How Implicit Sequence Learning and Explicit Sequence Knowledge Are Expressed in a Serial Response Time Task

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Sequence learning in the serial response time task (SRTT) is one of the few learning phenomena that are widely agreed to be implicit in nature (i.e., that learning may proceed in the absence of awareness). Evidently, it is also possible to explicitly learn a sequence of events. In the past few decades, research into sequence learning largely focused on the type of representation that may underlie implicit sequence learning, and whether or not two independent learning systems are necessary to explain qualitative differences between implicit and explicit learning. Using the drift-diffusion model, here we take a cognitive-processes perspective on sequence learning and investigate the cognitive operations that benefit from implicit and explicit sequence learning (e.g., stimulus detection or encoding, response selection, or response facilitation). To separate the processes involved in expressing implicit versus explicit knowledge, we manipulated explicit sequence knowledge independently of the opportunity to express such knowledge. Performance data from this experiment was fed into a dynamic drift-diffusion model that allowed us to disentangle the contributions of the above-mentioned processes to sequence-learning effects. Results revealed three findings that are relevant for sequence learning theories. We discuss how the diffusion model may be helpful in future research addressing these theories.

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Sequence learning in the serial response time task (SRTT) is one of few learning phenomena where researchers agree that such learning may proceed in the absence of awareness. In the classical paradigm (Nissen & Bullemer, 1987), stimuli are presented on a computer screen, and participants are instructed to press corresponding keys on the keyboard as quickly and accurately as possible. Unbeknownst to participants, stimuli are not presented in a random order, but follow an underlying sequential regularity. Over the course of learning, participants respond more quickly and accurately to stimuli that are presented in regular (compared with non-regular) stimulus locations. However, participants often fail to express any explicit sequence knowledge in direct tests of such knowledge, including verbal report, cued or free generation tasks, recognition tests, or process-dissociation measures (Buchner, Steffens, Erdfelder, & Rothkegel, 1997; Cohen, Ivry, & Keele, 1990; Curran & Keele, 1993; Destrebecqz & Cleeremans, 2001; Frensch & Rünger, 2003; Haider & Frensch, 2005; Willingham, Greeley, & Bardone, 1993; Willingham, Nissen, & Bullemer, 1989). It has therefore been concluded that, at least under specific circumstances, sequence learning may proceed in the absence of awareness. Yet, participants may also obtain conscious sequence knowledge during learning. When trying to use this explicit knowledge to improve task performance, different processes are involved than in the expression of implicit knowledge. As a consequence, SRTT performance is often driven by a mixture of the sets of processes involved in expressing implicit and explicit knowledge. Hence, pinpointing empirical findings to implicit learning is difficult, slowing theoretical progress. Here we use drift-diffusion models to identify the processes involved in expressing implicit sequence knowledge and separate them from processes involved in expressing explicit knowledge.

In the remainder of the introduction, first we briefly discuss theories of implicit and explicit sequence learning. Next, the drift-diffusion model is introduced, as well as its application to the SRTT in the present study.

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Processes and representations underlying implicit sequence learning

Despite a broad agreement that sequence learning may occur implicitly, there is no consensus on the representations underlying sequence learning (for a review, see Abrahamse, Jiménez, Verwey, & Clegg, 2010): In a standard SRTT, stimulus locations and motor responses follow the same sequence, allowing for (at least) four different types of representations that could subserve sequence learning. We first discuss two types of simple representations: associations between subsequent responses, and between subsequent stimuli.

Drawing on early findings of an involvement of motor areas in sequence learning, associations between responses (frequently coined as the formation of R–R associations) has been one of the first explanations of sequence learning. Importantly, the standard SRTT effect seems to be driven by effector-independent representations (Cohen et al., 1990; Keele, Jennings, Jones, Caulton, & Cohen, 1995). Willingham, Wells, Farrell, and Stemwedel (2000) proposed that the representations underlying implicit sequence learning comprise sequences of response locations (see also Willingham, 1999). In addition, Verwey and Clegg (2005) found evidence for effector-specific sequence learning after extensive practice.

In addition to response-based learning, some studies found evidence for purely perceptual learning, considered to be subserved by associations between consecutive stimuli (S–S learning): Howard, Mutter, and Howard (1992) demonstrated that participants could learn a stimulus sequence from mere observation. Mayr (1996) found learning of a sequence of stimulus locations that was unrelated to another sequence of key presses (see also Haider, Eberhardt, Esser, & Rose, 2014).

In the dual-systems model (Keele, Ivry, Mayr, Hazeltine, & Heuer, 2003), these simple associations can be located in the *unidimensional* system, which is considered to comprise multiple dimension-specific modules that allow for independent processing of stimulus and response features. The acquired representations in this system are thought to be inaccessible to consciousness. Going beyond simple associations, the dual-systems model also postulates a *multidimensional* system that may integrate information from multiple dimensions, for instance, stimulus and response features. This system is thought to depend on attention and its contents are accessible to consciousness.

As one example for complex representations that integrate information from stimulus and response, *response-effect learning* (or R–S learning) has been proposed. It refers to the formation of associations between compounds comprising of the current trial's response and the stimulus presented in the subsequent trial (Hoffmann, Sebald, & Stöcker, 2001; Ziessler & Nattkemper, 2001). However, Abrahamse et al. (2010) argued that response-effect learning resembles the anticipation of an outcome of an action, the principle underlying the ideomotor theory to action control (Shin, Proctor, & Capaldi, 2010), and suggested that the ideomotor principle might be restricted to explicit sequence learning.

Another form of associations between stimuli and responses are considered in S–R learning, which considers compounds comprising the current trial's stimulus and response. Initial evidence for S–R learning comes from studies manipulating the stimulus setup: Willingham et al. (1989) found only minimal transfer of a sequence of motor key presses after the stimulus setup changed. The authors concluded that sequence learning is neither perceptual nor purely motor, but that a sequence of "condition-action statements" (Willingham et al., 1989, p. 1058) is learned. Similarly, Schwarb and Schumacher (2010) found that sequence learning is disrupted if the S–R rules between a training and a transfer task are are changed. Furthermore, E. H. Schumacher and Schwarb (2009) found that a secondary task requiring parallel response selection disrupted sequence learning, and Schwarb and Schumacher (2009) found that spatial response selection and spatial sequence learning (of stimulus locations and/or key presses) are related to almost entirely the same brain areas.

In the dual-systems-model, the two systems are considered to differ with respect to their accessibility to consciousness, their dependence on attention, and the representations subserving learning. Findings regarding the attentional demands of implicit sequence learning point into the direction that sequence learning relies on attention. For instance, Shanks, Rowland, and Ranger (2005) manipulated attentional load and found that sequence learning is moderated by attentional load. More importantly, Gaschler, Frensch, Cohen, and Wenke (2012) manipulated the task set via instructions and found that even under conditions where it is unlikely that participants acquired explicit sequence knowledge, instructions predicted which of two sequences were learned. In a similar vein, E. H. Schumacher and Hazeltine (2016) summarized their response-selection account as positing that not simple associations, but hierarchically organized representations containing features of stimuli and responses, task goals, and drives are acquired in sequence learning. Response selection is, however, typically considered to be a central process (Hazeltine & Schumacher, 2016), to be dependent on selective attention (i.e., the task set), and necessitates information about both stimuli and responses, The dual-systems model considers these features to be characteristic of the multidimensional learning system. In other words, a phenomenon described as implicit—that is, inaccessible to consciousness—is being explained by a process thought to be accessible to consciousness. This presents a challenge to the dual-systems model. What constitutes a dimension is, however, not well-defined in the model, and since its introduction there has been considerable debate whether the modules comprising the unidimensional system are separated along dimensions such as stimulus and response features, or whether the modules are separated along abstract feature dimensions such as location (Eberhardt, Esser, & Haider, 2017; Haider, Esser, & Eberhardt, 2020). If, indeed, the unidimensional learning system included a processing module specific to spatial location, stimulus and response locations could be represented together within such a module, providing the necessary information to subserve a response-selection mechanism.

Taken together, there is still considerable debate about the processes, representations, or systems underlying implicit sequence learning. This line of research is considerably complicated by the omnipresent possibility that empirical findings may be driven not only by implicit sequence learning, but may also (or only) reflect explicit knowledge.

Explicit sequence knowledge

The emergence of explicit sequence knowledge is accompanied with sudden decreases of response times during training (Haider & Frensch, 2005; Haider & Rose, 2007). Using a combination of EEG and fMRI studies, Rose, Haider, and Büchel (2010) and Wessel, Haider, and Rose (2012) found that such rapid decreases in response times were accompanied by increases in neural coupling between distant brain areas and an increase in neural activity in brain areas that have been discussed as being involved in the processing of predictions and prediction errors. They interpreted these findings as evidence in favor of an increase in error processing that may serve as an unexpected event that triggers the emergence of sequence awareness.

The *Unexpected Event Hypothesis* (Frensch et al., 2003; for a recent discussion, see Esser, Lustig, & Haider, 2021) postulates that experiencing an unexpected event triggers a search process that may result in the discovery of the sequential regularity. Multiple studies (Esser & Haider, 2017; Rünger & Frensch, 2008; Schwager, Rünger, Gaschler, & Frensch, 2012) found that inserting unexpected events into the SRTT indeed resulted in more explicit sequence knowledge. Other studies suggest that RT drops may not be a precursor of sequence awareness, but may rather indicate a switch from stimulus-based to plan-based action control: These studies found that effects of response-selection conflict or difficulty were reduced if participants acquired explicit sequence knowledge: Hoffmann and Koch (1997) found that RT differences between easy and difficult stimuli disappeared for explicit learners, Haider, Eichler, and Lange (2011) demonstrated that participants who showed an RT drop (i.e., explicit learners) also showed reduced Stroop-congruency effects. Tubau, Hommel, and López-Moliner (2007) found reduced response-repetition costs only for explicit learners, Koch (2007) found that participants who acquired explicit sequence knowledge showed reduced Simon effects.

Lustig, Esser, and Haider (2022) directly tested whether rapid RT decreases are a precursor of sequence awareness or an indicator of a switch to plan-based action control, a switch that is only possible after participants acquired explicit sequence knowledge. To this end, they manipulated the ease of producing RT drops in the SRTT by manipulating the RSI in either a predictable or a random fashion, assuming that if RT drops are a precursor of explicit knowledge, hampering such drops should reduce the acquisition of explicit sequence knowledge. If, instead, RT drops are indicative of a strategy shift from stimulus-based to plan-based action control that is possible as soon as explicit sequence knowledge has been acquired and the task design (and materials) allow to use this knowledge. Lustig et al. (2022) found that RT drops are not a precursor of explicit conscious insight, but rather a consequence of a switch to plan-based action control.

Separating the processes underlying the expression of implicit and explicit knowledge

Plan-based action control may be beneficial in some SRTT paradigms but not others. Barth (2018) reanalyzed two SRTT experiments using a drift-diffusion model. In Experiment 1, participants worked on probabilistic materials with 60% regular trials (i.e., with a probability of .6, the next stimulus follows the sequential structure). Such sequence materials are typically considered to enable robust sequence learning while participants remain largely unaware of the sequence (Barth, Stahl, & Haider, 2019; Jiménez & Méndez, 1999). By contrast, in Experiment 2, stimulus materials consisted of runs of 15 to 22 stimulus locations that followed a deterministic six-item first-order conditional sequence interrupted with runs of random trials of the same length. With these materials, participants were well able to acquire substantial amounts of explicit sequence knowledge. A comparison of both experiments revealed qualitatively different patterns of effects on diffusion model parameters. While these results may point to different representations underlying implicit versus explicit knowledge, they are more likely to reflect the switch to plan-based action control that was supported by deterministic but not probabilistic material. Note that the opportunity to gain explicit knowledge was confounded with the ability to switch strategy: Probabilistic materials did not allow for reliably predicting the next stimulus and therefore encourage stimulus-based action control. In contrast, materials with chunks of deterministic runs might encourage a switch to plan-based action control (if participants are able to detect differences between regular and deterministic chunks, e.g., by detecting changes in fluency). Here we aimed at removing this confound and to more conclusively separate the amount of participants' explicit knowledge from its expression. To identify the processes involved in the expression of implicit versus explicit knowledge, we used the diffusion model that is introduced next.

The Drift-Diffusion Model

The drift-diffusion model (DDM) has originally been proposed as a theory of memory retrieval (Ratcliff, 1978), but has been successfully applied to many speeded-choice tasks, furthering the understanding of the cognitive processes involved in these tasks (for reviews, see Ratcliff, Smith, Brown, & McKoon, 2016; Voss, Nagler, & Lerche, 2013; Wagenmakers, 2009).

Figure 1 illustrates the processing assumptions of the DDM. It is assumed that on each trial, evidence is accumulated in a noisy fashion to reach a decision about the to-be-selected response. The *average* rate of evidence accumulation (drift rate δ) is dependent on the quality of information from the stimulus or a match with memory. In the SRTT, harder-to-discriminate stimuli or more difficult S–R mappings should affect this parameter; moreover, if indeed consecutive S–R rules or R–R associations are learned in the SRTT, this would result in a memory match for regular responses and a mismatch for nonregular responses. The starting point of the decision process (parameter β) captures information that is already available before the stimulus is presented. In the SRTT, it may capture an anticipation of the to-be-selected response, which may also be driven either by R–R or S–R associations. The spread between both thresholds captures the decision criterion (i.e., response caution α). Extradecisional processes, such as stimulus detection, its encoding, and response execution are captured by nondecision time τ. If it is indeed the guiding of attention on the screen that mediates sequence learning, nondecision time should be affected by stimulus regularity. It is also possible to further disentangle stimulus processing and response-related differences in nondecision time for regular vs. nonregular responses by estimating an additional response-competition parameter ξ (Voss, Rothermund, Gast, & Wentura, 2013; Voss, Voss, & Klauer, 2010); purely-motor learning (effector-specific or not) could selectively mediate such a response-competition effect. The *full* DDM also assumes inter-trial variability in starting point, drift rate, and nondecision time; moreover, most recent advances in DDM modelling allow to capture temporal changes in parameter estimates (for an overview, see L. Schumacher, Schnuerch, Voss, & Radev, 2024), and there are first examples of how such models can be used to investigate learning curves (Cochrane, Sims, Bejjanki, Green, & Bavelier, 2023). Details on the DDM used in this study can be found in Appendix A.

Aims of the present study

To separate the processes underlying the expression of implicit versus explicit knowledge, we manipulated explicit sequence knowledge by revealing, to a subset of participants, the sequence of stimulus and response locations. Orthogonally, we manipulated the possibility to switch to plan-based action control by using either probabilistic or mixed-deterministic stimulus materials.

Participants who work on probabilistic materials and do not receive advance knowledge of the sequence may be considered our baseline condition, because such materials have been found to generate substantial sequence learning while participants remain largely implicit about the sequence (Barth et al., 2019; Jiménez & Méndez, 1999). It should therefore be possible to explore the processes involved in the expression of implicit sequence learning in this condition. Comparing this condition with participants who work on probabilistic materials but receive advance knowledge of the sequence, it is possible to explore whether explicit knowledge *per se* is expressed differently than implicit sequence learning. Comparing probabilistic and deterministic materials in fully explicit participants, it is possible to explore which processes are altered by switching to plan-based vs. stimulus-based action control. Finally, participants who did not receive advance knowledge of the sequence but worked on deterministic materials complete the picture: If deterministic materials indeed facilitate the acquisition of explicit sequence knowledge, these participants should also be able to switch to plan-based action control as soon as they acquired explicit sequence knowledge.

Method

Participants

One hundred and twenty-three participants (104 women) aged between 18 and 49 years ($Md = 23$ years) completed the study. Most were undergraduates from University of Cologne. Participants were randomly assigned to experimental conditions. They received either course credit or 7.50 Euro for their participation.

Materials and Procedure

Participants worked on an SRTT consisting of 14 blocks with 144 trials each (for a total of 2,016 responses). The experiment was run on 24" LCD monitors with a screen resolution of $1{,}920 \times 1{,}080$px. The viewing distance was

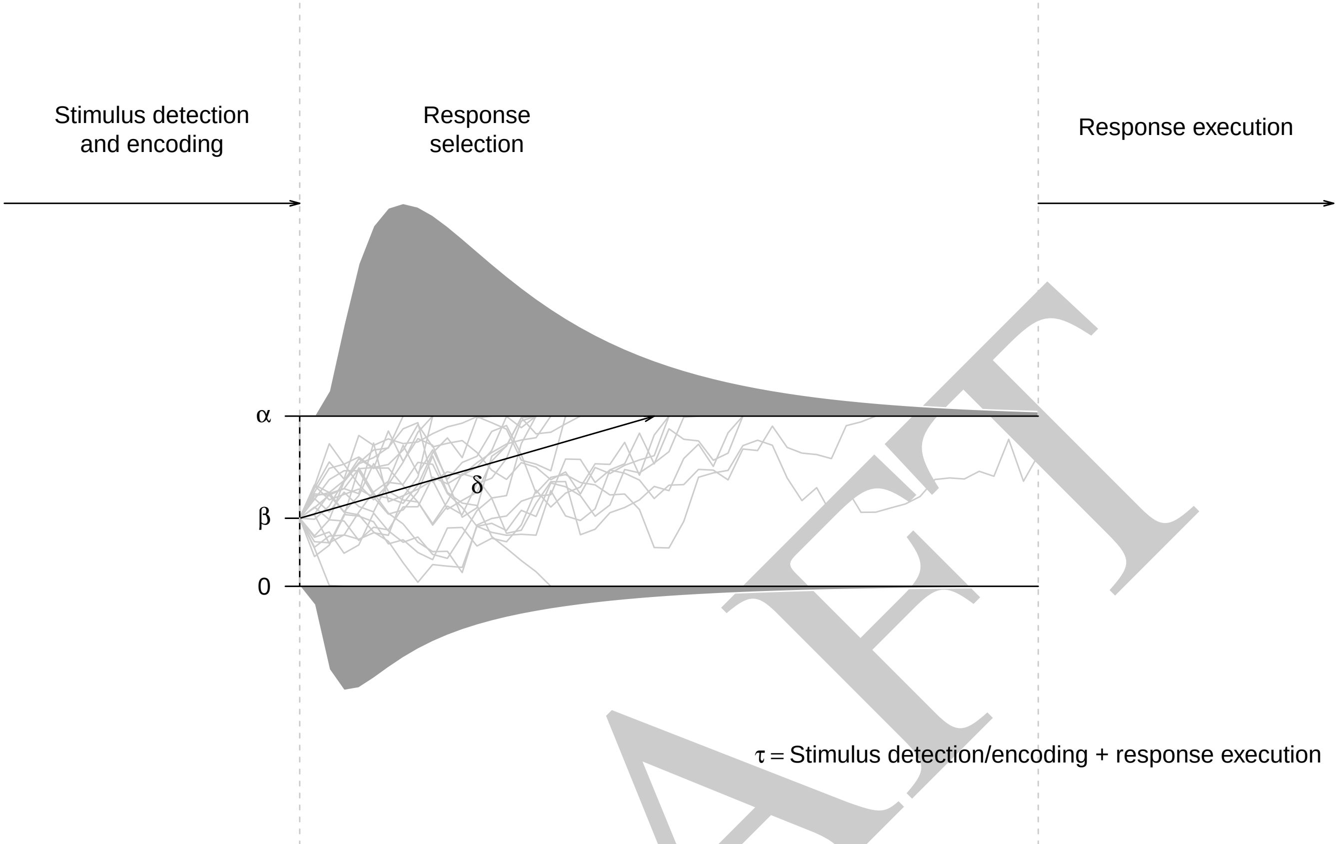

Figure 1. The diffusion model. On each trial, the decision process (depicted as grey lines) begins at a starting point that is determined by parameter β. The spread of the thresholds is determined by parameter α. Evidence is accumulated in a random-walk fashion. When one of the two thresholds is reached, a decision is made. The average rate of evidence accumulation is determined by parameter δ. The decision process is preceded by stimulus encoding and succeeded by response execution, the duration of both processes is captured by nondecision time τ. This basic diffusion model may be extended by response-execution bias ξ and intertrial variabilites for core parameters.

approximately 60cm. A horizontal sequence of six black squares (72px each) with mid-gray outlines were presented on a black screen. The distance between squares was 72px. Each screen location corresponded to one of six keys on a QWERTZ keyboard (from left to right Y, X, C, comma, period, minus), which were marked with red stickers. Participants were instructed to place their ring, middle, and index fingers of both hands on these keys. They were instructed to press the corresponding key whenever a square's color changed from black to mid-gray. On each trial of the SRTT, after a response-stimulus interval (RSI) of 250ms, the imperative stimulus was presented until a response was given. If a response was given before the stimulus had occurred, for 2sec, participants were reminded to press a key only after the stimulus had occurred. To obtain a significant proportion of error responses, we used a response deadline of 500msec. To allow participants to get used to the task, in the first block, we used response deadlines of 900, 800, 700, 600msec for 24 trials each before switching to 500msec for the remainder of the experiment. If the response deadline had been exceeded, a warning sign together with a reminder to answer more quickly, even at the expense of committing more errors, was presented for 1200msec. If the wrong key had been pressed, "wrong key" was presented for 300msec.

For each participant anew, we generated a random permutation of the six possible stimulus locations which served as the six-item sequence. For participants in the *probabilistic sequence* conditions, stimulus locations followed this sequence with a probability of .6; otherwise, another stimulus location was randomly selected from a uniform distribution (excluding immediate repetitions). For participants in the *mixed-deterministic sequence* conditions, stimulus locations deterministically followed this six-item sequence in deterministic blocks; in random blocks, stimulus locations were randomly selected from a uniform distribution (excluding immediate repetitions). The order of random vs. deterministic blocks was randomly selected for these participants: Either blocks

1, 3, 5, 7, 9, 11, 13, or 2, 4, 6, 8, 10, 12, 14 were deterministic. Note that in random blocks, approximately 1/5 = 20% of stimuli followed the sequence by chance. Hence, all participants received stimulus materials that consisted of approximately 60% regular stimulus locations.

Prior to the SRTT, participants in the *sequence concealed* conditions did not receive any a-priori information that stimulus locations follow an underlying sequential structure. By contrast, participants in the *sequence revealed* conditions were informed that stimulus locations followed such a regularity. If these participants worked on probabilistic materials, they were informed that on 60% of trials, the stimuli would be presented in regular location, and in 40% of trials, they would be randomly selected. If these participants worked on mixed-deterministic materials, they were informed about the blocked structure of deterministic vs. random blocks, with exact information about which in blocks stimuli would follow the sequence and in which blocks stimulus locations would be randomly selected. Moreover, participants in the *sequence revealed* conditions were explicitly encouraged to try to use their advance sequence knowledge to optimize task performance. They were then informed about the exact six-item structure of their sequence (e.g., "2–1–6–5–3–4") and they performed 18 trials of the sequence (i.e. three repetitions of the full sequence).

Following the SRTT, we assessed explicit sequence knowledge in a post-experimental interview. Participants were told that they had been assigned to an experimental condition with or without a sequential structure, and were asked to indicate if they believed that they were in a sequenced or a random condition. If they believed that they were in a sequence condition, they were then asked to freely reproduce the sequence. Finally, all participants were asked to reproduce the sequence in a forced-choice manner. Participants were then thanked and debriefed.

Design

Between participants, we manipulated *material* (probabilistic vs. mixed deterministic) and *instructions* (sequence concealed vs. sequence revealed). Each participant worked on 14 SRTT blocks that were collapsed into seven *block pair*s.

Within probabilistic materials, two trial types may be distinguished: *Nonregular* trials that did not follow the six-item sequence, and *regular* trials that did follow the sequence. With mixed-deterministic materials, each block pair was composed of a random block (where stimuli were randomly selected) and a deterministic block (where stimuli always followed the sequence). Hence, three trial types may be distinguished: *Nonregular* trials and *regular* trials from random blocks (remember that single transitions could follow the sequence by chance), and *deterministic* trials from deterministic blocks.

Data preparation

Because an SRTT with a response deadline can be a demanding task, we screened participant data for the proportion of too-slow responses and error rates: We excluded participants who, in one of block pairs 2-7, exceeded an error rate of 50% or responded too slowly on more than 30% of trials. We also excluded data of two participants who did not finish the study and of five participants whose response times were not properly saved.

Furthermore, trials that followed an erroneous response or a response that exceeded the response deadline were excluded from analyses. We also excluded the first four trials of each block, and trials with responses faster than 20ms or slower than 2s. Trials that followed an erroneous response or a response that exceeded the response deadline were excluded from analyses. We also excluded the first four trials of each block, and trials with responses faster than 20ms or slower than 2s.

Results

Response times and error rates

We first analyzed response times and error rates. For ease of interpretation, we report three separate analyses for both RTs and errors: One for the data from the probabilistic groups, and one each for the deterministic and random blocks from the mixed-deterministic groups. Subsequently, we report analyses of two distinct types of error responses: Errors that follow the regularity of motor responses, and errors that do not follow that regularity.

Probabilistic materials. Figure 2 shows mean response times for correct responses and error rates for the probabilistic materials. Analyzing RTs for correct responses using a 2 (*instructions*: sequence concealed vs. revealed) × 2 (*stimulus-location regularity*: regular vs. nonregular) × 7 (*block pair*) ANOVA, we found a main effect of *block pair*, $F(2.95, 306.84) = 267.55$, $p < .001$, $\hat{\eta}^2_G = .148$, reflecting the decreasing RTs over blocks. We also found a main effect of *stimulus-location regularity*, $F(1, 104) = 194.80$, $p < .001$, $\hat{\eta}^2_G = .423$, and a significant two-way interaction of *block pair* and *stimulus-location regularity*, $F(2.79, 290.40) = 59.80$, $p < .001$, $\hat{\eta}^2_G = .028$: Responses were increasingly faster for regular compared with nonregular trials, indicating sequence-specific learning. Responses in regular trials were descriptively faster in the sequence-revealed (compared with the sequence-concealed) condition,

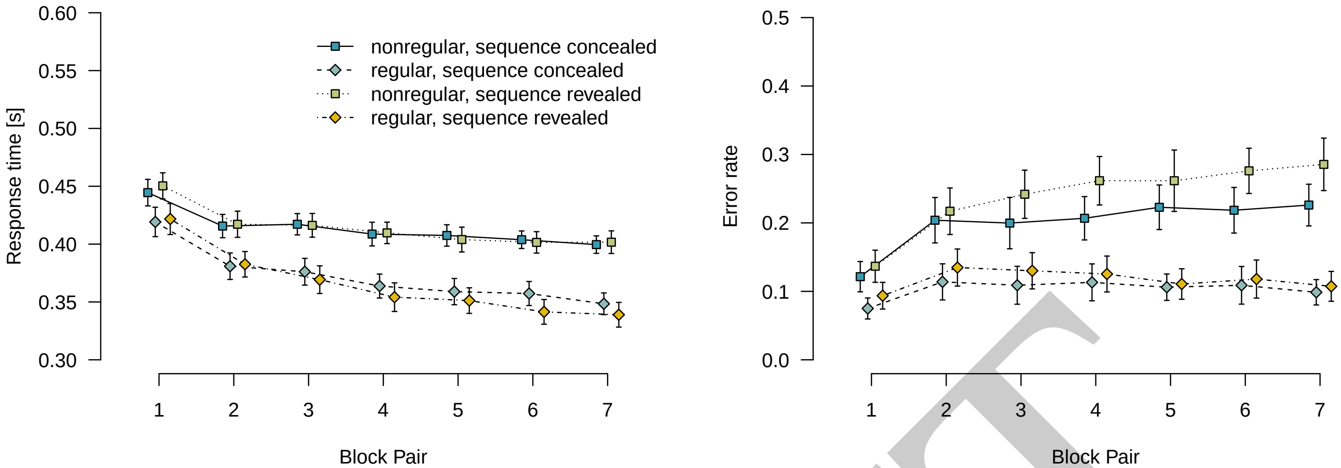

Figure 2. Response times for correct responses, and error rates in probabilistic materials. Error bars represent 95% (between-subjects) confidence intervals.

but all remaining model terms were not significant, all other $ps \geq .135$.

An analogous ANOVA of error rates revealed a main effect of *block pair*, $F(4.63, 245.16) = 34.32$, $p < .001$, $\hat{\eta}^2_G = .099$, a main effect of *stimulus-location regularity*, $F(1, 53) = 277.26$, $p < .001$, $\hat{\eta}^2_G = .359$, and a two-way interaction of *block pair* with *stimulus-location regularity*, $F(5.17, 274.03) = 22.39$, $p < .001$, $\hat{\eta}^2_G = .050$: Error rates were increasingly higher for nonregular compared with regular trials, also indicating sequence learning. Neither the main effect of *instructions*, $F(1, 53) = 2.98$, $p = .090$, $\hat{\eta}^2_G = .033$, nor the interaction of *instructions* with *block pair* was significant, $F(4.63, 245.16) = 0.80$, $p = .544$, $\hat{\eta}^2_G = .003$. These above effects were qualified by a significant three-way interaction, $F(5.17, 274.03) = 2.48$, $p = .031$, $\hat{\eta}^2_G = .006$ and a two-way interaction of *instructions* with *stimulus-location regularity*, $F(1, 53) = 4.06$, $p = .049$, $\hat{\eta}^2_G = .008$. To disentangle these interactions, we analyzed regular and nonregular trials separately. Analyzing only regular trials, we found only a main effect of *block pair*, $F(4.69, 248.42) = 9.08$, $p < .001$, $\hat{\eta}^2_G = .041$, reflection increasing error rates over blocks, all other $ps \geq .348$. By contrast, analyzing only nonregular trials, we found a main effect of *block pair*, $F(1, 53) = 4.41$, $p = .040$, $\hat{\eta}^2_G = .054$, $F(5.22, 276.40) = 37.58$, $p < .001$, $\hat{\eta}^2_G = .183$, $F(5.22, 276.40) = 1.91$, $p = .090$, $\hat{\eta}^2_G = .011$, and a main effect of *instructions*, $F(1, 53) = 4.41$, $p = .040$, $\hat{\eta}^2_G = .054$, with more errors in the sequence-revealed condition. The interaction of *block pair* and *instructions*, reflecting the descriptive observation that the difference between conditions increased over block pairs, was not significant, $F(5.22, 276.40) = 1.91$, $p = .090$, $\hat{\eta}^2_G = .011$.

To summarize, for participants working on probabilistic materials, we found robust sequence learning in both RTs and error rates. Revealing the sequence to such participants had only small effects on RTs: Responses were only descriptively faster for regular trials. However, error rates were higher for nonregular trials. We interpret this finding as first evidence that participants in the sequence-revealed condition actually tried to use their explicit sequence knowledge, but were hard-pressed to do so. In the probabilistic material group, top-down attempts to apply explicit knowledge appear to have interfered with performance (instead of facilitating it). Interference is suggested by the specificity of the finding; in an alternative account in terms of a more liberal decision criterion (e.g., by frustrating participants with a virtually impossible task), RTs for nonregular trials and error rates for regular trials should also have been affected. More research is needed to better pin down such a possible interference and to determine its boundary conditions.

Deterministic blocks of mixed-deterministic materials. Figure 3 shows mean response times for correct responses and error rates in deterministic blocks. Analyzing RTs for correct responses using a 2 (*instructions*: sequence concealed vs. revealed) $\times$ 7 (*block pair*) ANOVA, we found a main effect of *block pair*, $F(2.79, 136.47) = 128.09$, $p < .001$, $\hat{\eta}^2_G = .312$, reflecting decreasing RTs over blocks. We also found a main effect of *instructions*, $F(1, 49) = 11.64$, $p = .001$, $\hat{\eta}^2_G = .164$, RTs were faster in the *sequence-revealed* condition. Although, descriptively, the RT difference between sequence concealed vs. revealed conditions decreased, these main effects were not qualified by an interaction, $F(2.79, 136.47) = 2.10$, $p = .108$, $\hat{\eta}^2_G = .007$.

An analogous ANOVA for error rates revealed only a main effect of *block pair*, $F(4.31, 210.95) = 10.21$, $p < .001$, $\hat{\eta}^2_G = .048$, reflecting decreasing error rates over blocks. Neither the main effect of *instructions*, $F(1, 49) = 3.01$, $p = .089$, $\hat{\eta}^2_G = .044$. nor the interaction were significant, $F(4.31, 210.95) = 0.88$, $p = .481$, $\hat{\eta}^2_G = .004$.

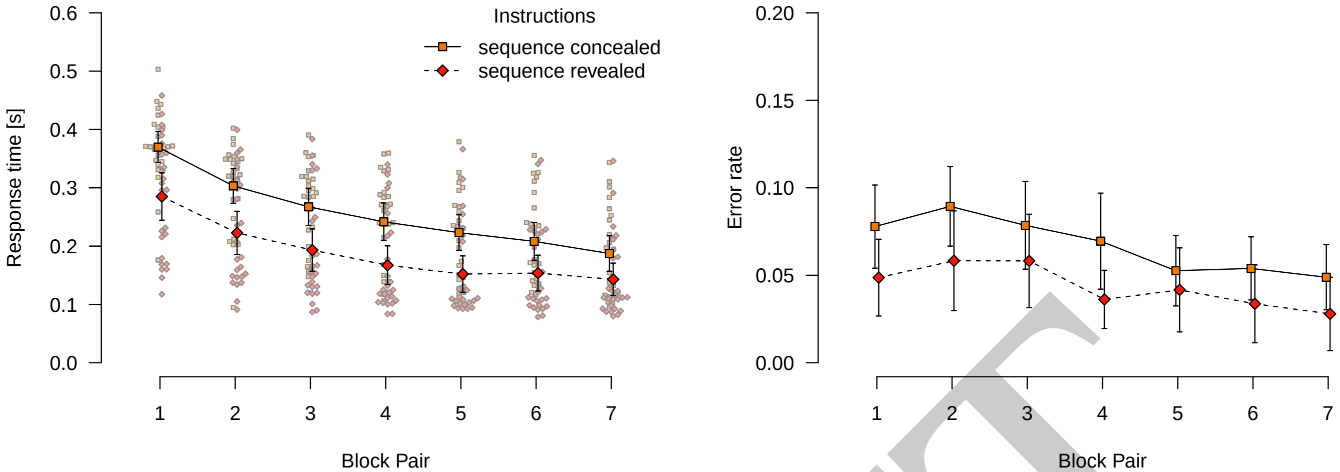

Figure 3. RTs (for correct responses) and error rates in deterministic blocks. Error bars represent 95% (between-subjects) confidence intervals.

We conclude that, in the deterministic blocks, participants were well able to use their explicit knowledge to improve task performance. Although participants in the sequence-concealed condition have acquired substantial amounts of sequence knowledge (likely explicit knowledge; see the results of the post-experimental interview reported below), the speed with which they performed the task did not reach that of participants in the sequence-revealed condition (while both reached comparable levels of accuracy).

Random blocks of mixed-deterministic materials. Figure 4 shows mean response times for correct responses and error rates in random blocks. Note that, in random blocks, it is also possible to distinguish between nonregular and regular stimulus locations because in a fifth of trials, stimulus locations adhere to the sequence by chance. Analyzing RTs for correct responses using a 2 (*instructions*: sequence concealed vs. revealed) $\times$ 2 (*stimulus-location regularity*: regular vs. nonregular) $\times$ 7 (*block pair*) ANOVA, we found a main effect of *block pair*, $F(3.80, 185.98) = 19.64$, $p < .001$, $\hat{\eta}^2_G = .070$, with RTs decreased over blocks. We also found a main effect of *stimulus-location regularity*, $F(1, 49) = 44.62$, $p < .001$, $\hat{\eta}^2_G = .075$, with faster responses for regular (vs. nonregular) stimulus locations. This effect of regularity indicates that sequence learning was expressed in these blocks. The interaction of *block pair* and *stimulus-location regularity* was not significant, $F(3.74, 183.35) = 0.59$, $p = .657$, $\hat{\eta}^2_G = .002$. We did not find an effect of revealing explicit sequence knowledge on RTs: All model terms including *instructions* (main effect and interactions) were not significant, all $ps \geq .161$.

Mirroring RT results, a parallel ANOVA for error rates revealed main effects of *block pair*, $F(4.67, 228.97) = 10.88$, $p < .001$, $\hat{\eta}^2_G = .068$, and *stimulus-location regularity*, $F(1, 49) = 29.39$, $p < .001$, $\hat{\eta}^2_G = .042$. The interaction of *block pair* and *stimulus-location regularity* was not significant, $F(5.18, 253.76) = 1.72$, $p = .128$, $\hat{\eta}^2_G = .009$. All model terms including *instructions* were not significant, all $ps \geq .164$.

To summarize, participants who worked on mixed-deterministic materials expressed sequence learning not only in deterministic blocks (where it is possible to process the task in a plan-based fashion), but also in the random blocks (where only stimulus-based action control is adaptive).

More errors through sequence learning?

In the probabilistic and random (but not deterministic) materials, a stimulus was sometimes presented in a nonregular stimulus location and thus prompted a nonregular response. In this case, two distinct types of error responses may be distinguished: Error responses that follow the regularity of motor responses (i.e., rule-adhering errors), and error responses that do not follow that regularity. If, over the course of learning, participants tend to generate rule-adhering errors more frequently, this would indicate that response-selection processes (i.e., processes that may impact *which* response is selected) are involved in sequence learning. To test this notion, we analyzed error responses (excluding post-error and post-feedback trials as well as response repetitions) and calculated the proportion of rule-adhering errors.

Analyzing these proportions with an ANOVA reveals a main effect of *material*, $F(1, 101) = 7.16$, $p = .009$, $\hat{\eta}^2_G = .025$, with more rule-adhering errors in probabilistic materials, all other $ps \geq .125$.

We also tested these proportions against chance baseline (i.e., $1/4 = .25$, given that response repetitions and correct responses are excluded from this analysis). The proportion

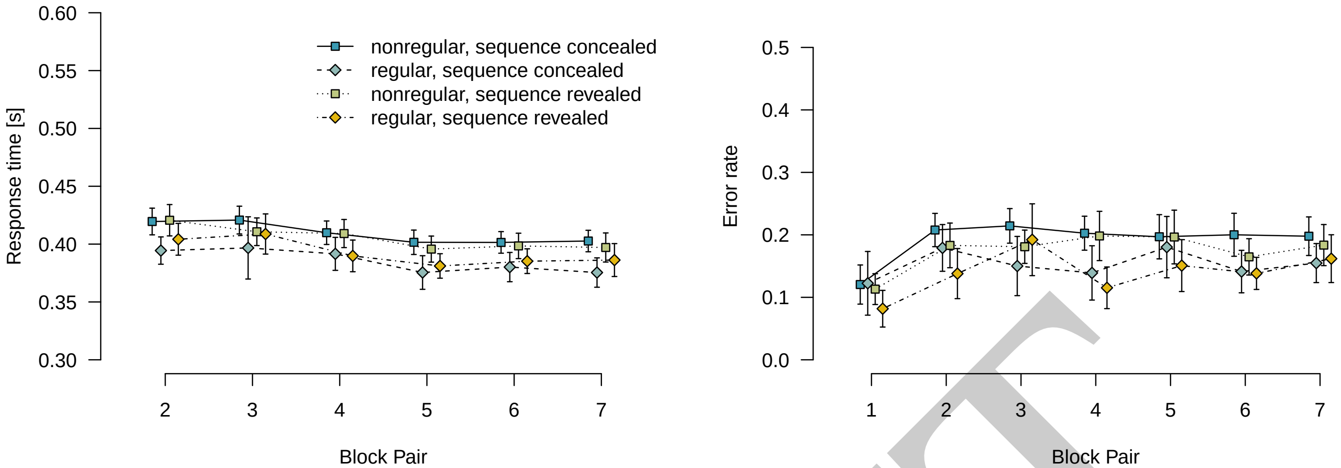

Figure 4. RTs (for correct responses) and error rates in random blocks. Error bars represent 95% (between-subjects) confidence intervals.

of rule-adhering errors exceeded the chance baseline in both conditions: For random blocks of mixed-deterministic material, it was $M = 0.28$, 95% CI $[0.26, \infty]$, $t(101) = 2.21$, $p = .015$. For probabilistic materials, it was $M = 0.33$, 95% CI $[0.31, \infty]$, $t(101) = 6.19$, $p < .001$. This trend toward rule-adhering errors suggests that response selection may have been impacted by sequence learning. The effect was stronger for participants who worked on probabilistic materials, which might be explained with differences in processing mode, or with different representations underlying sequence-specific effects in these conditions.

Faster errors through sequence learning?

We also analyzed response times (see Figure 5) for error responses (again excluding post-error trials) and found a main effect of *response regularity*, $F(1, 76) = 60.49$, $p < .001$, $\hat{\eta}^2_G = .049$, a main effect of *block pair*, $F(3.14, 238.48) = 25.97$, $p < .001$, $\hat{\eta}^2_G = .106$, and their interaction, $F(2.85, 216.53) = 4.68$, $p = .004$, $\hat{\eta}^2_G = .016$. Moreover, the interactions of *material* and *response regularity*, $F(1, 76) = 15.45$, $p < .001$, $\hat{\eta}^2_G = .013$, and of *block pair* and *response regularity* were significant, $F(2.85, 216.53) = 4.68$, $p = .004$, $\hat{\eta}^2_G = .016$, all other ps $\geq .144$.

To disentangle these interactions, we analyzed probabilistic and random materials separately (note that the deterministic material contained no relevant trials): For probabilistic materials, we found a main effect of *block pair*, $F(4.09, 180.10) = 20.39$, $p < .001$, $\hat{\eta}^2_G = .126$, a main effect of *response regularity*, $F(1, 44) = 99.80$, $p < .001$, $\hat{\eta}^2_G = .140$, and their interaction, $F(4.21, 185.35) = 5.40$, $p < .001$, $\hat{\eta}^2_G = .026$, all other other ps $\geq .135$. Participants not only produced an above-chance proportion of rule-adhering errors, but these error responses also became increasingly faster over blocks. For random materials, we only found a main effect of *block pair*, $F(2.41, 74.62) = 8.93$, $p < .001$, $\hat{\eta}^2_G = .096$, reflecting decreasing RTs over blocks, and a main effect of *response regularity*, $F(1, 31) = 4.96$, $p = .033$, $\hat{\eta}^2_G = .010$. all other ps $\geq .274$, In the random blocks, responses were also faster for rule-adhering (or motor-regular) responses.

In sum, the effect of motor regularity on response times mirrored the result that rule-adhering errors are chosen above chance. In other words, when stimuli were presented in nonregular locations and a wrong key was chosen, participants were not only more likely to select a regular response, but were also faster when doing so. It is not clear whether such an effect may be attributable to changes in response tendencies or response-selection learning, or whether this is a motor-specific effect attributable to extensive practice of the same consecutive responses.

Post-experimental interview

Participants were asked whether they believed they have been working on materials containing a sequence (and to name that sequence); and then were presented with each stimulus and asked to select the next one in the sequence (i.e., forced choice). We first analyzed how many participants indicated that they believed that they were in a sequenced condition. For mixed-deterministic materials, 25 out of 26 participants in the sequence-revealed condition indicated that they were in a sequenced condition; 20 out of 23 participants in the sequence-concealed condition indicated the same. For participants who worked on probabilistic materials, only 12 out of 26 participants in the sequence-revealed condition and 14 out of 27 participants in the sequence-concealed condition believed that they had worked on sequenced materials.

Regarding forced-choice performance, we analyzed the pro-

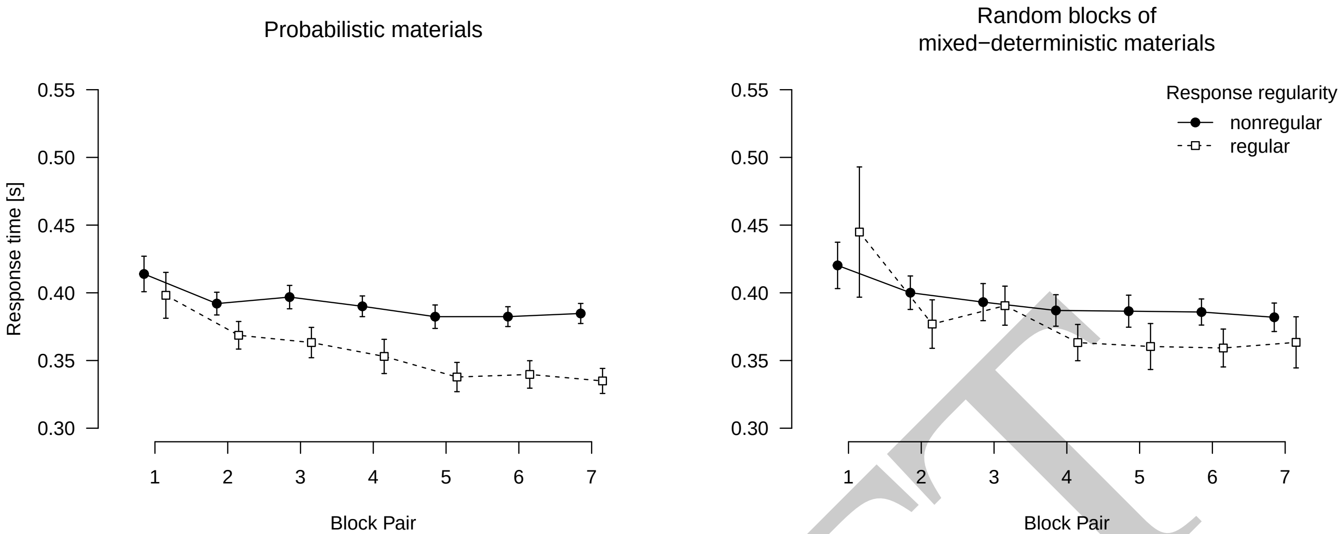

Figure 5. Response times for error responses. Error bars represent 95% within-subjects confidence intervals.

portion of correct responses using a 2 (*material*: probabilistic vs. mixed deterministic) $\times$ 2 (*instructions*: sequence concealed vs. sequence revealed) ANOVA that revealed a main effect of *material*, $F(1,101) = 26.11$, $p < .001$, $\hat{\eta}^2_G = .205$, a main effect of *instructions*, $F(1,101) = 3.67$, $p = .058$, $\hat{\eta}^2_G = .035$, and no interaction, $F(1,101) = 0.35$, $p = .555$, $\hat{\eta}^2_G = .003$. We also tested forced-choice performance against chance baseline ($1/5 = .2$) using planned contrasts. Performance in the probabilistic/sequence-concealed condition did not differ from chance $M = 0.29$, $t(101) = 1.34$, $p = .091$. (with a small number of participants showing above-chance performance). Participants in the probabilistic/sequence-revealed condition performed above chance, $M = 0.38$, $t(101) = 2.59$, $p = .005$. With mixed-deterministic materials, both groups of participants clearly performed above chance ($M = 0.60$, $t(101) = 5.55$, $p < .001$ in the sequence-concealed condition, and $M = 0.77$, $t(101) = 8.28$, $p < .001$ in the sequence-revealed condition).

Participants who worked on mixed-deterministic materials were well able to acquire substantial amounts of explicit sequence knowledge that they were also able to verbally report in our post-experimental interview. Participants who had received advance knowledge about the sequence performed better than those who had not. In contrast, most participants who worked on probabilistic materials were not able to acquire substantial amounts of such knowledge. Those who had received advance knowledge about the sequence could report above-chance knowledge on the forced-choice questions, but the amount of knowledge was small (i.e., much smaller than that obtained by participants in the mixed-deterministic/sequence-concealed group). Most of these participants appear to have forgotten the structure of the sequence, perhaps because they were not able to use this knowledge to improve their SRTT performance. A complete overview of results from the post-experimental interview can be found in Appendix B.

Model-based analyses

In a next step, we applied the diffusion model to the present data. We first report parameter estimates for the whole sample of participants. In a second step, we contrasted the parameters involved in the expression of implicit knowledge from those reflecting the expression of explicit knowledge in a plan-based fashion. To this end, we report modelling results for a subset of participants who (1) worked on probabilistic materials, were not revealed any sequence knowledge, and, according to the post-experimental interview, remained fully implicit about the sequence, and (2) for a subset who worked on mixed-deterministic materials, were instructed about the sequence, and reported comprehensive explicit sequence knowledge.

Whole sample. Parameter estimates are depicted in Figures 6-10. We report Bayes Factors (BF) for model comparisons that tested the effects of experimental manipulations on model parameters.

Starting point. The *starting point* parameter captures information that is available *before* the evidence accumulation process starts (i.e., before the imperative stimulus is presented). In the present application of the diffusion model, it could be biased either towards regular (i.e., upper boundary) or towards nonregular responses (i.e., lower boundary). Figure 6 shows parameter estimates of the starting point. Participants who worked on probabilistic materials were increasingly biased to select regular responses: In both the sequence-concealed condition ($BF_{10} > 1{,}000$) and the

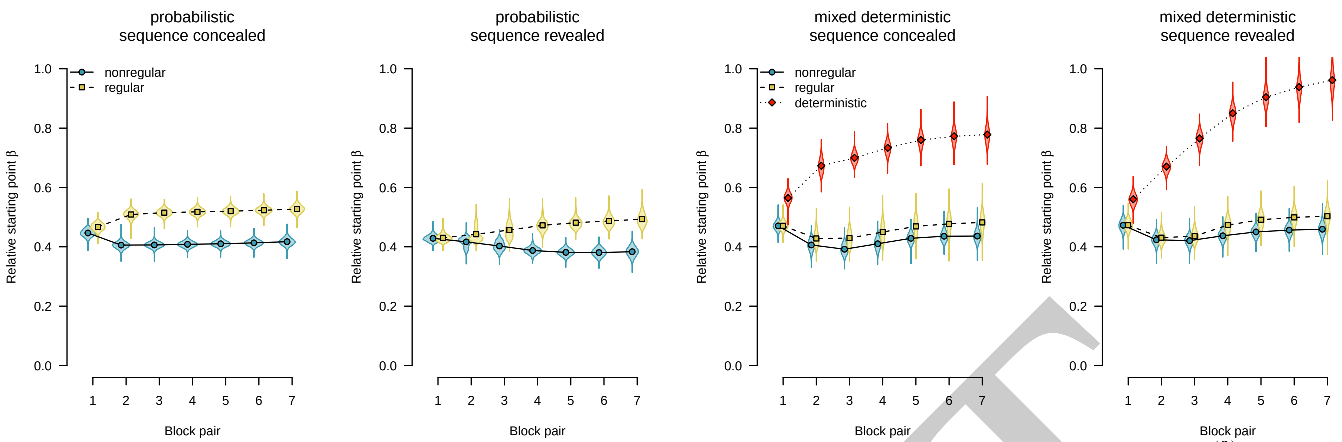

Figure 6. Starting point of the diffusion process. Points represent posterior means of the group-level parameters $\mu_{kb}^{(\beta)}$.

sequence-revealed condition ($BF_{10} > 1{,}000$) the BF clearly favored the alternative hypothesis of an effect of regularity.

Participants who worked on mixed-deterministic materials showed a strong bias towards the regular response in deterministic compared with random blocks: In both the sequence-concealed condition ($BF_{10} > 1{,}000$) and the sequence-revealed condition ($BF_{10} > 1{,}000$), Bayes Factors clearly favored the alternative hypothesis of greater starting point estimates in deterministic (vs. random) blocks. Comparing regular and nonregular trials in random blocks, we found evidence against an effect of regularity (sequence concealed: $BF_{01} = 6.63$, sequence revealed: $BF_{01} = 4.75$).

Drift rate. The drift rate reflects the speed of evidence accumulation (i.e., information uptake from the stimulus and/or a match with memory). Figure 7 shows drift-rate estimates. With probabilistic materials, the expression of sequence learning is mediated by faster evidence accumulation for regular (compared with nonregular) trials. In the sequence-concealed condition, we found $BF_{10} > 1{,}000$, in the sequence-revealed condition, we found $BF_{10} > 1{,}000$. By contrast, with deterministic materials, we consistently found evidence against an effect on drift rate. Comparing deterministic with random blocks, we found evidence against an effect in both the sequence-concealed ($BF_{01} = 15.72$) and the sequence-revealed condition ($BF_{01} = 11.26$). Comparing regular and nonregular trials in random blocks also revealed evidence against an effect of regularity, (sequence concealed: $BF_{01} = 3.13$, sequence revealed: $BF_{01} = 9.61$).

Boundary separation. The boundary separation parameter reflects response caution: Higher values reflect more separated boundaries, hence more cautious responding. Figure 8 shows boundary separation parameter estimates. In all conditions, we find strong evidence for an overall decrease in response caution (all $BF_{10} > 1{,}000$), Participants responded more liberally over time to accommodate the time pressure in this experiment. However, in deterministic blocks, participants were able to exploit the speedup attributable to changes in other model parameters (starting point and nondecision time) to maintain higher response caution (sequence concealed: $BF_{10} = 112.84$, sequence revealed $BF_{10} > 1{,}000$).

Nondecision time. In the diffusion model, the *nondecision time* parameter subsumes all processes (i.e., perceptual and motor) occurring before and after the response-selection decision.

Figure 9 shows nondecision times as a function of stimulus regularity. With probabilistic materials, we find evidence for the absence of sequence-specific effects, with $BF_{01} = 6.15$ in the sequence-concealed condition, and $BF_{01} = 3.74$ in the sequence-revealed condition. We therefore conclude that, if participants are performing the SRTT in a stimulus-based fashion, it is neither stimulus detection nor encoding that mediate the expression of sequence learning.

A similar pattern can be observed in participants who worked on mixed-deterministic materials: When considering random blocks, we find evidence for an absence of a difference in nondecision time attributable to sequence learning, with $BF_{01} = 36.93$ in the sequence-concealed condition, and $BF_{01} = 33.85$ in the sequence-revealed condition.

By contrast, with mixed-deterministic materials, we find strong evidence for a rapid decrease in nondecision time for deterministic compared with random materials, with $BF_{10} > 1{,}000$ in the sequence-concealed condition, and $BF_{10} > 1{,}000$ in the sequence-revealed condition. We interpret this finding as indicative that a switch to plan-based action control allows participants to largely skip the process of stimulus detection and encoding; instead, during the RSI, they already prepare a response that is executed as soon as something appears on the screen.

Response competition. We applied an extended diffusion model with an additional *response-competition* parameter

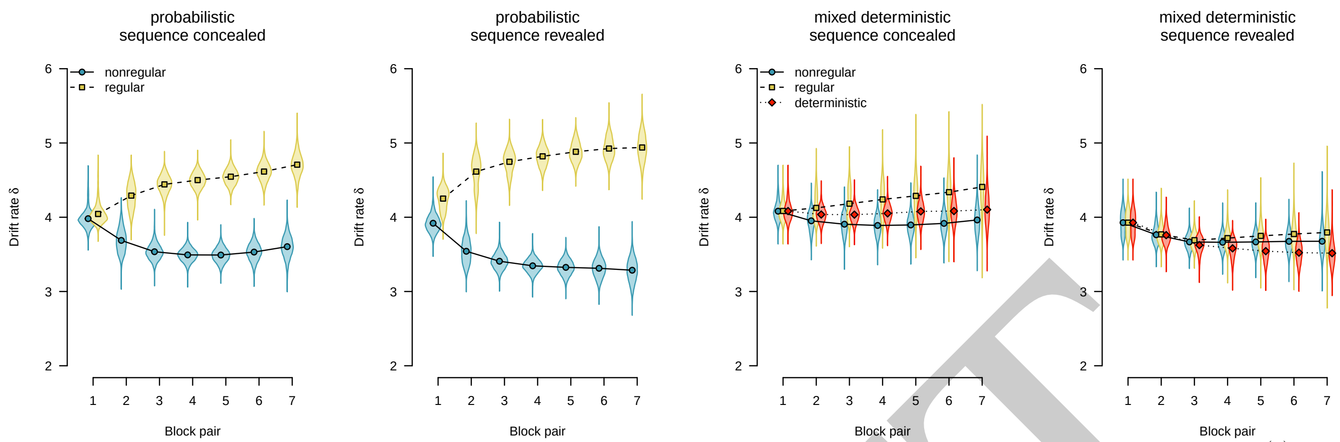

Figure 7. Average evidence accumulation (drift rate). Points represent posterior means of the group-level parameters $\mu_{kb}^{(\nu)}$.

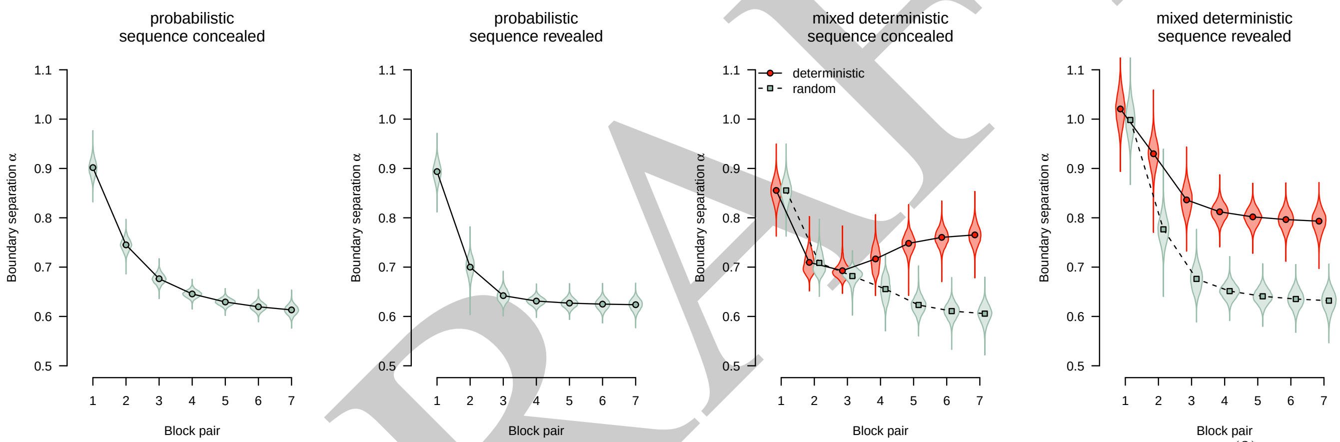

Figure 8. Boundary separation (response caution). Points represent posterior means of the group-level parameters $\mu_{kb}^{(\beta)}$.

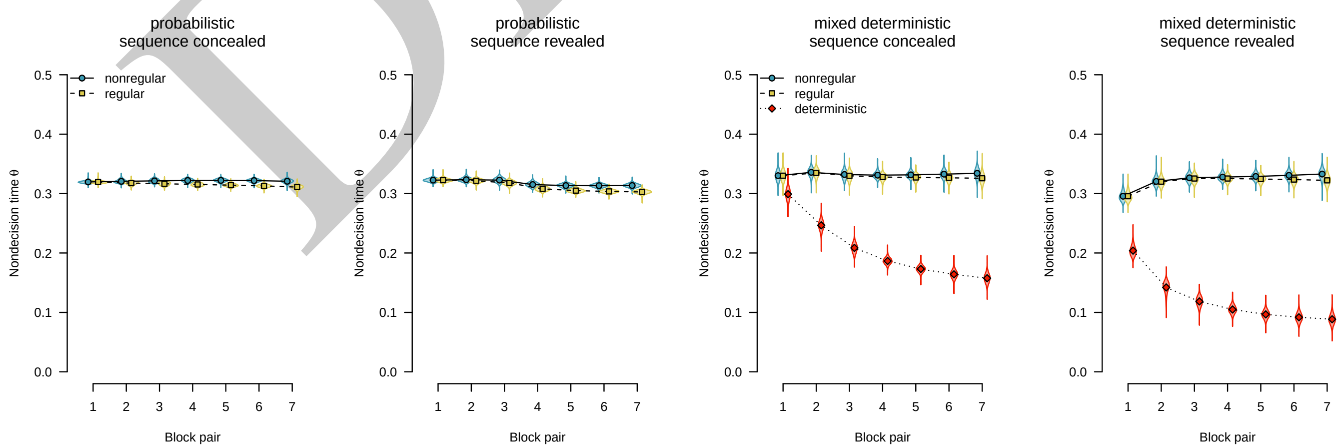

Figure 9. Nondecision times, separated by stimulus-location regularity. Points represent posterior means of the group-level parameters $\mu_{kb}^{(\theta)}$.

reflecting differences in nondecision times between motor-regular and motor-nonregular responses.

Figure 10 shows response-competition parameter estimates. For probabilistic materials, we found clear evidence for a response competition effect, (sequence concealed: $BF_{10} >$ 1,000, sequence revealed $BF_{10} >$ 1,000). For deterministic materials, we found such an effect if the sequence was concealed, $BF_{10} = 62.61$; but found evidence against such an effect if the sequence was revealed, $BF_{01} = 47.43$.

Subset analyses. To more clearly pin down the expression of implicit versus explicit sequence knowledge, using the post-experimental-interview data, we classified participants (within each condition) into three groups: (1) Participants who indicated that they probably were in a random condition and only reproduced less than two transitions correctly in both the forced-choice and free-recall test (henceforth coined *implicit* groups), (2) participants who indicated that they probably were in a sequenced condition, and reproduced six transitions correctly in both free-recall and forced-choice test (the *explicit* group), and (3) participants who fell in-between these criteria (the *intermediate* groups). We then re-estimated the DDM for these sub-groups if there were at least four participants in the respective group, and compared parameter estimates across groups.

Results showed that, in general, the overall patterns of parameter estimates were not affected by the amount of explicit knowledge: Parameter patterns were largely identical across all participants in the probabilistic groups (regardless of whether they had received advance knowledge about the sequence, or had acquired some explicit knowledge during their time on the task). Similarly, parameter patterns were also largely identical among the subgroups working on mixed-deterministic material, regardless of the source or amount of explicit knowledge.[1] These findings demonstrate that the presence of explicit knowledge *per se* does not necessarily affect performance. Participants also need the opportunity, afforded by the deterministic blocks, to express that knowledge in a plan-based manner.

To characterize the expression of implicit sequence knowledge, we used the parameter estimates from the group who worked on probabilistic materials in the sequence concealed condition and did not show any indication of explicit knowledge (i.e., the *implicit* subgroup). These participants could only perform the task in a stimulus-based manner. The left panels of Figure 11 show parameter estimates for this subgroup. In line with our whole-sample results, if the SRTT is performed in a stimulus-based fashion and participants remained implicit about the sequence, such implicit learning affects the response-selection process, with a tendency to select the rule-adhering response (starting point β), and faster evidence accumulation for rule-adhering stimuli (drift rate δ). We found no effect of stimulus regularity on nondecision time θ, but a robust effect of motor regularity (response competition ξ).

To characterize the expression of explicit knowledge, we used the parameter estimates from the group of participants who worked on mixed-deterministic materials, received full advance sequence knowledge, and were able to report the complete sequence at the end of the experiment. These participants most likely performed the task in a plan-based fashion. The right panels of Figure 11 show parameter estimates for this subgroup. Plan-based action control in deterministic blocks was reflected in an anticipation of the next response (starting point β), indicating that response selection is almost completed when the stimulus appears on the screen. Evidence accumulation from the stimulus (drift rate δ) was not affected by a switch to plan-based action control, indicating that in such a processing mode, the little information that is necessary to select the response (i.e., the appearance of a stimulus on the screen) is processed as efficiently as in random blocks. Nondecision time θ was dramatically reduced in deterministic blocks (compared with random blocks), indicating that stimulus detection and/or encoding can be bypassed. Participants were also able to use their performance advantage to respond more cautiously in deterministic versus random blocks (boundary separation α). There was no effect of motor regularity on nondecision time (i.e., no response-competition effect).

To summarize, implicit knowledge affected the drift rate as well as the starting point of the diffusion process, and also caused response competition. In contrast, expressing explicit knowledge in a plan-based fashion did not affect the drift rate; it was most prominently reflected in a decrease of nondecision time and an effect on the starting point. While the starting point was affected in both cases, implicit sequence knowledge selectively involved an effect on drift rate, and plan-based expression of explicit knowledge selectively affected overall nondecision time.

Discussion

We set out to pinpoint the cognitive processes that are involved in the expression of implicit versus explicit sequence knowledge. We found that implicit sequence knowledge gradually affects cognitive processes during stimulus-

[1] Participants who worked on mixed-deterministic materials and received advance knowledge of the sequence but were, according to our criteria, classified as being implicit about the sequence also showed an above-zero response-competition effect. Evidently, these participants failed to remember the sequence or did not read the instructions properly and, therefore, also engaged in stimulus-based processing of the SRTT.

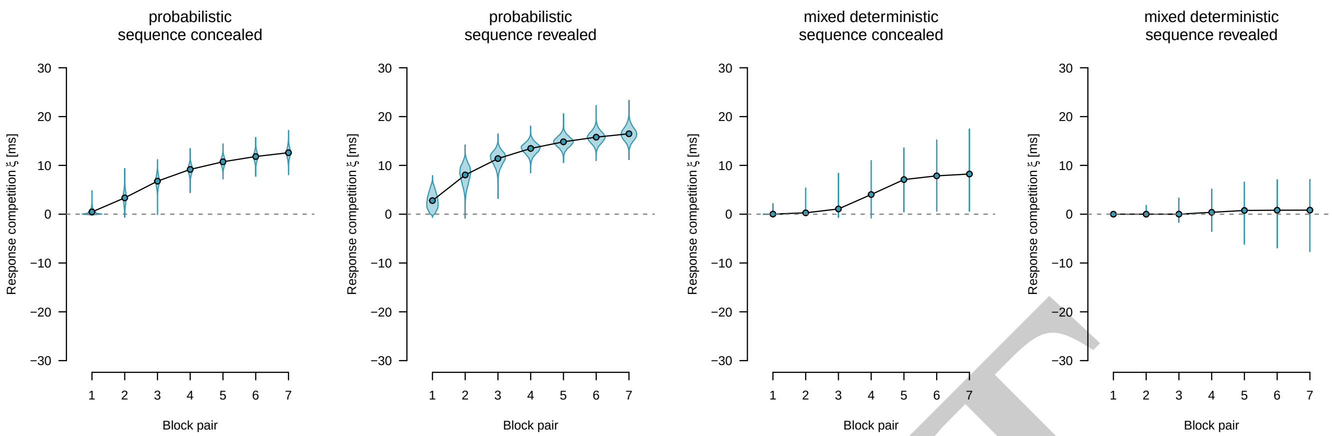

Figure 10. Response-competition parameter ξ, capturing differences in nondecision time between motor-regular and motor-nonregular responses. Positive values imply faster responses for motor-regular responses. Points represent posterior means of the group-level parameters $\mu_{kb}^{(\xi)}$.

based task processing, whereas explicit knowledge supports a switch to plan-based processing.

In our baseline condition (probabilistic materials, sequence concealed), we found that sequence learning was expressed by a combination of effects on starting point, drift rate, and response-competition bias. Over the course of training, the starting point was shifted towards the regular response, indicating that even before the imperative stimulus was presented, the response-selection process was increasingly biased towards the rule-adhering response option. Moreover, as suggested by higher drift rates for regular trials, evidence accumulation was faster for rule-adhering trials, indicating that either the information from the imperative stimulus or the stimulus-response rule was processed more efficiently. Nondecision time was invariant to stimulus-location regularity, but varied by response-location regularity (i.e., we found an effect of response competition), indicating an additional learning effect at the motor level. To summarize, response selection appears to be involved in implicit sequence learning. This is in line with previous findings supporting S–R representations (Schwarb & Schumacher, 2012), and suggests the involvement of a multidimensional system (i.e., combining stimulus and response dimensions). In addition, we found evidence for response-competition bias toward the regular responses, suggesting the involvement of motor facilitation. As the present study confounded effectors with response locations, it could be explained by both effector-specific or general effects (Verwey & Clegg, 2005; Willingham et al., 2000). Future research is needed to separate these two factors and their effects on the response-competition parameter.

Participants who worked on probabilistic materials and received advance knowledge of the sequential structure, and were encouraged to use this knowledge, were hard-pressed to express this extra knowledge. Overall, the performance pattern of this group was highly similar to that of the sequence-concealed group, with sequence learning being reflected in effects on starting point, drift rate, and response competition. Compared with the sequence-concealed condition, the effect on drift rate was increased, whereas the effect on starting point was reduced. Future research is needed to determine whether these differences are robust and reflect participants' attempts to express their explicit knowledge.

By contrast, participants who worked on mixed-deterministic materials showed a qualitatively distinct pattern of parameter estimates. It was characterized by a much stronger effect on the starting point and a steep reduction in nondecision time. In addition, boundary separation was increased in the deterministic blocks. There were no effects on drift rate or the response-competition parameter. This parameter pattern suggests that participants engaged in plan-based task performance, using their explicit knowledge to anticipate the stimulus and prepare their response. This anticipation was so successful (i.e., the starting point was so strongly shifted towards the *regular* boundary) that participants needed to extract only very little information from the stimulus during the decision process. (The present finding of no effect on drift rate in the deterministic condition should therefore be interpreted with caution: It may simply reflect the fact that, in our study, virtually no information needed to be sampled from the stimulus.) Because plan-based performance speeded up participants' responses in the deterministic blocks, they could afford to increase their response caution (i.e., boundary separation) in these blocks.

Participants who worked on mixed-deterministic materials but did not receive advance sequence knowledge showed a similar pattern, with smaller effects overall. In this condition, a substantial subset of participants have apparently acquired explicit sequence knowledge and switched to a plan-based

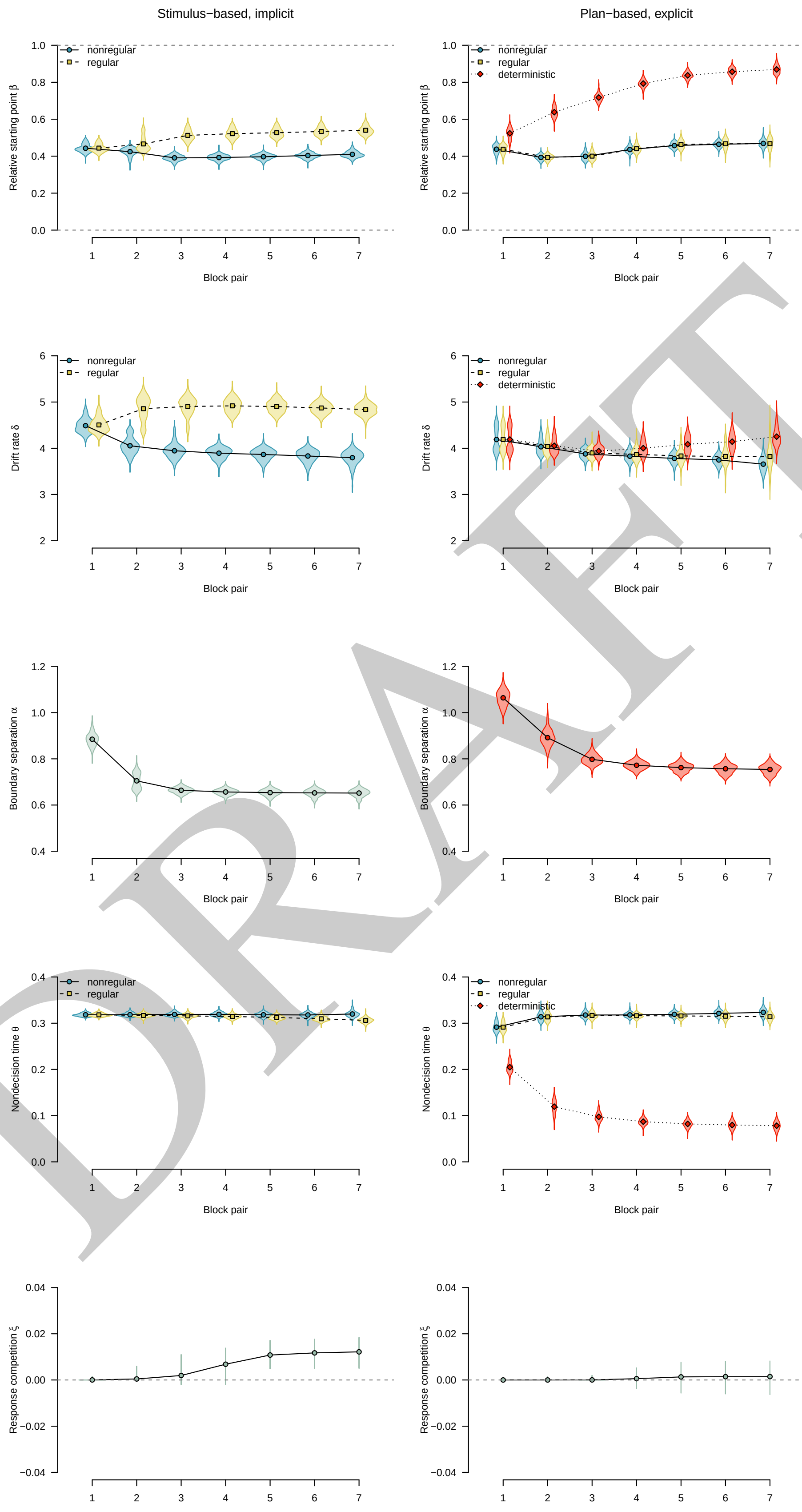

Figure 11. DDM parameters for stimulus-based (on the left) versus plan-based SRTT performance (on the right).

processing mode. The only difference was the (small) effect on the response-competition parameter, which was found in the mixed-deterministic/sequence-concealed group but not in the sequence-revealed group. Because the proportion of regular motor key presses is comparable between all four conditions, the absence of a response-competition effect for the mixed-deterministic/sequence-revealed group suggests that this parameter does not capture a purely motor-learning effect that is a mere by-product of repeatedly performing the same sequence of motor key presses. Instead, it might depend on performing the task in a stimulus-driven manner. Because participants who worked on mixed-deterministic materials in the sequence-revealed condition were able to work in a plan-based fashion from the very start, they might not have engaged in a sufficient amount of stimulus-based task performance in order to acquire a response-competition effect. In contrast, participants who worked on mixed-deterministic materials in the sequence-concealed condition were not able to engage in plan-based task performance from the start. The response-competition effect may be explained by the notion that this learning effect develops if and only if participants perform the task in a stimulus-based fashion. Clearly, future empirical work is needed to clarify the interpretation of this effect.

Limitations. It may be argued that our manipulation of sequence knowledge was not successful, given that revealed sequence knowledge was largely forgotten with probabilistic materials. However, we found a clear effect of instructions on error rates for nonregular trials, indicating that at least some participants tried to implement their sequence knowledge while performing the task.

Instead of reflecting the absence of implicit learning effects on stimulus detection or encoding, the lack of an effect on nondecision time may point to the fact that both stimulus detection and encoding were relatively easy in our experiment (i.e., a floor effect). Alternatively, such a learning effect may truly be nonexistent. Earlier findings of purely observational (Howard et al., 1992; Song, Howard, & Howard, 2008) or parallel learning of stimulus locations (Mayr, 1996) may then reflect either an artifact of explicit knowledge or implicit learning of spatial locations in a unidimensional system (c.f., Eberhardt et al., 2017) that is expressed at the response-selection stage.

The DDM has been widely successful in capturing and explaining performance in many speeded-choice tasks, and we therefore deem it an excellent starting point for modelling performance in the SRTT. However, it makes a set of processing assumptions. Most importantly, it assumes that stimulus encoding, response selection, and response execution are organized sequentially, an assumption that might be violated in sequence learning, given that parallel architectures have been proposed for motor-behavior tasks such as the SRTT (e.g., Logan, 1988; Verwey, Shea, & Wright, 2015). Hence, unless the model receives further validation for SRT tasks, the present set of findings may be alternatively accounted for by theories involving parallel processes.

As another point of criticism, it may be argued that the DDM, as a decision model, may be less useful for conditions involving plan-based actions to the degree that plan-based action control requires little information from the stimulus to arrive at a decision. Note, however, that the DDM was developed for decisions from memory, and the use of explicit knowledge may well be characterized as involving such memory-based decisions (i.e., recalling the next element of the sequence).

Future Directions. Extensions of the SRTT allow to orthogonally manipulate stimulus vs. motor sequences by changing the stimulus-response mapping on each trial (e.g., Eberhardt et al., 2017; Goschke & Bolte, 2012) Such extended designs provide the opportunity to validate the DDM's application to the SRTT, and to further pin down the interpretation of the observed parameter changes: To clarify how to interpret the response-competition effect that we found for stimulus-based implicit learners, it could be tested whether motor sequences, but not stimulus sequences selectively influence this parameter. Moreover, the effector-specificity of this effect could be investigated using a transfer task where effectors are changed but response locations are kept constant (e.g., Verwey & Clegg, 2005). If sequence learning of stimulus locations guides spatial attention on the screen (as suggested by Mayr, 1996), it should selectively influence stimulus detection (i.e., nondecision time). In the present work, we did not find such an effect, but stimulus detection was very easy; increasing the difficulty of stimulus detection (e.g., by presenting irrelevant stimuli in the other locations) might give rise to an effect of sequence learning on stimulus detection when responses are unrelated to stimulus locations.

It is an unresolved issue whether two distinct learning systems (one multidimensional, one unidimensional) are necessary to explain the pattern of findings in the sequence-learning literature (Barth, Stahl, & Haider, 2023), one of the reasons being that it is not clear along which dimensions information is considered to be processed separately within the unidimensional system. Our findings indicate that response selection is the locus of sequence learning in the SRTT, and that, therefore, only joint representations of stimulus and response features may subserve the standard SRTT effect. A unidimensional learning system that is separated along the lines of stimulus and response can, therefore, not explain our findings. However, if the unidimensional system is separated along abstract features such as location (as suggested by Eberhardt et al., 2017; Haider et al., 2020), a unidimensional learning system could indeed provide the information necessary to guide spatial response selection. With the diffusion model introduced here, it would be possible to more directly test the separation of information processing that is implied by modularization. For instance, if other stimulus features not only affect stimulus processing (i.e., nondecision time) but also response-selection parameters, this would clearly speak against such modularized processing (Barth et al., 2023).

In the present work, we used a regression approach at the group-level means to model the changes in parameter estimates over the course of learning. Most recently, considerable efforts have been made to model both gradual and sudden shifts in parameter estimates (Gunawan, Hawkins, Kohn, Tran, & Brown, 2022; L. Schumacher et al., 2024). Such non-stationary models may be used to model individual learning curves at the level of a single transition, providing a principled on-line measure of a switch to plan-based action control in the SRTT. Moreover, these methods allow to investigate whether *implicit* sequence learning is indeed a gradual or a sudden phenomenon (c.f., Musfeld, Souza, & Oberauer, 2023). For a regression-based approach, recent advances in Bayesian estimation carry the potential to facilitate such endeavors: Henrich, Hartmann, Pratz, Voss, and Klauer (2023) implemented the seven-parameter DDM in Stan (Carpenter et al., 2017), a probabilistic programming language that uses Hamiltonian Monte Carlo, a sampling algorithm that provides better computational efficiency than the sampling algorithms used in the present work (Betancourt, 2017).

Conclusion. The present study is the first to use the diffusion model to analyze processes underlying performance in the SRTT. In this first step, we focused on the effects of implicit learning and plan-based expression of explicit knowledge. Our results demonstrate the usefulness of the diffusion model in research on implicit learning. They indicate that implicit sequence learning in the SRTT guides response selection, supporting either multidimensional accounts of implicit sequence learning (E. H. Schumacher & Hazeltine, 2016) or, alternatively, unidimensional accounts that assume that features from the same abstract dimension (e.g., spatial location) of both stimulus and response are jointly represented (Haider et al., 2020).

In addition, we find evidence for response competition that is independent of response selection. More research is needed to investigate whether this effect represents effector-specific motor learning (Verwey & Clegg, 2005) or is linked to abstract response categories (Willingham et al., 2000). Supporting the recent tests of the unexpected-event hypothesis (Lustig et al., 2022), strong decreases in response time are readily accounted for as a consequence of a switch to plan-based action control. This switch is possible only after the sequence already has become explicit, and only if the structure of the task makes such a change beneficial for performance. When implemented, such a strategy shift results in an anticipation of the next response even before the imperative stimulus is presented, allowing participants to largely bypass stimulus processing (as reflected in reduced interference effects in Stroop and Simon tasks, Haider et al., 2011; Koch, 2007).

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Appendix A
Model specification

We implemented the drift-diffusion model in JAGS (Plummer, 2003). Response times and accuracy on each trial n were modeled as coming from a Wiener distribution with the models' *core* parameters boundary separation α_{ik^*b}, starting point β_n, drift rate δ_n and nondecision time τ_n

$$y_n \sim \mathcal{W}\left(\alpha_{ik^*b}, \beta_n, \delta_n, \tau_n\right)$$

Boundary separation is assumed to vary by participant i and block pair b. For mixed-deterministic materials, it also varies by condition k^*, denoting deterministic vs. random blocks.

$$\alpha_{ik^*b} = \zeta^{(\alpha)}_{ik^*b}$$

The other core parameter are assumed to vary by trial, and are assumed to come from truncated normal distributions with standard deviations s_i.

$$\beta_n \sim \mathrm{N}^{.99}_{.01}\left(\zeta^{(\beta)}_{ikb} + p^{(\beta)}\kappa^{(\beta)}_{ij}, s^{(\beta)}_i\right)$$

$$\delta_n \sim \mathrm{N}\left(\zeta^{(\delta)}_{ikb} + p^{(\delta)}\kappa^{(\delta)}_{ij}, s^{(\delta)}_i\right)$$

$$\tau_n \sim \mathrm{N}_{.001}\left(\zeta^{(\theta)}_{ikb} + p^{(\theta)}\kappa^{(\theta)}_{ij} + \zeta^{(\xi)}_{il} + p^{(\xi)}\kappa^{(\xi)}_{il}, s^{(\tau)}_i\right)$$

where ζ_{ikb} is an individual's condition (nonregular, regular, deterministic) mean in block pair b, p is a scaling factor, and κ_{ij} represent an individual's stimulus-location-dependent deviations from the individual's condition mean.

Participant-level parameters ζ_{ikb} are assumed to be normally distributed, e.g.

$$\zeta^{(\beta)}_{ikb} \sim \mathrm{N}\left(\mu^{(\beta)}_{kb}, \sigma^{(\beta)}\right)$$

where

$$\sigma^{(\beta)} \sim q^{(\beta)} t^+_{df=I-1}$$

and q is a scaling factor, and t^+_{df} is a half-t distribution with $I-1$ degrees of freedom restricted to positive values.

In the SRTT, response times and accuracy vary substantially by stimulus and/or response location. Therefore, for each participant i and stimulus location $j = 1, ..., 6$, we included normally distributed parameters κ_{ij} to capture such differences

$$\kappa^{(\beta)}_{ij} \sim \mathrm{N}\left(\mu^{\kappa^{(\beta)}}_j, \sigma^{\kappa^{(\beta)}}_j\right) \text{ for } j = 1, ..., 5$$

and

$$\kappa^{(\beta)}_{i6} = -\sum_{j=1}^{5} \kappa^{(\beta)}_{ij}$$

The

$$\mu^{\kappa^{(\beta)}}_j \sim \mathrm{N}(0,1) \text{ for } j = 1, ..., 5$$

and

$$\mu^{\kappa^{(\beta)}}_6 = -\sum_{j=1}^{5} \mu^{\kappa^{(\beta)}}_j$$

Standard deviations were modeled as coming from a half-t distributions

$$\sigma^{\kappa^{(\beta)}}_j \sim t^+_{df=I-1}$$

The condition means are defined as the weighted sum of one or more shifted and stretched exponential functions $f(b)$,

$$\mu_{kb} = \sum_{m=1}^{3} w_{km} f_m(b)_{\lambda_m, \gamma_m, \upsilon_m, \iota_m}$$

We use these functions in a similar fashion as model terms in linear models: Condition means are the weighted sum of multiple temporally-changing functions (instead of regression coefficients), and the condition weights w_{km} chosen in a way that the first function is equivalent to an intercept term, the second function is equivalent to the effect of regular vs. nonregular trials, and the third function is equivalent to the effect of deterministic trials vs. the average of regular and nonregular trials; amounting to a Helmert coding scheme.

The functions (depicted in Figure A1) are defined as

$$f_m(b) = \upsilon_m + (\iota_m - \upsilon_m) e^{-\left(\frac{b}{\lambda_m}\right)^{-\gamma_m}}$$

where υ_m is the initial limit, ι_m is the final limit. λ_m is the temporal location of the inflection point of this function, and γ_m is a stretching exponent (shifting the function's steepness).

The final limit ι_m may be re-written as

$$\iota_m = \frac{\gamma_m \psi_m B}{\lambda_m \Gamma(\gamma_m^{-1})} + \upsilon_m$$

where B is the number of block pairs, $\Gamma(.)$ is the Gamma function, and ψ_m is the *average effect*, i.e., the average difference between $f_m(b)$ and the initial limit υ_m.

We use these average effects ψ_m as the target of inference to test for overall changes (first function), the effect of nonregular vs. regular trials (second function), and the effect of deterministic vs. random blocks (third function). Bayes Factors (*BF*) are calculated using the Savage-Dickey density ratio (Wagenmakers, Lodewyckx, Kuriyal, & Grasman, 2010) from logspline densities (Kooperberg & Stone, 1992).

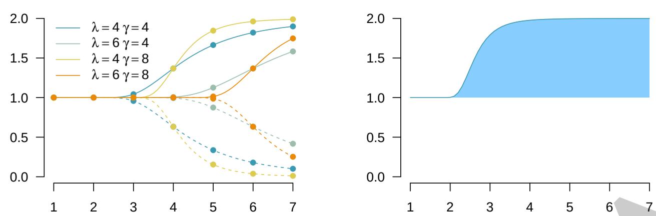

Figure A1. Left panel: Shifted and stretched exponential functions for different values of λ (location) and γ (shape), with $\upsilon = 1$ and $\iota \in \{0, 2\}$. Right panel: The average effect ψ corresponds to the area under the curve (blue) between initial limit and the function's value $f(b)$.

Appendix B
Direct Measures of Explicit Sequence Knowledge

Table B1

Number of correctly reproduced transitions in free-recall and forced-choice tests. Numbers for only those participants who indicated that they were in a sequenced condition are given in parentheses.

	Forced choice						
Free recall	0	1	2	3	4	5	6
probabilistic, sequence concealed							
0	8 (1)	1 (1)	2 (2)	.	.	.	1 (0)
1	1 (1)	2 (0)	2 (2)	2 (1)	.	.	.
2	1 (1)	.	.	.	.	.	.
3	.	1 (1)	1 (1)	.	.	.	.
4	.	1 (1)	.	.	.	1 (1)	.
5	.	.	.	.	.	.	.
6	.	.	.	.	.	1 (0)	2 (1)
mixed deterministic, sequence concealed							
0	.	1 (1)	1 (0)	1 (0)	.	.	.
1	1 (1)	.	2 (2)	.	.	.	.
2	.	1 (1)	3 (2)	1 (1)	.	.	.
3	.	.	.	.	.	.	.
4	.	.	.	.	.	.	.
5	.	.	.	.	.	.	.
6	.	.	.	1 (1)	1 (1)	2 (2)	8 (8)
probabilistic, sequence revealed							
0	7 (1)	.	1 (1)	.	.	.	.
1	.	2 (2)	2 (1)	.	1 (0)	.	.
2	.	.	.	.	.	.	.
3	2 (0)	.	.	2 (2)	1 (0)	1 (1)	.
4	.	.	1 (0)	.	.	.	.
5	.	.	.	.	.	.	.
6	.	.	.	1 (1)	1 (1)	1 (0)	3 (2)
mixed deterministic, sequence revealed							
0	.	1 (1)	.	.	.	.	.
1	.	2 (1)	.	.	.	.	.
2	.	.	.	.	.	.	.
3	1 (1)	1 (1)	.	.	1 (1)	.	1 (1)
4	.	.	.	.	.	.	1 (1)
5	.	.	.	.	.	.	.
6	.	.	1 (1)	.	2 (2)	.	15 (15)