finding the test item faster. Because the sequence employs new target screen locations, it is termed *new-transfer sequence*.

For each new-transfer sequence, the unused items were randomly drawn with the constraint that all unused locations would be used equally often insofar as possible (some locations had to be used once less often). As a result of differing learning phase frequencies between the test and the background items in this condition, however, one could predict a similar behavioral pattern based on both (frequency or serial position focused) explanations. Although this is inevitable in the current design, we rule out the frequency explanation in Experiment 2. The second and third types of transfer sequences were used to evaluate the influence of item–item associations and to compare it to the one of item–position associations.

For the mini-blocks in the *random-transfer sequences*, again one sequence element always appeared at a target screen location that was used for the same serial position as during learning (test condition). The remaining three sequence elements were selected from one of the target screen locations with random order in the learning phase (random items were assigned randomly to serial positions; background condition). More precisely, target screen locations used during the learning of the random sequences were mixed with one target screen location used in one of the fixed sequences. Because random target screen locations co-occurred within mini-blocks during the learning phase, we expected weak item–item associations. Exposure to one item should result in some activation of the three other screen locations pertaining to the same item pool (item–item associations). In contrast, a successive activation of the current serial position within the mini-block (as assumed by serial position theories), should lead to the activation of items that repeatedly occurred at this serial position (serial position–item associations). Even though we assume item–item and serial position–item associations will both contribute to per-

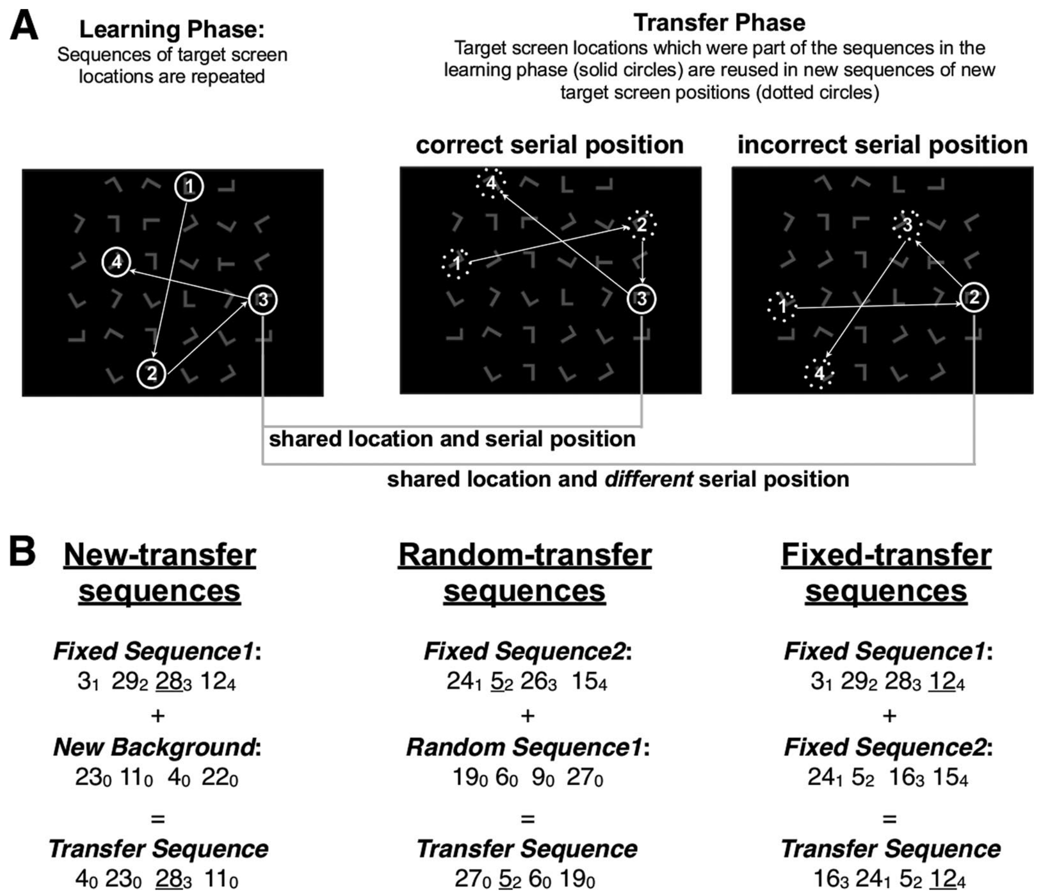

Figure 3. Basic principles and examples of transfer sequences. (A) The basic principle of the transfer sequences was to reuse single target screen locations that were part of a repeated sequence during learning. In the transfer sequences, these single target screen locations were then part of new sequences. In principle, then, they could either appear at their correct or incorrect serial position. (B) The three different panels show examples of the different transfer sequences (see panel header). In each panel, the two sequences that have been used to construct a transfer sequence of the respective condition are shown. The subscripts indicate the serial position of the items where applicable (random and new sequence items did not have a fixed order and hence no fixed serial positions, indicated by the 0s). The underlined number indicates the test item that will be reused in the transfer sequence. Below these (after the = sign), one example resulting from the combination of these sequences is shown. Note that in each case, the underlined item is the item from the fixed sequence that did not change its serial position. The examples used correspond to the actual screen location/condition assignments that were used for some of the participants. The used assignment was varied between subjects.

formance, serial position–item associations should be faced with a rather weak competitor in the random-transfer sequences.

In mini-blocks of the *fixed-transfer sequences*, targets only appeared at the screen locations that were used in the two fixed sequences of the learning phase. One item was placed at its trained serial position (test condition). The others were taken from the alternative sequence and were randomly ordered (for each sequence), excluding the possibility that such a sequence item appears at its correct serial position and ensuring equal use of sequence items (background condition). Consider the fixed sequence *A-B-C-D*. The second fixed sequence is denoted as *a-b-c-d*. An example would be the sequence *c-a-C-b*, where *a*, *c*, and *b* denote the first, third, and second target screen locations from one fixed sequence, and *C* is the third target screen location from the other fixed sequence. A chaining approach (based on item–item associations) would predict that encountering element *a* will lead to activation of element *b* and thus interfere with the search for element *C*. Hence, *C* should not be found faster than the targets in background condition.

In all three transfer conditions, the fixed sequence target screen locations in test trials were distributed equally over the four possible serial positions. Each participant received a different random order of the mini-blocks belonging to different transfer sequence conditions. Eight sequences of each of the three transfer conditions made up the last block (totaling 24 mini-blocks), and so the last block was of the same length as the learning blocks.

Design. The design utilized two repeated-measures independent variables in the learning blocks, Learning Condition (fixed sequence vs. random sequence) and Block, as well as two repeated-measures factors in the transfer block, Transfer Sequence (new-transfer sequence vs. random-transfer sequence vs. fixed-transfer sequence) and Trial Condition (background vs. test condition). The dependent variable was participants' response times to targets at screen locations in learning and transfer.

Assessment of explicit knowledge. Following the end of the computer-based part of the experiment, all participants were tested for their explicit knowledge of the fixed sequences used during the learning phase. The instructor provided each participant with a sheet containing two grids of the same form as the possible positions on the screen (a 6×6 square with omitted corners). Participants were then informed about the existence of two repeated fixed sequences in the experiment and were asked to try to recall at which screen locations and in which order the targets appeared most often during the experiment. The cells in the grid indicated the different locations on the screen. Half of the participants were asked to mark the target screen locations directly into a provided empty grid, using the numbers 1–4 to indicate the order of target locations. The other half of the participants were provided with a grid in which the cells were numbered 1–32. They were asked to name the screen locations by saying the corresponding numbers in the respective order. We acknowledge that assessing the explicit knowledge after the transfer phase might potentially underestimate the explicit knowledge that existed during learning, as some knowledge might get lost due to interference caused in the transfer phase. As described below, however, we apply a very conservative threshold (excluding all participants that reported more than one item correct in either sequence).

Results

For all analyses of reaction times (RTs), error trials as well as trials following incorrect responses were excluded. To eliminate the influence of outliers, analyses were based on median RTs for each participant in each of the factor cells (Luce, 1986). Hence, "mean RTs" refers to the mean of medians of participants for each factor cell. According to convention, we label all results with $ps \leq .05$ as significant. Regarding the numerical description, we report the exact p values for all $ps > .001$ (rounded to three decimal places). We used a significance level of $\alpha = .05$ (two-tailed) throughout.

All statistical analyses were conducted in R (R Development Core Team, 2010). The overall error rate in Experiment 1 was 1.3%. There was no speed–accuracy tradeoff, as assessed by the correlation between raw RTs and accuracy, $t(19)$[3] $= 0.34$, mean $r = .00$.

Learning phase. Participants reacted faster to fixed rather than to random sequences. The mean RT difference between the two sequence conditions was 112 ms. Over the course of the experiment, RTs decreased faster for fixed than for random sequence trials. A 2 (Learning Condition: fixed vs. random sequence) $\times$ 10 (Block) two-way within-subjects analysis of variance (ANOVA) reflects this development in a significant interaction of the factors Learning Condition and Block, $F(9, 180) = 2.99$, $p = .002$, $\eta_p^2 = .13$. By the end of learning, there was a substantial basis for transfer. Data from the last five blocks showed shorter RTs for trials from fixed sequence as opposed to random mini-blocks, $F(1, 20) = 12.04$, $p = .002$, $\eta_p^2 = .38$. This indicates that learning had taken place in the fixed sequence condition by the second half of learning. A corresponding analysis for individual mean error rates did not yield any effects (all $ps > .10$).

Transfer phase. Figure 4 depicts the mean RTs in the test and background conditions in the three transfer sequences and the last learning block for comparison. Visual inspection reveals a clear speed advantage of trials in the test condition over trials in the background condition in the new-transfer sequences, and less so in the random-transfer sequences. In the fixed-transfer sequences, responses in the test condition were *slower* than responses in the background condition. A 2 (Trial Condition: test vs. background) $\times$ 3 (Transfer Sequence: new, random, and fixed) repeated-measures ANOVA confirmed these impressions. The interaction between Trial Condition (background vs. test) and Transfer Sequence (new-transfer, random-transfer, fixed-transfer sequences) was significant, $F(2, 40) = 11.36$, $p < .001$, $\eta_p^2 = .36$. There were no main effects of Trial Condition, $F(1, 20) < 1$, or of Transfer Sequence, $F(2, 40) < 1$. A corresponding analysis for individual mean error rates did not yield any effects (all $ps > .10$).

For the RTs, single t tests for trial type for each of the transfer sequences indicated that there was a difference between test and background trials in the new-transfer sequences, $t(20) = 2.74$, $p = .037$, $d = 0.38$, but no significant difference in the random-transfer sequences, $t(20) = 0.93$, $p = .36$. In the fixed-transfer sequences, the reversed difference was significant as well, $t(20) = -3.06$, $p = .018$, $d = 0.69$ (for all t tests, Bonferroni-corrected p values are reported [three comparisons]).

Explicit knowledge. We computed a recall score to quantify participants' explicit knowledge. This score was based on the estimated probability of a certain number of correct guesses. This probability was estimated by generating 10^7 random sequences of the 32 possible numbers and counting the number of events where 0, 1, 2, 3, or 4 sequence elements corresponded to a sequence selected randomly without replacement (see Rünger & Frensch, 2008). The procedure resulted in probability estimates of obtaining X hits (X = 0, 1, 2, 3, 4) simply by chance. Then, for the explicit reports obtained from the interviews, the number of hits (a correct item at the correct serial position) was counted for each participant, and the respective probability score was assigned to that participant. Note that in accordance with our stance that serial position–item associations are an important part of sequence knowledge, we did not count correct transitions between successive target screen locations if they were at the incorrect serial position. The probability score was subtracted from 1 to obtain the probability that guessing did not influence the pattern. The same procedure was repeated for each sequence guess, and the two scores were added. Finally, the score was normalized in such a way that reporting the two fixed sequences correctly would give a score of 1 and reporting the most probable answer under the assumption of random guessing (no item correct in each sequence) would give a score of 0. If the score of a participant was ≥ 0.5, the person's data were excluded from the all analyses. This corresponds to guessing more than two sequence elements correctly (one item in either sequence) and is therefore a rather conservative cutoff. Six participants met this criterion. The exclusion did not differ between the two differ-

[3] The correlation could be calculated only for 20 participants, because one participant did not exhibit variance in error (did not make a single error during the entire experiment)—hence, the reduced degrees of freedom.

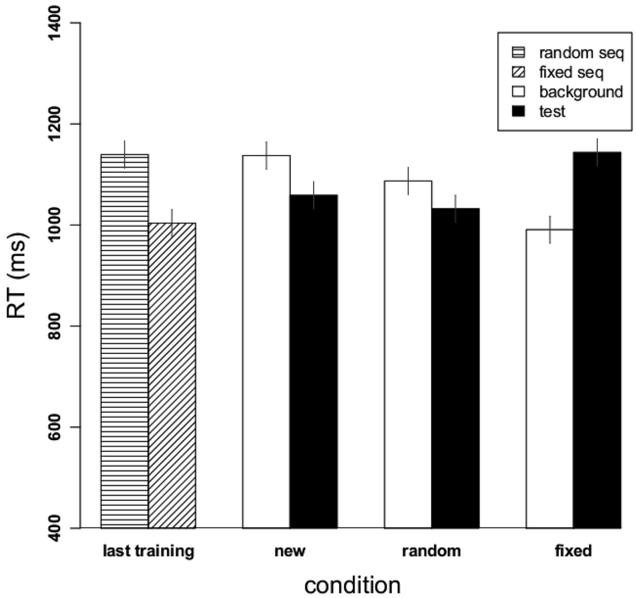

Figure 4. Transfer reaction times (RTs) as a function of Transfer Sequence and Trial Condition in Experiment 1. The first two bars show (from left to right) the mean RTs in the last learning block (fixed and random condition). The following three pairs of bars show mean RTs in the three transfer sequences, where the labels correspond to the respective trial condition name. Bars for the transfer data indicate confidence intervals for within-subject designs (Loftus & Masson, 1994), where we used the residual mean sum of squares of the interaction effect of a 2 (Trial Condition: test vs. background) × 3 (Transfer Sequence: new-transfer-sequence, random-transfer sequence, fixed-transfer sequence) within-subjects analysis of variance (ANOVA). Bars for the learning data were computed using the respective ANOVA of the learning data.

ent procedures of how participants had to express explicit knowledge: Three participants were excluded from those who had to make crosses on the sheets themselves, and three from the group who had to report numbers verbally. The mean of the explicit knowledge score for the remaining participants was 0.23 (SD = 0.23).

We obtained no indication that the RT results might be affected by explicit knowledge. We used the mean percentage RT difference between the fixed and random sequences in the last three learning blocks as a learning score. There was no correlation (Spearman's rho) between this score and the extent of explicit knowledge ($r = -.15$, $p = .489$). Similarly, we calculated correlations between the RT effects in the new-, random- and fixed-transfer sequences and the extent of verbal knowledge. All correlations were non-significant (all ps $> .10$).

Discussion

Experiment 1 had two main results. First, sequence knowledge developed during the learning phase. Responses to fixed sequences were faster than responses to random sequences. Second, the transfer phase disentangled this sequence knowledge into two components: serial position–item associations and item–item associations. When target locations in the test condition corresponded to the learned serial position–item contingencies (new-transfer sequences), participants found these targets faster than target positions not used during learning. When, in addition to correspondence with serial–position item associations, interference of weak item–item association (random-transfer sequences) was possible, the advantage of test over background target screen locations weakened. Finally, the difference reversed when interference due to strong item–item associations was possible (fixed-transfer sequences). We effectively pitted serial position–item associations against item–item associations and showed that the observed difference in favor of the background condition can be interpreted as resulting from a stronger influence of item–item associations.

Although the obtained pattern of results is consistent with the contribution of both item–item associations and position–item associations to overall sequence knowledge, the obtained advantage of test over background target screen locations in the new-transfer sequences might also be explained in alternative ways. Specifically, differences in the frequencies of presentation during the learning phase could partly account for this difference. That is, it could be argued that participants were faster in detecting test target screen locations that had been frequently presented during the learning phase than background screen locations that had never been shown before. This is an important limitation to the interpretability of our results, and we therefore address it directly in Experiment 2.

First evidence countering the frequency argument can be derived from a comparison of the last learning block and the transfer block. As can be seen in Figure 4, participants responded to targets in the test condition of the new-transfer sequence at similar speed as in the fixed sequences of the last learning block (mean difference = 55 ms), $t(20) = 1.23$, $p = .232$. This finding contradicts the interpretation that global effects induced by the introduction of new sequence types and locations could have produced the observed difference of condition in the fixed-transfer sequences. Therefore, for the new-transfer sequences, we conclude that the advantage of targets trained at this serial position in the fixed sequences over novel targets seems to result from a preserved benefit of finding the trained targets rather than in costs of locating targets at novel positions. In addition, the small RT difference is notable because in the transfer-phase, only serial position–item associations could be of help in finding the target, but in the last learning block, item–item associations could also have been helpful.

The methodological novelty of our study consists in the use of new target screen locations in the test phase (also see Schuck et al., in press). Using previously unused items to construct transfer sequences is an important improvement over previous attempts to measure serial position–item associations because it avoids interference from item–item associations. In a Hebb learning study by Cumming, Page, and Norris (2003), for instance, the transfer lists were constructed in a way that the items in the wrong serial position were part of a prior learned sequence (similar to our fixed-transfer sequences). In this design, it is likely that the background elements lead to activations of certain elements via learned item–item associations. As our results show, the use of multiple items from prior learned sequences causes interference that masks a possible effect of serial position knowledge (compare the results in our new- and fixed-transfer sequences). Thus, interference might be responsible for the failure to find an advantage for sequence elements that remained at their correct serial position in Cumming et al.'s study. Because we used novel sequence elements for which no item–item transitions could have been learned in a learning phase, we avoided this problem in our design. Moreover, whereas our findings are in line with existing work on implicit artificial grammar learning experiments by Gomez and Schvaneveldt (1994), our research tested the acquisition of position–item associations more directly. In Gomez and Schvaneveldt's study, it would also have been possible that by being exposed to pairs of letters, participants were unable to learn higher order (remote) item–item associations between letters. This was not the case when participants saw entire strings of letters.

Finally, two further aspects are noteworthy about the task we used. First, due to the uniform RSI, the paradigm is different from other investigations in which participants incidentally learned a temporal structure (e.g., Shin, 2008; Shin & Ivry, 2002; Stadler, 1995). Second, the paradigm we developed here is similar to pure perceptual learning as shown by Remillard (2003). In this study, participants also experienced sequences of target screen locations that were independent of motor responses. Remillard showed that participants can acquire such information implicitly but focused on first- and second-order transition probabilities and did not test for serial position associations.

Experiment 2

The learning phase was identical to the one described in Experiment 1, but we adapted a new-transfer sequence condition in the transfer phase. Test target screen locations appeared not only at their correct serial positions, as had been the case in Experiment 1, but also at the three serial positions within a mini-block at which they had never been shown during the learning phase. Comparing RTs to target screen locations that violated the learned serial position–item contingencies with locations did not made it possible to test for serial position knowledge without relying on a comparison with other items.

Method

Participants. Thirty-six participants, predominantly students at Humboldt-Universität, took part in the experiment in exchange for course credit or financial reward (6€). Seven participants were excluded from analysis because they expressed full or partial explicit knowledge of the sequence (see the Explicit Knowledge section for details). The remaining 29 participants had a mean age of 27.9 years, and 14 were male.

Materials and procedure. The learning phase of Experiment 2 was identical to the learning phase in Experiment 1. In the transfer phase, only the new-transfer sequences were used. In contrast to Experiment 1, test items now appeared at their correct serial position as well as at all possible incorrect serial positions. A target location trained at serial position 2 in one of the fixed sequences of the learning phase, for example, could appear at the serial positions 1, 2, 3, and 4, with the distances to its original position being -1, 0, $+1$, and $+2$, respectively. Because there were eight possible test items (in the learning phase, all participants were presented with two fixed sequences of four items each), presenting each once at every serial position required $4 \times 4 \times 2 = 32$ mini-blocks in the transfer block. Thus, the transfer block was slightly longer than the preceding learning blocks (128 vs. 96 trials, respectively).

Explicit knowledge assessment. To assess participants' explicit knowledge, we conducted post-experimental interviews that were similar to those used in Experiment 1. Participants were first asked whether they had noticed that the location of a target was predictable and were asked to provide a confidence rating for their answer. Then, each participant was informed that two sequence types (fixed and random) had been used throughout the experiment and that at some locations the target appeared only very rarely. Finally, participants were asked to recall as precisely as they could the two fixed sequences, the two random sequences, and the locations at which the target almost never appeared. Participants were asked to indicate these positions on a sheet containing grids of the same form as the possible positions on the screen, that is, a 6×6 square with omitted corners.

Results

Mean RTs were computed as in Experiment 1. Likewise, erroneous trials and trials following errors were excluded from analyses. The overall error rate was at 2.0%. There was no speed–accuracy tradeoff (mean $r = .02$), $t(28) = 1.59$, $p = .123$.

Learning phase. Participants detected the target faster in fixed than in random sequence trials. The mean RT difference between the two sequence conditions items was 88 ms. Also, the difference between the two conditions increased with learning. As in Experiment 1, we obtained an interaction of Learning Condition and Block, $F(9, 252) = 2.32$, $p = .016$, $\eta_p^2 = .08$, and a main effect of Learning Condition (fixed vs. random sequences) for the last five learning blocks, $F(1, 28) = 13.93$, $p < .001$, $\eta_p^2 = .33$. The same analyses with mean error rates did not yield any significant results (all $ps > .10$).

Transfer phase. First, we considered the mean difference between RTs in test trials at their correct (*correct condition*) and incorrect (*deviant condition*) serial positions. Second, we distinguish between deviations occurring before (*too early condition*) and deviations occurring after the correct original position (*too late condition*) and compare these to test trials from the correct condition. Because the variability of the main difference score (correct vs. deviant) across participants was rather high ($SD = 353$ ms),[4] we excluded participants from this analysis if their difference exceeded the mean difference by $>\pm 2$ *SD* (two participants).

As depicted in Figure 5, response times to incorrectly positioned test items were considerably slower than response times to correctly positioned test items (mean difference = 129 ms), $t(26) = 2.62$, $p = .043$, $d = 0.49$. Furthermore, we found a marginal significant difference between too early trials and correct test trials, $t(26) = 2.33$, $p = .083$, $d = 0.37$ (mean difference = 110 ms). Too late trials also differed marginally significant from correct test trials, $t(26) = 2.36$, $p = .078$, $d = 0.56$ (mean differ-

[4] The likely main contributing fact to this increased variability is that the difference score was based on only a few data points per participant (8 RTs in the correct condition and potentially even less, if a participant had made one or more errors in this condition). When all participants were considered, the mean effect was still positive (63 ms) but was below the criterion of significance ($p = .175$; the p value hence changed from .175 to .007 by excluding two out of 29 participants).

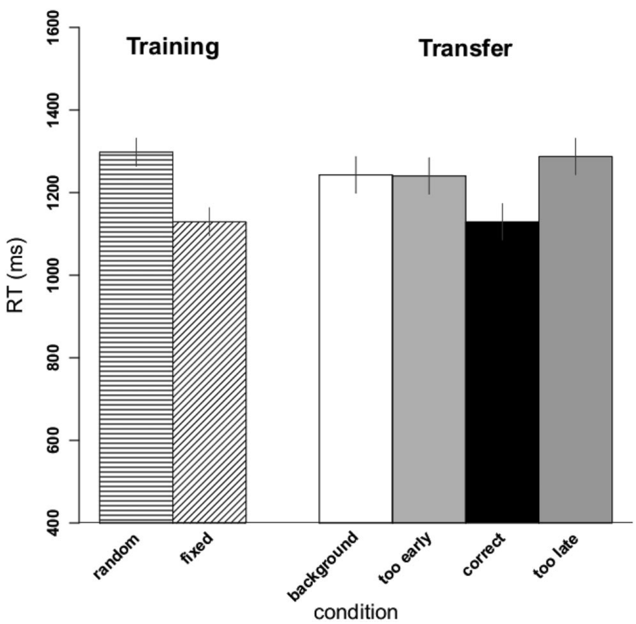

Figure 5. Reaction times (RTs) of transfer and learning trials in Experiment 2. Bars show RTs in the various conditions, where the first two bars represent the random and fixed sequence condition from the last learning block, and the four right bars represent the different conditions in the transfer block. Computation of bars is equivalent to Figure 4 despite the fact that for the transfer data, we used the terms from a one-way analysis of variance with factor condition (too early, correct, too late).

ence = 158 ms). The difference between too early and too late trials (47 ms) was not significant, $t(26) < 1$ (for all t tests, Bonferroni-corrected p values are reported [three comparisons]).

Explicit knowledge. To evaluate explicit knowledge of the fixed sequence, participants' answers to the fixed sequence were analyzed in the same way as in Experiment 1. As mentioned, seven participants' reports exceeded the threshold of 0.5, and their data were excluded from RT-based analyses. After their exclusion, the mean explicit knowledge score was low ($M = 0.30$, $SD = 0.29$), and there was no relation between the learning score (same as in Experiment 1) and explicit knowledge ($r = .04$, $p = .848$). Likewise, the correlation of the verbal knowledge with the RT difference between correct and deviant trials in the transfer was negligible ($p > .10$).

Discussion

By providing a direct comparison of test items at correct and at incorrect serial positions, Experiment 2 avoided the problems inherent in Experiment 1 (i.e., a confound of potential frequency knowledge and serial position–item association). The results of Experiment 2 are clear: Participants responded faster to test items that were presented at their correct serial position than to test items that were presented at incorrect serial positions. Thus, the results further support the claim that in implicit sequence learning, positional cues are stored and used in form of serial position–item associations to predict upcoming events. This is in line with findings from verbal learning, such as position-consistent inter-list intrusions[5] (Conrad, 1960; Melton & von Lackum, 1941).

Experiment 2 challenges theories of serial order, such as Botvinick and Plaut's (2006) model of serial short-term memory (compare, e.g., Frensch & Miner, 1994, for a link between short-term memory and implicit sequence learning). The model by Botvinick and Plaut is based on a recurrent neural network architecture that can be interpreted as an "integrative chaining" account (Mayr, 2009). Roughly speaking, the model allows for associations to be established between internal memory states and a currently encountered item (e.g., a word or syllable). By means of its recurrent connections, the internal memory integrates each encountered event into its current memory state and hence forms an integrative representation of the recent past. For example, if the model during learning is repeatedly presented with the sequence *A-B-C-D*, then the internal memory state before the model encounters item *D* is an integrated memory of *A-B-C* and likely some start marker (i.e., the fixation cross upfront). This memory state is associated with item *D*.

Overall, such a mechanism can facilitate the search for target screen locations that have repeatedly occurred in a fixed sequence (e.g., element *D*). However, in the case that novel items precede a known item, the model facilitates search for the known item in a way that seems inconsistent with the data obtained in Experiment 2. Although participants show costs when the known target screen location is presented prior to or after its original serial position (e.g., item *D* at position 2 instead of position 4), the model predicts a different pattern. Each novel item the model encounters changes the internal memory state so that it becomes less similar to any state that is associated with a sequence item. Hence, the model predicts worse performance as it encounters more novel items before a sequence item. In short, the more novel items precede the known item, the weaker the prediction should be and therefore prediction of the test item would be *stronger* when it is placed prior to rather than at its original position. This was not the case in the present data, as a linear regression with all test items (regardless of deviant or correct) as the dependent variable and the serial position of appearance as a factor did not yield a significant influence of the serial position (significance of predictor serial position: $p = .109$; overall $R^2_{\text{adj}} = .017$).

Experiment 3

Experiments 1 and 2 provided evidence that serial position information can be acquired implicitly in a visual search paradigm. As discussed in the introduction, for a sequence to exhibit serial position–item contingencies, identifiable cues that signal the beginning of a sequence are necessary (also see Henson, 1998, for related ideas).

In the previous experiments, a fixation cross appeared at the beginning of each sequence and might have served as the cue that is necessary to consistently structure the temporal/serial information. In Experiment 3, we randomized the segmentation of trials into mini-blocks by the fixation cross during the learning phase. Accordingly, a reliable cue to associate target locations with serial position information was no longer available. Experiment 3, thus,

[5] There, it was found that in verbal recall, items from List 1 that were wrongly recalled in List 2 were more likely to be recalled at the serial position they had in their original List 1.

served two purposes. First, it tested whether the serial position information was implicitly learned in a situation in which no external cues were available that consistently signaled the beginning of the sequences. The explanation we offered so far predicts that without start/end cues, no serial position knowledge should be acquired, and the new-transfer sequence effect should disappear. Therefore, Experiment 3 also tested the validity of the conclusions offered in Experiments 1 and 2. If indeed the response time difference between test and background target screen locations in the new-transfer sequence condition reflects implicit learning of serial position information, then that particular response time difference should be much less pronounced when extraction of position information is made difficult. Second, except for distinguishing between inter-item associations and serial position knowledge, another alternative account can be ruled out with this experiment. It is conceivable that participants show smaller search times for target screen locations presented at their trained serial position (compared to any other target locations) based on distribution-knowledge operating within a limited window of trials. Participants might expect the target at a screen location on a given trials imply because it has not been placed there for the last few trials and is therefore "due" (similar to a gambler's fallacy; compare Masson, 2009). Although this form of knowledge about the recent past might in principle account for some of the results in Experiments 1 and 2, its potential effect should not deteriorate substantially in cases where the fixation mark is no longer consistently placed as a start-marker of the fixed sequences. Moreover, this account would predict shorter RTs in too-late than in too-early trials, which we did not find in Experiment 2.

Method

Participants. Twenty-four participants were recruited in exchange for course credit or financial reward (6€). The mean age was 28.8 years, and 5 were male.

Materials and procedure. Participants performed the same visual search task as in Experiments 1 and 2. In the learning phase, the construction of fixed and random sequence conditions was the same as in the previous experiments. However, the segmentation into mini-blocks was altered. In the learning phase, the fixation cross appeared randomly after 3, 4, or 5 trials (all transitions of distances were equally probable). As a consequence, the fixation cross no longer reliably indicated the beginning of a sequence. Extraction of serial position information and learning of position–item associations was thus more difficult than before, if not impossible. The ambiguous ordering of serial position–item associations is a useful test of our notion that these associations caused the effect observed in Experiment 1.

In the transfer phase, we used the same three transfer conditions as in Experiment 1. The fixation cross appeared in a regular fashion in all transfer conditions (i.e., after each fourth trial, as in Experiment 1). The regular fixation cross was re-introduced in the transfer phase to provide better comparability between the results from Experiments 1 and 3.

Explicit knowledge assessment. To assess participants' explicit knowledge about the sequences, a recognition test was administered after the experiment. We used a recognition test to have an even more sensitive measure for explicit knowledge. Participants were provided with 12 possible sequences depicted in the form of numbers on a grid (as in Experiments 1 and 2, where participants had to fill in the numbers themselves). Participants were allowed to check four possibilities.

Results

As in the previous experiments, errors and responses following errors were excluded from all statistical analyses described in the next section. Again, individual median RTs were computed for each factor cell. The overall error rate was 1.69%. No speed–accuracy tradeoff was observed, $t(22) = 1.18$, $p = .251$, with a mean correlation of $r = .02$.

Learning phase. The mean RT difference between the fixed and random sequence condition was 63 ms. As in Experiments 1 and 2, there was an interaction between Block and Learning Condition during the learning phase, $F(9, 207) = 2.10$, $p = .031$, $\eta_p^2 = .08$, as well as a clear RT difference between fixed and random sequence trials during the last five blocks of learning, $F(1, 23) = 11.04$, $p = .003$, $\eta_p^2 = .33$. In contrast, an overall ANOVA for the mean error rates with all learning blocks did not yield a significant interaction, $F(9, 207) < 1$.

Transfer phase. Figure 6 shows the mean RTs to test and background target screen locations in the three transfer conditions and in the fixed and random sequence conditions in the last learning block. The pattern indicating different forms of sequence knowledge in Experiment 1 (see Figure 4) was not observed in the present results. For instance, RTs in the background condition in new-transfer sequences seemed to be faster than RTs in the test trials. There was neither a main effect of Transfer Sequence (new-transfer sequence vs. fixed-transfer sequence vs. random-transfer sequence) nor of Trial Condition (background vs. test),

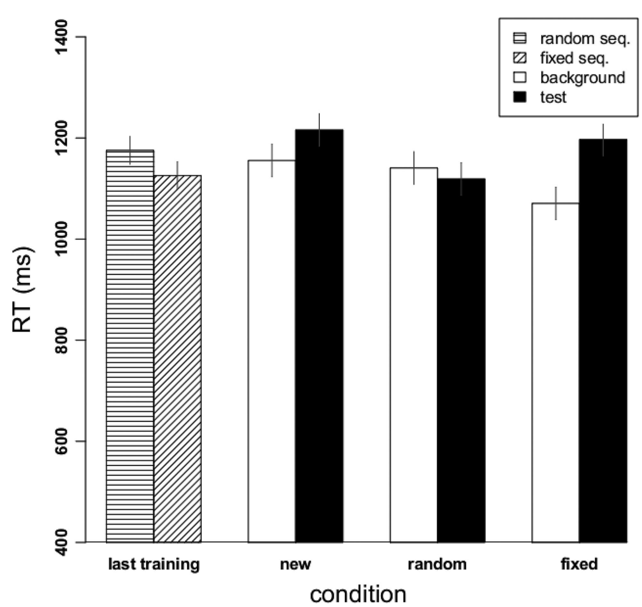

Figure 6. Transfer reaction times (RTs) as a function of Transfer Sequence and Trial Condition in Experiment 3. Arrangement, labels, and coloring of bars are the same as in Figure 4. The four pairs of bars show (from left to right) the mean RTs in the last learning block as well as in the three Transfer Sequences (again, separately for the different trial conditions). Bars indicate 95% confidence intervals (see Figure 4).

with $F(2, 46) < 1$, and $F(1, 23) = 1.74$, respectively. The interaction between Trial Condition (test vs. background) and Transfer Sequence (new-transfer sequence, random-transfer sequence, fixed-transfer sequence) was marginally significant, $F(2, 46) = 2.65$, $p = .081$, $\eta_p^2 = .10$. Single comparisons indicate that in contrast to Experiments 1 and 2, there was no significant RT difference for test trials and background trials in the new-transfer sequence condition, $t(23) = 1.09$, $p = .857$. Moreover, we observed no significant difference between test and background trials in the fixed-transfer sequence condition, $t(23) = 2.19$, $p = .115$. The respective difference in the random-transfer sequence condition was not significant, $t(23) = 1.34$, $p = .580$ (reported p values are Bonferroni-adjusted for three comparisons). Likewise, the corresponding analysis with error rates did not yield a significant main effect of Trial Condition, $F(1, 23) < 1$. The main effect of Transfer Sequence, however, was significant, $F(2, 46) = 5.19$, $p < .009$, $\eta_p^2 = .18$. The interaction of both factors was not significant, $F(2, 46) = 1.66$, $p = .201$. The main effect of Transfer Sequence was driven by lower error rates in the fixed transfer sequences than in the random- and new-transfer sequences (ps $< .01$ for both comparisons).

Explicit knowledge. None of the participants recognized both sequences correctly. Because the chances of guessing *one* sequence correctly with four trials and a pool of 12 potential sequences were relatively high, we did not exclude any participant.

Discussion

Experiment 3 tested whether the regularly appearing fixation cross in Experiments 1 and 2 served as an external start/end cue to extract serial position–item contingencies. To test this assumption, the fixation cross was made to appear at irregular intervals in the learning phase of Experiment 3. As a consequence, we obtained no RT advantage for test trials compared to background trials in the new-transfer sequence test. The results therefore support the notion that a start/end cue is a mandatory precondition for the implicit acquisition of serial position knowledge. Others have addressed the question of the importance of consistent start cues for serial learning (mostly with the so called spin-list technique; e.g., Kahana, Mollison, & Addis, 2010). Interestingly, Kahana et al. (2010) found that participants were still able to learn serial structures in a situation where no reliable start cue was available. This is in line with our finding, as we also found learning. As in all experiments before, the analysis of the learning phase revealed a significant main effect of Learning Condition in the last five learning blocks, confirming that participants were still able to extract structure from the fixed and random sequences so that they could speed up their responses with practice relative to the randomly ordered sequences.

The pattern of transfer results in Experiment 3 can be contrasted with Experiment 1. When consistent start cues are available, item–item as well as serial position–item associations are acquired implicitly (Experiment 1), whereas only evidence for item–item associations was found in Experiment 3 when no such cues were available. In the fixed-transfer sequences, participants responded more slowly to the test items than the background items. Whereas the latter had been presented within the same fixed sequence during the learning phase and were therefore linked to each other by item–item associations, the former had been taken from the other fixed sequence of the learning phase and therefore were not supported by item–item associations.

Further research will have to examine whether external start cues are a general requirement for implicitly acquiring associations between item and serial position. It is conceivable that salient pair transitions between items might serve as a starting-cue for ordinal information. For instance, Cohen et al. (1990) discussed whether statistical features of the sequence might serve as start cues, noting that "unique associations may serve as a sort of flag that defines the start of a structure" (p. 29). Furthermore, Saffran, Newport, and Aslin (1996) documented that streams of syllables that are presented without any temporal or other marker can nevertheless be parsed into words based on drops in pair transition probability at the border of words, and data of Pacton et al. (2001) suggest that ordinal position can play a role in implicitly acquired knowledge about structure within words.

General Discussion

The experiments reported here provide evidence for the acquisition of serial position knowledge in an implicit sequence learning paradigm. Participants learned implicitly that (a) a specific event was to be expected because another specific event had just occurred before and (b) a specific event was to be expected because this event is associated with a particular serial position. The acquisition of serial position–item associations depended on the existence of a cue that reliably indicated the start of each new sequence. Although the importance of start markers has been recognized before (e.g., Cohen et al., 1990), it had been linked to the organization of a sequence into subsequences (chunking). Here, we linked the role of start markers to the acquisition of serial position–item associations. The reported findings provide a starting point for a better understanding of what kinds of sequential regularities participants can potentially learn in an implicit sequence learning task.

Our data suggest that chaining-based and serial position knowledge were both used to derive predictions about the location of the next target. This is significant because (a) a direct assessment of serial position knowledge (position–item associations) in an implicit learning task with humans was missing until now and (b) very few of the previously reported studies concerned with serial learning directly addressed both kinds of representations of serial order within the same experiment. Our pattern of results seems incompatible with the assumption that chaining is the only mechanism that supports implicit sequence learning.

We used theoretical insights supported by data from working memory tasks and verbal list learning and applied it to an implicit learning paradigm. The relation between implicit learning and working memory has been investigated before and has resulted in a variety of findings that are relevant here (e.g., Frensch & Miner, 1994, 1995). One interesting study concerning the relation of implicit memory and serial working memory comes from Stadler (1993). Stadler investigated whether the Hebb effect can be transferred to an implicit memory task. The Hebb effect is the phenomenon of performance improvements if lists in a serial recall paradigm are repeated (Hebb, 1961). Participants are asked to recall a just-presented list in the correct serial order. Because participants can recall the list directly following presentation, the primary task is a working memory task. Because Hebb (1961) found that participants' performance increased for lists when they were repeated within the experimental session, it suggests a long-term component of the observed performance in the working memory task. Stadler showed in his study that the same observations hold true when the learning situation is incidental and the knowledge of the sequences is implicit. Hence, this work suggests a fundamental link between working memory, long-term memory, and implicit memory tasks. Consequently, he and other researchers (e.g., Cumming et al., 2003) regard the Hebb repetition paradigm as an implicit learning task. Under the premise that this paradigm constitutes an implicit learning situation, Cumming et al. (2003) examined serial position effects similar to those investigated here. They used a Hebb repetition paradigm with 10 element sequences of numbers with every third sequence being repeated. In transfer lists, the serial position of every other list item was preserved, and for the remaining filler items, the sequence position of the items was violated. In their first experiment, Cumming et al. found a small but reliable advantage for the items that retained their correct serial position. In a second experiment, the effect vanished after removing a possible influence of short-term memory traces of position–item associations. This study highlights two aspects of the study of position–item associations. On the one hand, the authors' view supports a possible link between data from the Hebb repetition paradigm and implicit serial learning. On the other, however, it leaves great uncertainty to the basis of this claim. As Cumming et al. themselves note, the "Hebb effect is not simply a result of motor learning" (p. 60). Additionally, Cumming et al.'s results seem specifically to suggest that serial order processes in short-term memory do not seem to be the same in long-term memory. Second, the study has some disadvantages concerning the test of serial position–item associations. As explained above, we believe using more than one element from a learned sequence can lead to interference between item–item and serial position–item associations. Our results support this proposition: In a transfer sequence where we used more than one sequence element (fixed-transfer sequence), we found no evidence for serial position–item associations. However, we resolved these difficulties by using transfer sequences with single sequence elements at their correct serial position preceded and followed by novel elements. Thus, our paradigm provides a better test for position–item associations.

Our emphasis in the present article is on the concept of implicit sequence learning. An important issue therefore concerns the importance of our findings for other implicit sequence learning experiments. Potentially, the generalization of the results might be limited because (a) we used short sequences and (b) sequences were separated by a cue (the fixation cross). Experiment 3 specifically suggests that external anchor cues might be crucial for acquiring associations between item and serial position. A careful review of the implicit learning literature suggests, however, that similar conditions were met in other experiments (e.g., Perlman & Tzelgov, 2009; Stadler, 1989; Tamayo & Frensch, 2007; Tunney, 2003; Ziessler, 1998). Perlman and Tzelgov (2009, Experiment 1), for instance, also used short spatial sequences (4 or 5 in length), which were clearly separated for the participants by intervening irrelevant trials. Tunney (2003; see also, e.g., Perlman & Tzelgov, 2009; Stadler, 1989; Tamayo & Frensch, 2007; Ziessler, 1998) provided one instance where start cues have also been used in a choice reaction task with a regular sequence. There, the words "START" and "END" had been inserted between sequences generated by an artificial grammar. Given the present results, it is likely that the reported learning in this paradigm also profits from serial position information provided by the cues. Although our results showed that inserting segmentation cues randomly into the ongoing stream of trials disrupted the acquisition of serial position–item associations, it is unclear whether such associations could be acquired in situations where no start markers are provided, such as in the common SRT task (Nissen & Bullemer, 1987). Some researchers discussed that statistical subtleties (such as changes in transition probabilities) might be used as start markers (Cohen et al., 1990), and this notion is in line with findings from the implicit learning of word segmentation (Saffran et al., 1996). Furthermore, the observation that memory representations of longer sequences often entail a hierarchical structuring in forms of chunks shares some similarity to our work. Our findings suggest that item–serial position associations depend on anchors.

Similarly, literature on chunking in sequence learning has stressed that temporal or structural factors influence chunking (e.g., Koch & Hoffmann, 2000; Koch, Philipp, & Gade, 2006; Stadler, 1993). The fixation cross that we varied between Experiments 3 and 1 might also be seen as such a factor. Therefore, our research concurs with the finding of learning benefits when a consistent grouping of the ongoing stream of trials is possible. Whereas this has been shown to influence performance in sequence learning experiments with longer sequences before (Jones & McLaren, 2009; Koch, Reverberi, & Rumiati, 2006), we showed that such performance benefits in general could also arise from serial position–item associations that support the memory search of the next item. Finally, some research demonstrates sequence learning based on anchor-specific chunking by far outweighs item–item associations. For instance, Perlman, Pothos, Edwards, and Tzelgov (2010) studied chunking on two sequences that were started by a context cue each. These two sequences differed (a) in learning frequency and (b) in the *last* elements. Surprisingly, participants performed the first elements of these sequences at different speeds even though they were identical. Sequence learning of identical item–item transitions and/or item–position contingencies differed substantially due to the context cue. Although we believe that the role of serial position–item associations in a standard version of a SRT without segmentation/start cues still needs to be explored, the discussed links clearly show the importance of our finding for implicit sequence learning in general.

However, two central theoretical issues remain unresolved. First, the nature of serial position encoding in implicit learning is still unknown, which concerns questions about how ordinal information is represented. The notion of serial position–item associations implies that there must be some internal representation of the current serial position. Although there is no evidence for the case of implicit learning, theoretical considerations can still be inspired by related work. The matter of serial position representations has been largely debated in various domains, mainly including work on working memory (e.g., Botvinick & Watanabe, 2007; Lewandowsky & Farrell, 2008; Maybery, Parmentier, & Jones, 2002; Ng & Maybery, 2002, 2005), motor learning (e.g., Ashe, Lungo, Basford, & Lu, 2006; Bengtsson, Ehrsson, Forssberg, & Ullen, 2004), and some recent neurophysiological work with animals (e.g., Isoda & Tanji, 2004; Ninokura, Mushiake, & Tanji, 2004; for a review, see Nieder & Dehaene, 2009). Today, the controversy mainly focuses on whether time or order information plays a crucial role in the coding of serial position (Lewandowsky & Farrell, 2008; Ng & Maybery, 2005). That is, people might learn to expect a specific target because a certain amount of time has passed or because a certain number of sequence elements have been encountered, respectively. Models including a time-dependent counter (e.g., Brown, Neath, & Chater, 2007; Brown et al., 2000) as well as those including a time-independent event/rank counter (e.g., Botvinick & Watanabe, 2007; C. Burgess, Schuck, & Burgess, 2011; Henson, 1998; Lewandowsky & Farrell, 2008; Schuck & Burgess, 2010) have been successful in accounting for a large variety of benchmark phenomena. Hence, the nature of positional codes is an important question for future research.

Second, it is unclear to which extent chaining models could account for the data. In this article, we have argued that the pattern of results in Experiment 2 cannot be explained by an account that assumes pairwise associations between the fixation cross and the sequence items. However, despite our reasoning, simulation studies will have to determine the potential of chaining models. Botvinick and Plaut (2006), for instance, proposed a novel recurrent neural network account that can explain a remarkable range of benchmark phenomena of serial behavior that has long been thought not to be explainable by chaining-like accounts. Moreover, despite the apparent dichotomy between chaining like and serial position mechanisms, we believe that the integration of different types of serial learning in implicit sequence learning is to be a major theoretical challenge for future work (for related ideas in working memory, see Marshuetz, 2005; but see also early experiments by Ebenholtz, 1963).

Overall, we have presented the central theoretical concerns that we cannot resolve with the present findings. Nevertheless, we argue that the convergence of the reported findings with the literature on serial learning strongly supports the need for a broader conception of implicit sequence learning. As our work shows, this conception can be inspired by research on other forms of serial behavior.

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Received April 19, 2011
Revision received August 16, 2011
Accepted August 28, 2011 ■