Parallel Acquisition of Uncorrelated Sequences is Hard to Find

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The distinction between implicit and explicit learning is fundamental to theories of human learning. However, it remains an open question whether implicit and explicit learning are based on a single, unitary learning meachnism, or multiple learning mechanisms or systems. The dual-systems model (Keele, Ivry, Mayr, Hazeltine, & Heuer, 2003) posits that, in addition to a multidimensional learning system that is accessible to consciousness, implicit learning may also proceed in a unidimensional learning. Learning in this system is considered to proceed within a set of dimension-specific, encapsulated processing modules, where strong separation between different kinds of information protects against interference. Parallel acquisition of multiple uncorrelated sequences has been considered crucial evidence in favor of encapsulated processing. However, recent work has demonstrated that parallel learning is also well accounted for by a single learning mechanism, and can therefore not provide convincing evidence for encapsulated processing. In a series of three experiments, we therefore aimed at testing the assumption of encapsulated processing more stringently. To this aim, we orthogonally manipulated sequences of stimulus and response features, and tested for selective influence of these sequences on the cognitive processes that are involved in SRTT performance. In Experiments 1 and 2, stimulus colors and response locations followed independent six-item probabilistic sequences. In Experiment 3, stimulus colors and stimulus locations followed such independent sequences. Replicating previous findings, we found learning of sequences of response locations. By contrast, we consistently found evidence against learning of sequences of stimulus colors or stimulus locations. First implications for the debate on encapsulated processing, and the organization of sequence learning systems, are discussed.

Keywords: implicit learning, sequence learning, encapsulated processing

The distinction between implicit and explicit learning is fundamental to theories of human learning. Implicit learning refers to learning that proceeds in the absence of awareness; explicit learning occurs when consciously accessible propositions are formed about what has been learned (Shanks, 2010). Important evidence supporting the distinction between implicit and explicit learning comes from work with the serial response time task (SRTT, Nissen & Bullemer, 1987). In this task, subjects are instructed to respond to sequentially presented stimuli with an assigned response; typically the stimuli are squares at different screen locations, the responses to be made are key presses on a standard computer keyboard. If a stimulus appears at one of the marked lo-cations, the participant should respond with the corresponding key. Importantly, the locations of the stimuli are not selected randomly, but (mostly) follow an underlying sequence (e.g. 3–4–2–1–3–1–2–4). Participants show accelerated responses and/or lower error rates in the course of task processing; these performance gains are greater for transitions that follow the sequence than for transitions in which the sequence is violated. After completion of the SRTT, participants' sequence knowledge is measured by a measure of explicit knowledge. Participants often do not show any explicit sequence knowledge. This simple dissociation between performance gains in the SRTT and subsequently assessed explicit sequence knowledge is considered one of the key pieces of evidence for the existence of implicit learning processes.

There is no consensus whether these two forms of learning are also based on two different learning mechanisms or systems, or whether both phenomena can be explained with a single learning mechanism. Cleeremans and Jiménez (2002) assume that implicit and explicit learning are based on a unitary learning system. The acquired representations differ gradually in terms of their strength, their temporal sta-

bility and their distinctiveness; this *quality of representation* correlates with the accessibility of these representations to consciousness. The dissociation found between performance in the SRTT and measures of explicit sequence knowledge is explained by the fact that the SRTT is also sensitive to weak, implicit representations, whereas measures of explicit sequence knowledge are only sensitive to strong representations that are accessible to consciousness. The function of consciousness, according to Cleeremans and Jiménez (2002), is to be able to flexibly control the influence of the acquired representations on behavior.

The assumption of a unitary system is opposed by the assumption of two systems. Keele et al. (2003) differentiate between a unidimensional and a multidimensional learning system: In the multidimensional system, information from different feature dimensions can be processed together; the system depends on attention to protect it from overload. Processing in this system initially takes place automatically and without awareness. While learning in this system may initially proceed implicitly, the information processed in the system is in principle accessible to consciousness. By contrast, in the unidimensional system, processing takes place in a series of encapsulated, dimension-specific modules; this system operates independently of attention, because separate, encapsulated processing of feature dimensions already protects the system from overload. Because knowledge is this system is strongly separated, it is also not accessible to consciousness. The two systems thus differ in terms of their dependence on attention, their accessibility to consciousness, and the encapsulation of feature-specific information in specialized modules. In addition to the above-mentioned dissociation of implicit and explicit knowledge, the influence of attention (but see Rowland & Shanks, 2006) and the postulated encapsulation within the unidimensional system were examined.

Crucial evidence for encapsulated processing in a unidimensional learning system comes from studies that found parallel acquisition of multiple uncorrelated sequences. In a seminal study, Mayr (1996) found that a sequence of stimulus locations could be learned in parallel to a sequence of response locations. In a series of three experiments, Goschke and Bolte (2012) found parallel acquisition of uncorrelated spatio-visual, spatio-motor, phonological and color sequences, and concluded that that these are processed separately in encapsulated modules that are specific to either stimulus or response features. Eberhardt, Esser, and Haider (2017) and Haider, Esser, and Eberhardt (2020) also found that several sequences can be learned in parallel. However, if the two sequences overlap with respect to an abstract feature dimension (e.g. a visuo-spatial stimulus sequence and a motor-spatial response sequence), the two sequences could not be learned in parallel. The authors concluded that de-

structive interference occurred within a module that processes spatial features – the encapsulation within the unidimensional learning system could therefore best be described using abstract feature dimensions.

In theses studies, the conclusion that such parallel acquisition of uncorrelated sequences indeed proceeded in the absence of awareness frequently hinges on an a-posteriori classification of participants as implicit or explicit learners: If participants who were classified as implicit learners show a learning effect in the SRTT, it is concluded that learning is implicit in nature. However, in most of these studies, at least some participants acquired explicit sequence knowledge. It has been a long-standing debate in implicit sequence learning how to measure explicit sequence knowledge in a way that prevents this approach to be compromised by residual explicit sequence knowledge driving performance in the SRTT (for an overview, see Shanks, 2010; Timmermans & Cleeremans, 2015). Most recently, Shanks, Malejka, and Vadillo (2021) argued that, because the measure of explicit sequence knowledge will always be contaminated by measurement error, the approach to analyze a subset of participants who are considered to have acquired only implicit knowledge, and then to draw conclusions on the properties of implicit learning, is doomed to fail.

Barth, Stahl, and Haider (2023) demonstrated that parallel acquisition of uncorrelated sequences does not provide firm evidence for encapsulated processing: In a simulation study, a computational model assuming joint representations of response and task-relevant stimulus features was well able to predict learning effects for both sequences; hence, above-zero learning scores for both sequences do not preclude joint representations. Still, parallel acquisition of multiple sequences provides strong empirical tests of the assumption of encapsulated processing: Firstly, *absence of interference* between sequences of different feature dimensions is well predicted by encapsulated processing, but is difficult to reconcile with joint processing. Secondly, *selective influence* of perceptual sequences on stimulus processing, and selective influence of motor sequences on motor execution are again not easily explained with a joint memory mechanism.

Most recently, Barth, Stahl, and Haider (under revision) applied the drift-diffusion model (Ratcliff, 1978) to a standard SRTT where participants responded with spatial keying responses to spatially presented stimuli. There, they found that implicit sequence learning is largely expressed by changes in model parameters related to response selection (starting point and drift rate). Moreover, they also found evidence for an effect of response competition, with motor responses being faster for motor-regular compared with motor-nonregular responses, irrespective of the imperative stimulus that is presented on the screen or the response to be selected. The involvement of response-selection processes in the expression

of implicit sequence learning already indicates that implicit sequence learning is at least partly mediated by representations that contain information about both stimulus and response: In the standard SRTT paradigm, where a response is to be selected according to the location of the imperative stimulus, information about both stimulus and response are both necessary for response selection. It is therefore not plausible that stimulus and response are processed separately. Still, if the unidimensional learning system is organized along abstract feature dimensions such as spatial location, in the standard SRTT, learning effects at the response-selection stage may be mediated by a learning module that is specific to spatial features of both stimulus and response. The observed response-competition effect may hint at a secondary learning mechanism that relies on representations that are specific to motor-related information.

Aims of the present study

The present study was aimed at testing the assumption of encapsulated processing within a unidimensional learning system. In three experiments, participants worked on an extended SRTT with uncorrelated sequences of stimulus colors, stimulus locations, and response locations. To circumvent a contamination with residual explicit sequence knowledge, and in contrast to previous studies, we used probabilistic sequences for both stimulus and response sequences. In the standard SRTT design, such materials have been shown to enable robust sequence learning while participants remain largely unaware of the sequence (Jiménez & Méndez, 1999). We then used the drift-diffusion model described by Barth et al. (under revision) to test whether sequences of perceptual features (i.e., stimulus color and stimulus location) selectively influenced model parameters related to stimulus processing (i.e., stimulus detection and encoding), and whether sequences of response locations selectively influenced model parameters related to response execution (i.e., response competition). Such selective influence of different types of information on different processes involved in the expression of implicit sequence would provide strong evidence for separate (i.e., encapsulated processing) of such information.

To foreshadow, results were not as expected: While we could easily replicate learning of a sequence of response locations in this extended design, and, consistent with previous findings, such learning was largely expressed in model parameters related to response selection, we could not replicate previous findings of additional learning of sequences of stimulus colors or stimulus locations.

Experiment 1

Utilizing the extended SRTT design, several studies demonstrated the parallel learning of a sequence of stimulus col-

ors and an independent sequence of response locations (e.g., Eberhardt et al., 2017). In Experiment 1, we aimed at replicating such parallel acquisition of independent sequences, and, in a second step, using the drift-diffusion model to test for selective influence of sequences on model parameters, where selective influence would indicate encapsulated processing, and non-selective influence would indicate joint processing. Specifically, assuming that the color of a centrally-presented imperative stimulus is processed in a module that is specific to either stimulus features or color, learning of a color sequence should selectively influence stimulus encoding (i.e., nondecision time θ), but not response selection or response execution. Also assuming that motor or spatial features of the response locations are processed in a separate module, learning the sequence of response locations should selectively influence response execution (i.e., response competition ξ), but not stimulus encoding or response selection. By contrast, if learning of both sequences results in sequence-specific changes of model parameters that are related to response selection, such a finding would speak against encapsulated processing.

Method

Participants. Thirty participants (16 women) aged between 18 and 64 years ($Md = 36.5$ years) completed the study. Participants were recruited on prolific.co and received 5.25 GBP for their participation.

Materials and Procedure. For each participant anew, we independently generated random permutations of the six possible stimulus colors and six possible response locations. On each trials, stimulus color and/or response location followed these sequences with a probability of .5 (independent of each other); otherwise, another stimulus color and/or response location was randomly selected from a uniform distribution (excluding immediate repetitions). In the first block, colors and locations were randomly chosen (excluding immediate repetitions).

All participants worked on 10 blocks (144 trials each) of an SRTT, where participants were instructed to press the key that corresponded to the color of the centrally-presented target stimulus. On each trial of the experiment, the mapping of stimulus colors to response keys was presented in the lower third of the screen. After 250msec, the imperative stimulus was presented. To obtain a significant proportion of error responses, we used a response deadline of 700msec. If the response deadline had been exceeded, a warning sign together with feedback was presented for 1200msec. If the wrong key had been pressed, "wrong key" was presented for 300msec.

Design and Data Preparation. The experiment followed a 10 (*block number*) × 2 (*stimulus-location regularity*: non-regular vs. regular) × 2 (*stimulus-color regularity*: nonregu-

lar vs. regular) within-subjects design. For analyses, blocks were collapsed into five *block pairs*. 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 nine participants who, in one of blocks 2-10, exceeded an error rate of 60% or responded too slowly on more than 15% of trials. 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.

Results and Discussion

We first analyzed response times and error rates with linear models (i.e., ANOVA) to determine whether participants had learned both sequences, and whether such learning effects were detectable with standard analysis procedures. We then applied the drift-diffusion model (for details, see the Appendix) to test for selective influence of stimulus and response sequences on model parameters.

Response times and error rates. Figure 1 shows response times and error rates. We analyzed response times using a 2 (*color regularity*: nonregular vs. regular) $\times$ 2 (*location regularity*: nonregular vs. regular) $\times$ 5 (*block pair*) repeated-measures ANOVA. We found a main effect of *block pair*, $F(2.57, 51.31) = 40.51$, $p < .001$, $\hat{\eta}_G^2 = .125$, RTs decreased over blocks. We also found a main effect of *location regularity*, $F(1, 20) = 92.09$, $p < .001$, $\hat{\eta}_G^2 = .026$, the interaction of *location regularity* and *block pair* trended to be significant, $F(3.10, 62.00) = 2.32$, $p = .082$, $\hat{\eta}_G^2 = .002$, both effects jointly indicating learning of the sequence of response locations. We also found a main effect of *color regularity*, $F(1, 20) = 13.03$, $p = .002$, $\hat{\eta}_G^2 = .003$ and an interaction of *color regularity* with *block pair*, $F(3.33, 66.53) = 5.10$, $p = .002$, $\hat{\eta}_G^2 = .006$, indicating learning of the sequence of stimulus colors, all other $ps \geq .668$. However, as can already be seen from Figure 1, the RT advantage for color-regular stimuli is not consistent with a learning effect: Its magnitude is largest in the first block pair $\Delta M = 17.64$, 95% CI [8.23, 27.04], and (descriptively) negative in the last block $\Delta M = -2.98$, 95% CI [-10.14, 4.18]. We, therefore, refrain from interpreting this result as clear evidence for learning of the color sequence.

An analogous ANOVA for error rates revealed a main effect of *block pair*, $F(3.29, 65.72) = 5.34$, $p = .002$, $\hat{\eta}_G^2 = .033$, error rates increased over blocks. We also found a main effect of *location regularity*, $F(1, 20) = 7.49$, $p = .013$, $\hat{\eta}_G^2 = .016$ together with an interaction of *location regularity* with *block pair*, $F(2.43, 48.64) = 6.30$, $p = .002$, $\hat{\eta}_G^2 = .022$, again indicating learning of the sequence of response locations. The main effect of *color regularity* was not signif-

icant, $F(1, 20) = 1.06$, $p = .316$, $\hat{\eta}_G^2 = .001$, the interaction of *color regularity* with *block pair* was also not significant, $F(3.60, 71.96) = 1.26$, $p = .295$, $\hat{\eta}_G^2 = .004$, all other $ps \geq .393$.

Model-based analyses. Figure 2 shows parameter estimates from the drift-diffusion model. We report Bayes Factors (*BF*) for model comparisons that tested the effects of experimental manipulations on model parameters.

Starting point β was invariant to both regularities, the *BF* consistently favored the absence of an effect of *location regularity* ($BF_{01} = 8.51$), *color regularity* ($BF_{01} = 8.96$), or both regularities combined ($BF_{01} = 7.59$). Drift rate δ was higher for location-regular trials, $BF_{10} = 7.82$, and trials that were regular with respect to both sequences, $BF_{10} > 1,000$. The *BF* for an effect of *color regularity* on drift rate was inconclusive, $BF_{01} = 1.32$. Boundary separation α (response caution) decreased over blocks, $BF_{10} > 1,000$. These results indicate that only evidence accumulation (i.e., drift rate δ) was involved in the expression of learning of the sequence of response locations.

Nondecision time θ (capturing stimulus detection and encoding) was invariant to both regularities; the *BF* consistently favored the absence of an effect of *location regularity* ($BF_{01} = 26.14$), *color regularity* ($BF_{01} = 26.93$), or both regularities combined ($BF_{01} = 26.05$). We also found strong evidence *against* an effect of response competition, $BF_{01} = 23.13$. These results indicate that neither stimulus detection and encoding nor response execution were involved in the expression of learning in this experiment.

Experiment 1 tested whether participants were able to learn a sequence of stimulus colors and a sequence of response locations in parallel. Analyses of response times and error rates indicated robust learning of the sequence of response locations. By contrast, while color regularity affected response times to some degree, the pattern of results is inconsistent with a learning effect, and we therefore refrain from interpreting our results as evidence for learning of the color sequence. Parameter estimates from the drift-diffusion model confirm this overall impression: Learning of the sequence of response locations is expressed by a higher drift rate for regular response locations, while all other model parameters were invariant to our manipulations. Surprisingly, response competition (i.e., differences in nondecision time for motor-regular compared with motor-nonregular responses) seemed to be absent in this study. Overall, however, the results from this experiment should be interpreted with caution: We had to exclude a substantial proportion of participants because error rates were exceedingly high or responses were too slow – either the task was too demanding, or participants were not motivated to work on such a demanding task in an online setting. We tried to address these problems in Experiment 2.
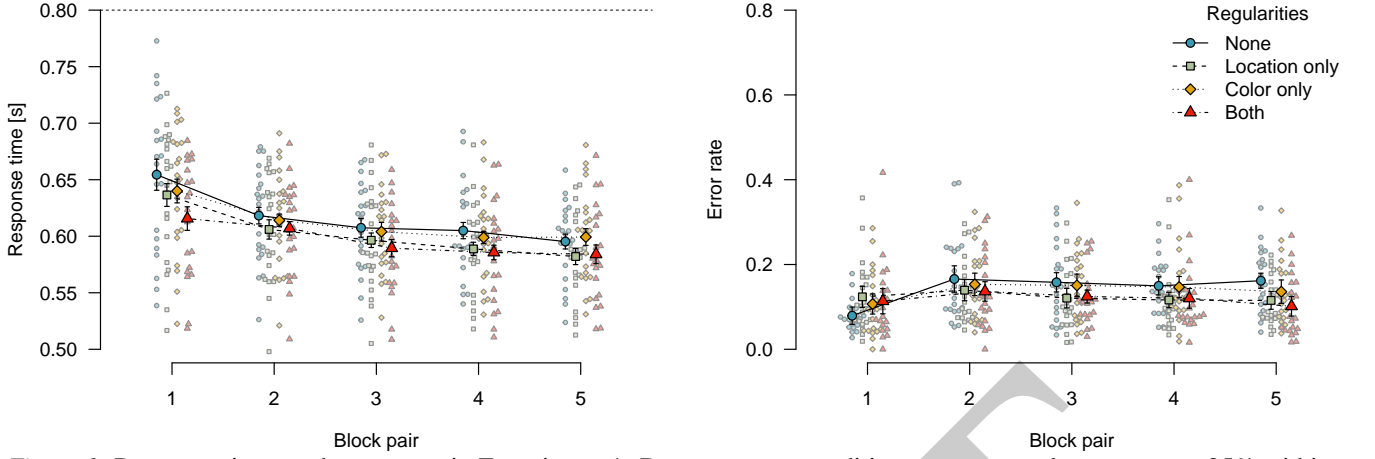
Figure 1. Response times and error rates in Experiment 1. Dots represent condition means, error bars represent 95% within-subjects confidence intervals. Small dots represent individual participants' mean response times and error rates.
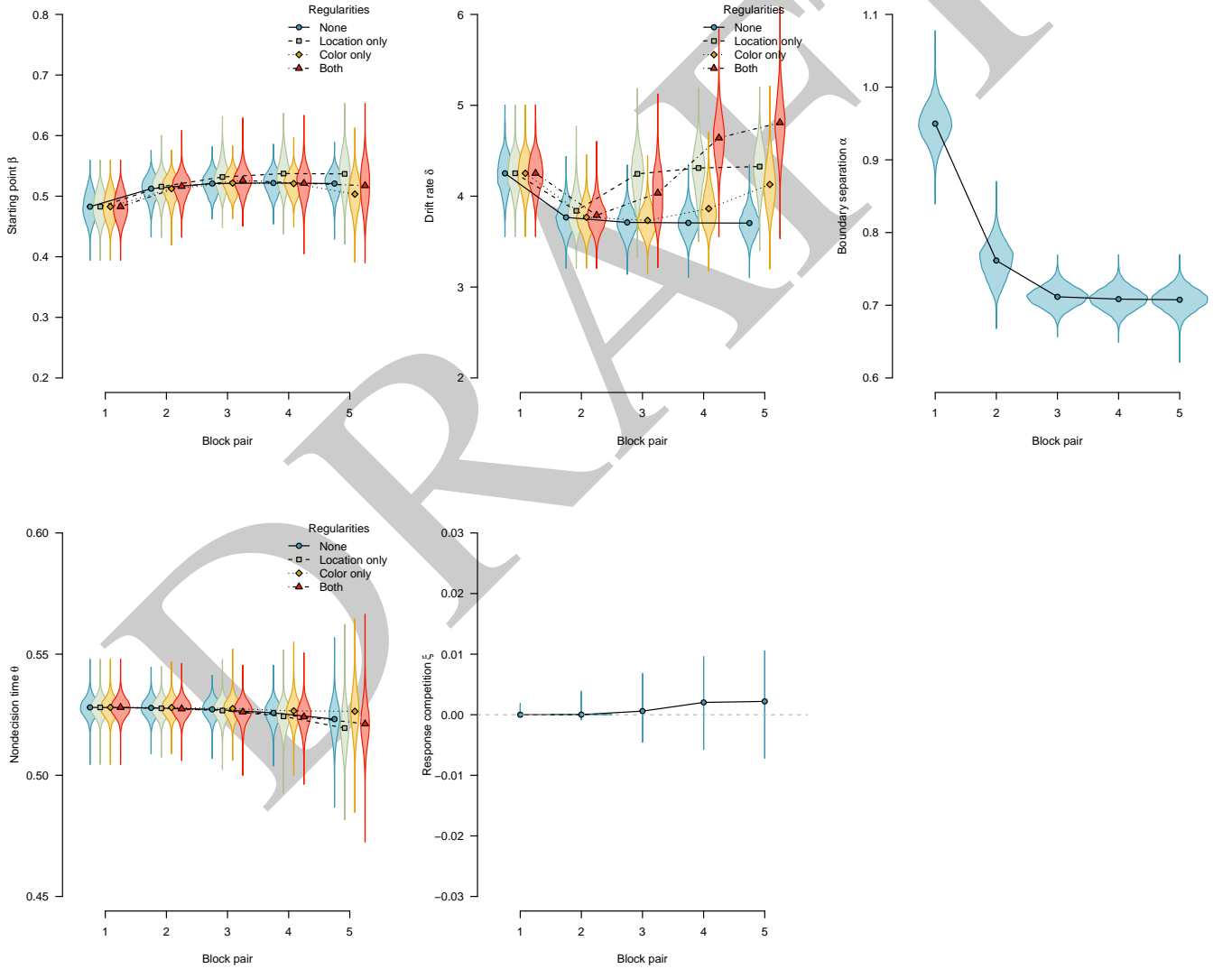

Figure 2. Parameter estimates from Experiment 1. Points represent posterior means of the group-level parameters μ_{kb}, violins represent their corresponding posterior densities.

Experiment 2

In Experiment 1, we found robust learning of a sequence of response locations, while results regarding the learning of the sequence of stimulus colors were hard to interpret. Our failure to replicate the learning of the color sequence may be attributable to low power (and low precision), because we had to exclude too many participants. To reduce the proportion of participants who exceeded our exclusion criteria (i.e., response times exceeded the response deadline and/or very high error rates), we conducted Experiment 2 in our laboratory with a relaxed response deadline (800ms instead of 700ms). We also changed the stimulus display and trial sequence to more closely resemble the experimental procedure used by Eberhardt et al. (2017) who successfully demonstrated learning of sequences of both stimulus colors and response location.

Method

Participants. Forty-seven participants (33 women) aged between 19 and 44 years ($Md = 24$ years) completed the study. Most were undergraduates from University of Cologne. Participants received either course credit or 7.50 Euro for their participation.

Materials and Procedure. For each participant anew, we independently generated random permutations of the six possible stimulus colors and six possible response locations. On each trial, stimulus color and/or response location followed these sequences with a probability of .6 (independent of each other); otherwise, another stimulus color and/or response location was randomly selected from a uniform distribution (excluding immediate repetitions). In the first block, colors and locations were randomly chosen (excluding immediate repetitions).

On each trial, the color-to-response mapping array was presented in a lower half-circle around the center of the screen. After 300ms, a colored circle was presented in the center of the screen for 80ms and then disappeared. The mapping array disappeared as soon as the participant pressed one of the six response keys and the next trial started.

Design and Data Preparation. The experiment followed a 14 (*block number*) × 2 (*stimulus-location regularity*: nonregular vs. regular) × 2 (*stimulus-color regularity*: nonregular vs. regular) within-subjects design. For analyses, blocks were collapsed into seven *block pairs*. Five participants had to be excluded because they had already participated in a similar study and could therefore not be considered to be naïve with respect to the sequential structure of the task. We screened participant data for the proportion of too-slow responses and error rates: 26 participants were be excluded because, in one of block pairs 2-7, their responses exceeded an error rate of 30% or they responded too slowly on more than 30% of trials. 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 and Discussion

We first analyzed response times and error rates with linear models (i.e., ANOVA) to determine whether participants had learned both sequences, and whether such learning effects were detectable with standard analysis procedures. We then applied the drift-diffusion model to test for selective influence of stimulus and response sequences on model parameters.

Response times and error rates. Figure 3 shows response times and error rates from Experiment 2. We analyzed response times using a 2 (*color regularity*: nonregular vs. regular) × 2 (*location regularity*: nonregular vs. regular) × 7 (*block pair*) repeated-measures ANOVA. We found a main effect of *block pair*, $F(2.83, 48.15) = 77.12$, $p < .001$, $\hat{\eta}_G^2 = .428$, and a main effect of *location regularity*, $F(1, 17) = 44.56$, $p < .001$, $\hat{\eta}_G^2 = .053$. We also found the two-way interaction of these factors, $F(3.23, 54.90) = 3.48$, $p = .019$, $\hat{\eta}_G^2 = .010$, response times were increasingly faster for location-regular compared with location-nonregular trials. By contrast, neither the main effect of *color regularity* ($F(1, 17) = 0.45$, $p = .512$, $\hat{\eta}_G^2 = .000$), not its interaction with *block pair* ($F(4.57, 77.69) = 0.18$, $p = .962$, $\hat{\eta}_G^2 = .001$) was significant, all other $ps \geq .180$. An analogous ANOVA for error rates revealed a main effect of *block pair*, $F(3.16, 53.76) = 3.48$, $p = .020$, $\hat{\eta}_G^2 = .034$. error rates increased over blocks, and a main effect of *location regularity*, $F(1, 17) = 22.93$, $p < .001$, $\hat{\eta}_G^2 = .056$, with more errors for location-nonregular compared with location-regular trials, all other $ps \geq .223$. We conclude that participants learned the sequence of response locations. To firmly conclude that participants did not learn the sequence of colors, we conducted an additional Bayesian ANOVA, comparing a model without *color regularity* with a model adding a main effect of *color regularity* (with $s = .5$); here, we found a $BF_{01} = 27,089.59$ in favor of the absence of an effect of *color regularity*. Therefore, analyses of both response times and error rates indicate that participants learned the sequence of response locations, but not the sequence of colors, or were not able to express such knowledge in the SRTT.

Model-based analyses

Starting point β varied by *location regularity*, $BF_{10} = 3.47$, but was invariant to *color regularity*, $BF_{01} = 11.52$, for trials that followed both sequences, the *BF* was inconclusive,
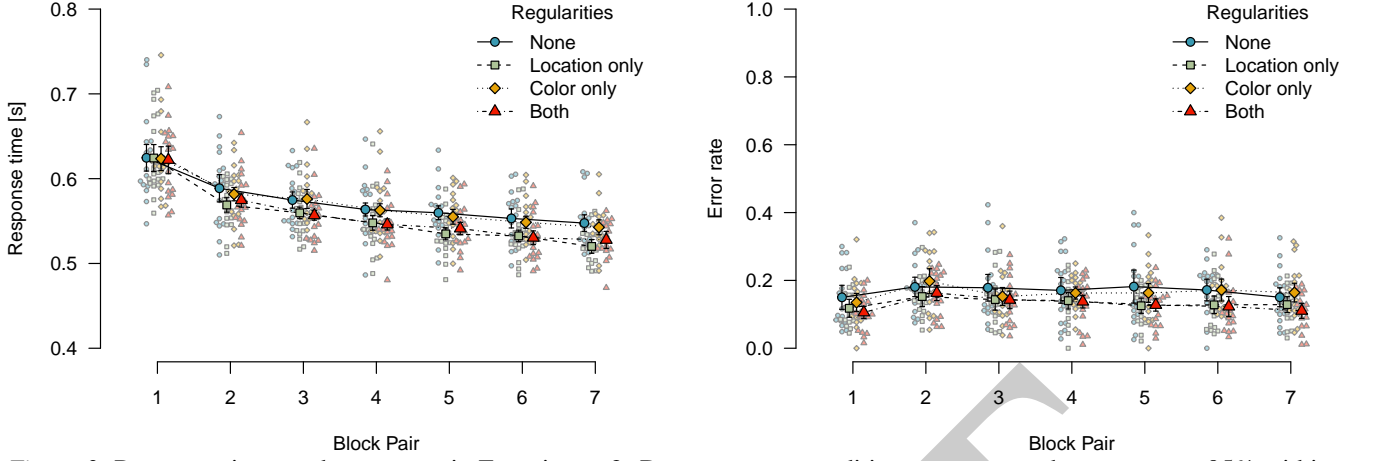
Figure 3. Response times and error rates in Experiment 2. Dots represent condition means, error bars represent 95% within-subjects confidence intervals. Small dots represent individual participants' mean response times and error rates.
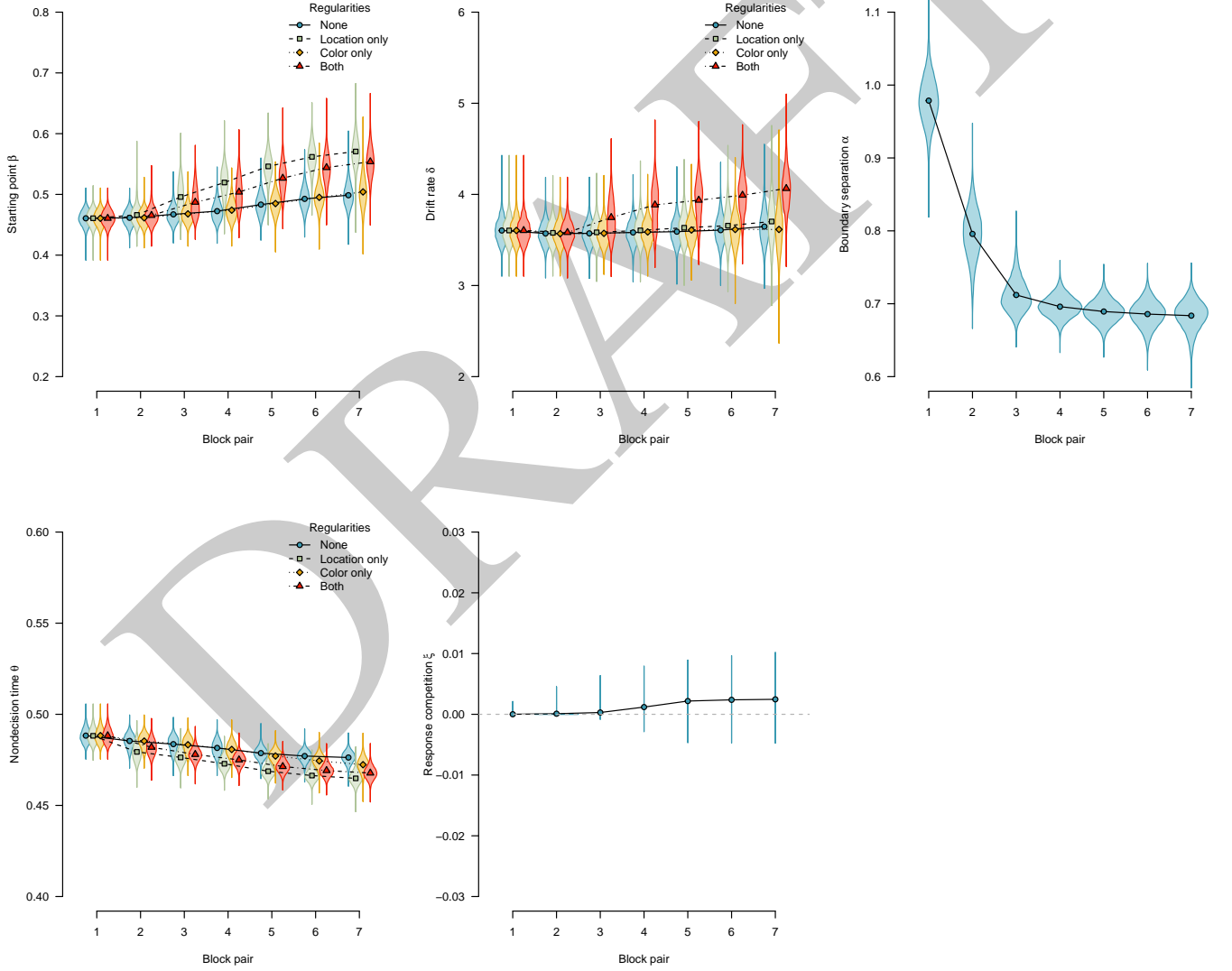

Figure 4. Parameter estimates from Experiment 2. Points represent posterior means of the group-level parameters μ_{kb}, violins represent their corresponding posterior densities.

$BF_{10} = 1.04$. Drift rate δ was invariant to both *color regularity*, $BF_{01} = 6.85$ and *location regularity* $BF_{01} = 6.54$; the *BF* comparing fully regular and fully nonregular trials was inconclusive, $BF_{10} = 1.20$. Boundary separation (i.e., response caution) decreased over blocks, $BF_{10} > 1,000$. Learning the sequence of response locations benefited response selection.

Nondecision time θ (capturing stimulus detection and encoding) was invariant to both regularities. *Color regularity* alone did not have an effect on nondecision time, $BF_{01} = 46.50$, the *BF* comparing location-regular and nonregular trials was inconclusive, $BF_{01} = 1.26$. For trials that followed both sequences, nondecision time was equal to nondecision time for nonregular trials, $BF_{01} = 8.64$. We also found evidence *against* an effect of response competition, $BF_{01} = 22.21$. We, therefore, conclude that neither stimulus processing nor response execution were affected by learning of the sequences.

Experiment 2 was aimed at replicating the learning of a sequence of stimulus colors in parallel with a sequence of response locations, and to test selective influence for both sequences on parameters of a drift-diffusion model. Comparing response times and error rates for regular and nonregular trials, we found robust learning of a sequence of response locations, but found strong evidence *against* learning of a sequence of stimulus colors. The pattern of results is mirrored in our model-based analyses: Learning of the sequence of response locations was expressed in parameters related to response selection, but model parameters were completely unaffected by the sequence of stimulus colors. We therefore conclude that participants learned the sequence of response locations, and that such learning benefits response selection. By contrast, participants did either not learn the sequence of stimulus colors, or were not able to express learning of the sequence in the SRTT.

Experiment 3

In Experiments 1 and 2, we aimed at replicating the parallel learning of a sequence of response locations and a sequence of stimulus colors. While we found robust learning of the sequence of response locations, we also found strong evidence against an effect of the sequence of stimulus colors on performance.

Experiment 3 was aimed at testing the parallel learning of a sequence of stimulus locations together with a sequence of stimulus colors. Mayr (1996) found parallel learning of a sequence of stimulus locations and a sequence of response locations. Moreover, Goschke and Bolte (2012) found, in their Experiment 2, concurrent learning of sequences of stimulus identity (letters), stimulus locations, and response locations. Eberhardt et al. (2017) found, however, that a sequence of

stimulus locations could not be learned in parallel with a sequence of response locations–the reason being that both sequences are spatially coded, and therefore result in interference. We, therefore, refrained from using two spatial locations in parallel, and instead combined the sequence of stimulus locations with a sequence of stimulus colors; response locations were randomly selected.

Method

Participants.   Fifty-three participants (37 women) aged between 18 and 50 years ($Md = 24$ years) completed the study. Most were undergraduates from University of Cologne. Participants received either course credit or 7.50 Euro for their participation.

Materials and Procedure.   For each participant anew, we independently generated random permutations of the six possible stimulus colors and six possible stimulus locations. On each trial, stimulus color and/or stimulus location followed these sequences with a probability of .6 (independent of each other); otherwise, another stimulus color and/or stimulus location was randomly selected from a uniform distribution (excluding immediate repetitions).

On each trial, the color-to-response mapping array was presented in the lower third of the screen. After 300ms, a colored square was presented in one of six possible stimulus locations in the upper third of the screen for 80ms and then disappeared. The mapping array disappeared as soon as participants pressed one of the six response keys and the next trial started.

Design and Data Preparation.   The experiment followed a 14 (*block pair*) $\times$ 2 (*stimulus-location regularity*: nonregular vs. regular) $\times$ 2 (*stimulus-color regularity*: nonregular vs. regular) $\times$ 2 (*spatial compatibility*: response and stimulus location incompatible vs. compatible) within-subjects design. For analyses, blocks were collapsed into seven *block pairs*. We excluded ten participants who, in one of block pairs 2-7, exceeded an error rate of 30% or responded too slowly on more than 10% of trials, or did not finish the study. 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. Moreover, trials that followed a spatially compatible trial were excluded from analyses, because with our materials (that excluded direct repetitions of both stimulus locations and required responses), the probability of spatial compatibility differed between trials that followed compatible versus incompatible trials (i.e., probabilities were .16 versus .20).

Results and Discussion

We first analyzed response times and error rates with linear models (i.e., ANOVA) to determine whether participants had learned both sequences, and whether such learning effects were detectable with standard analysis procedures. We then applied the drift-diffusion model to test for selective influence of sequences of stimulus colors and stimulus locations on model parameters.

Response times and error rates. Figure 5 shows response times and error rates from Experiment 3. We analyzed response times using a 2 (*color regularity*: nonregular vs. regular) $\times$ 2 (*stimulus-location regularity*: nonregular vs. regular) $\times$ 2 (*spatial compatibility*: incompatible vs. compatible) $\times$ 7 (*block pair*) repeated-measures ANOVA. We found a main effect of *block pair*, $F(4.60, 179.48) = 38.46$, $p < .001$, $\hat{\eta}_G^2 = .072$, and a main effect of *spatial compatibility*, $F(1, 39) = 456.52$, $p < .001$, $\hat{\eta}_G^2 = .206$, all other $ps \geq .169$.

To firmly conclude that participants did not learn the sequence of colors, we conducted an additional Bayesian ANOVA, comparing a model without *color regularity* with a model adding a main effect of *color regularity* (with $s = .5$); here, we found a $BF_{01} = 3.74 \times 10^7 \pm 7.10\%$ in favor of no effect of *color regularity*. We, therefore, conclude that participants did not learn the sequence of colors, or were not able to express such knowledge in the SRTT.

To firmly conclude that participants did not learn the sequence of stimulus locations, we conducted an additional Bayesian ANOVA, comparing a model without *stimulus-location regularity* with a model adding a main effect of *stimulus-location regularity* (with $s = .5$); here, we found a $BF_{01} = 42,479.81 \pm 16.36\%$ in favor of no effect of *stimulus-location regularity*. We, therefore, conclude that participants did not learn the sequence of stimulus locations, or were not able to express such knowledge in the SRTT.

Analyses of error rates mirrored these results: Also using a 2 (*color regularity*: nonregular vs. regular) $\times$ 2 (*stimulus-location regularity*: nonregular vs. regular) $\times$ 2 (*spatial compatibility*: incompatible vs. compatible) $\times$ 7 (*block pair*) repeated-measures ANOVA, we only found a main effect of *block pair*, $F(3.95, 154.10) = 3.75$, $p = .006$, $\hat{\eta}_G^2 = .012$, and a main effect of *spatial compatibility*, $F(1, 39) = 90.10$, $p < .001$, $\hat{\eta}_G^2 = .063$, all other $ps \geq .080$.

Model-based analyses. We analyzed responses for spatially incompatible trials using the drift-diffusion model (see the Appendix for details).

Analyses with the drift-diffusion model confirmed our results from linear models. Starting point β was invariant to *stimulus-location regularity*, $BF_{01} = 15.97$, *color regularity*, $BF_{01} = 12.65$, or both regularities combined, $BF_{01} =$ 19.10. Drift rate was invariant to *stimulus-location regularity*, $BF_{01} = 10.54$, *color regularity*, $BF_{01} = 2.11$, or both regularities combined, $BF_{01} = 13.60$. Boundary separation (i.e., response caution) decreased over blocks, $BF_{10} > 1,000$. Nondecision time θ (capturing stimulus detection and encoding) was invariant to *stimulus-location regularity*, $BF_{01} = 38.87$, *color regularity*, $BF_{01} = 32.59$, or both regularities combined, $BF_{01} = 39.51$. We, therefore, conclude that SRTT performance was not affected by both regularities, indicating that either participants did not learn the sequences, or were not able to express such knowledge in the SRTT.

General Discussion

In three experiments, we set out to investigate the assumption of encapsulated processing within a unidimensional sequence-learning system by testing for selective influence of uncorrelated sequences on stimulus processing, response selection, and motor execution. In line with previous research (Barth et al., under revision), learning a sequence of response locations was expressed in model parameters related to response selection. However, in all three experiments, and across both separate analyses of response times and error rates with linear models and joint analyses with the drift-diffusion model, we consistently found strong evidence against learning of perceptual sequences (i.e., sequences of stimulus colors or a sequence of stimulus locations). Before turning to the implications of these findings, we will first discuss possible limitations to our study.

Limitations

It might be argued that we found evidence against learning of perceptual sequences (of stimulus colors and stimulus locations) because in our task, both stimulus detection and encoding were so easy that implicit learning of both sequences could not substantially affect performance. If we had, instead, used stimuli that were more difficult to detect or encode, we could instead have observed performance effects for both sequences. Because of such a potential floor effect, Mayr (1996) used visually complex objects presented far apart from each other so that stimuli were difficult to discriminate and spatial orienting became necessary to perform the task. However, other studies reporting implicit learning of perceptual sequences (e.g., Eberhardt et al., 2017; Goschke & Bolte, 2012) used stimulus displays that were highly comparable to ours. We, therefore, deem it unlikely that the difficulty of detecting and encoding stimuli may completely explain the discrepancy between our findings here and the studies that found performance effects for perceptual sequences in the SRTT. Still, future research should investigate whether stimulus detection and encoding may benefit from perceptual sequence learning.
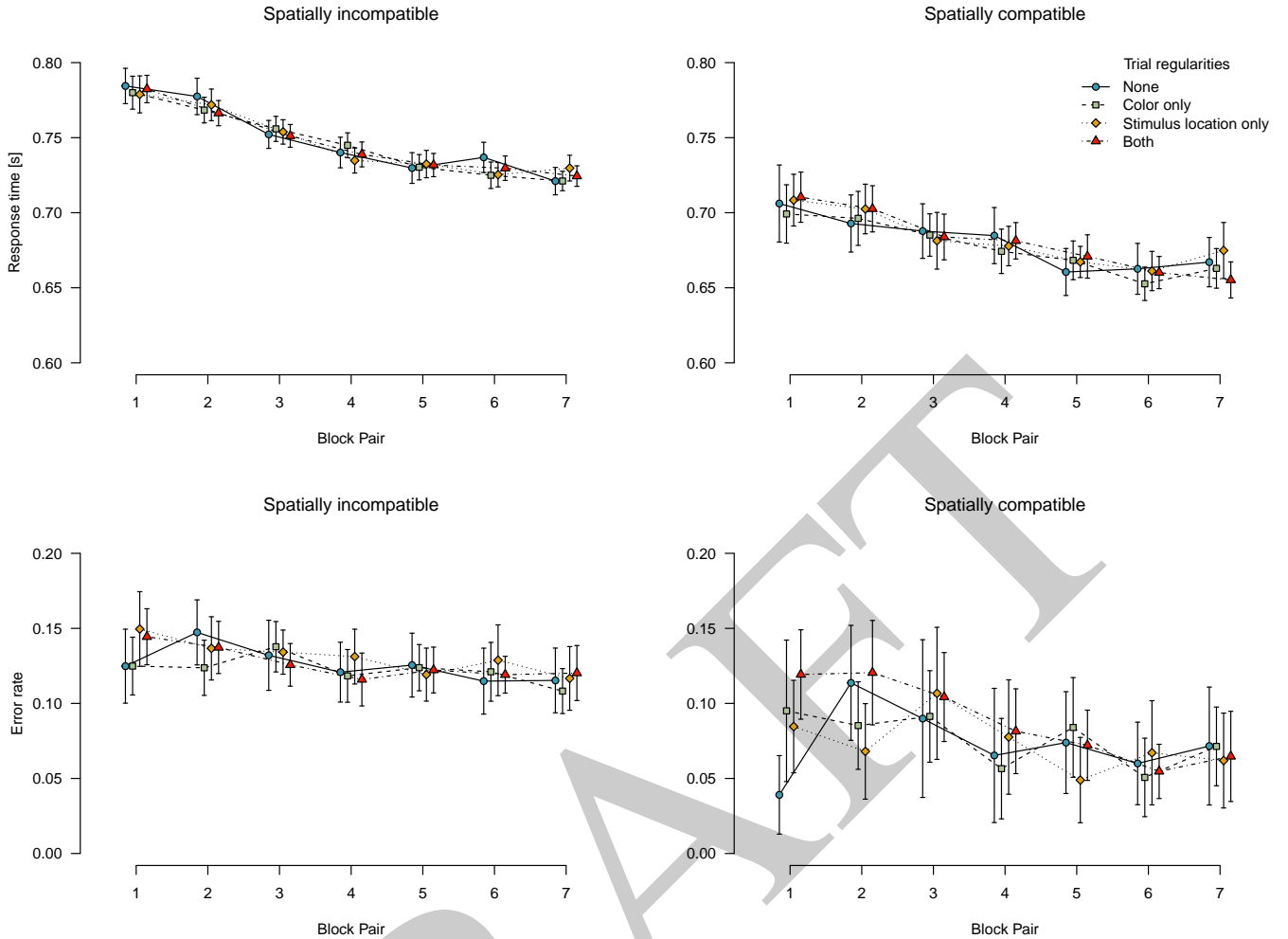
Figure 5. Response times and error rates in Experiment 3. Dots represent condition means, error bars represent 95% within-subjects confidence intervals. Small dots represent individual participants' mean response times and error rates.

Another difference between our study and the studies by Goschke and Bolte (2012) and Eberhardt et al. (2017) is that we used a response deadline to promote the proportion of error responses, which allowed us to reliably estimate the parameters of the drift-diffusion model. It might be argued that time pressure hampered implicit perceptual learning, and that we therefore did not observe learning of perceptual sequences. We deem such an explanation unlikely for three reasons: First, learning in the unidimensional system is considered to be automatic; in our view, if perceptual learning relied on resources that are shortened by time pressure, it could not be considered automatic in a meaningful way. Second, imposing a response deadline greatly reduces response time variability in the SRTT, which should make it easier, not more difficult, to detect even small learning effects. Third, in the present studies, we covered a substantial range of possible response deadlines (700-1,100ms), but this (between-experiments) manipulation had no effect on learning of the perceptual sequences.

It might be argued that we did not find learning of probabilistic perceptual sequences because implicit learning of perceptual sequences might be restricted to simple deterministic structures. While such an assertion may explain *that* we found evidence for the absence of learning of probabilistic perceptual sequences, it lacks an explanation *why* only deterministic sequences could be learned implicitly. On the contrary, such an explanation is, in our view, incompatible with the general conception of the phenomenon that is studied in implicit sequence learning: First, implicit sequence learning has frequently been described as the implicit learning of *probabilistic* regularities in the environment; implicit perceptual sequence learning would then not be covered by this definition. Moreover, it is, at the very least, unclear how a learning mechanism that is considered to proceed without effort and intention (i.e., automatically) could necessitate regularities being highly or fully deterministic, and completely fail if regularities are only probabilistic.
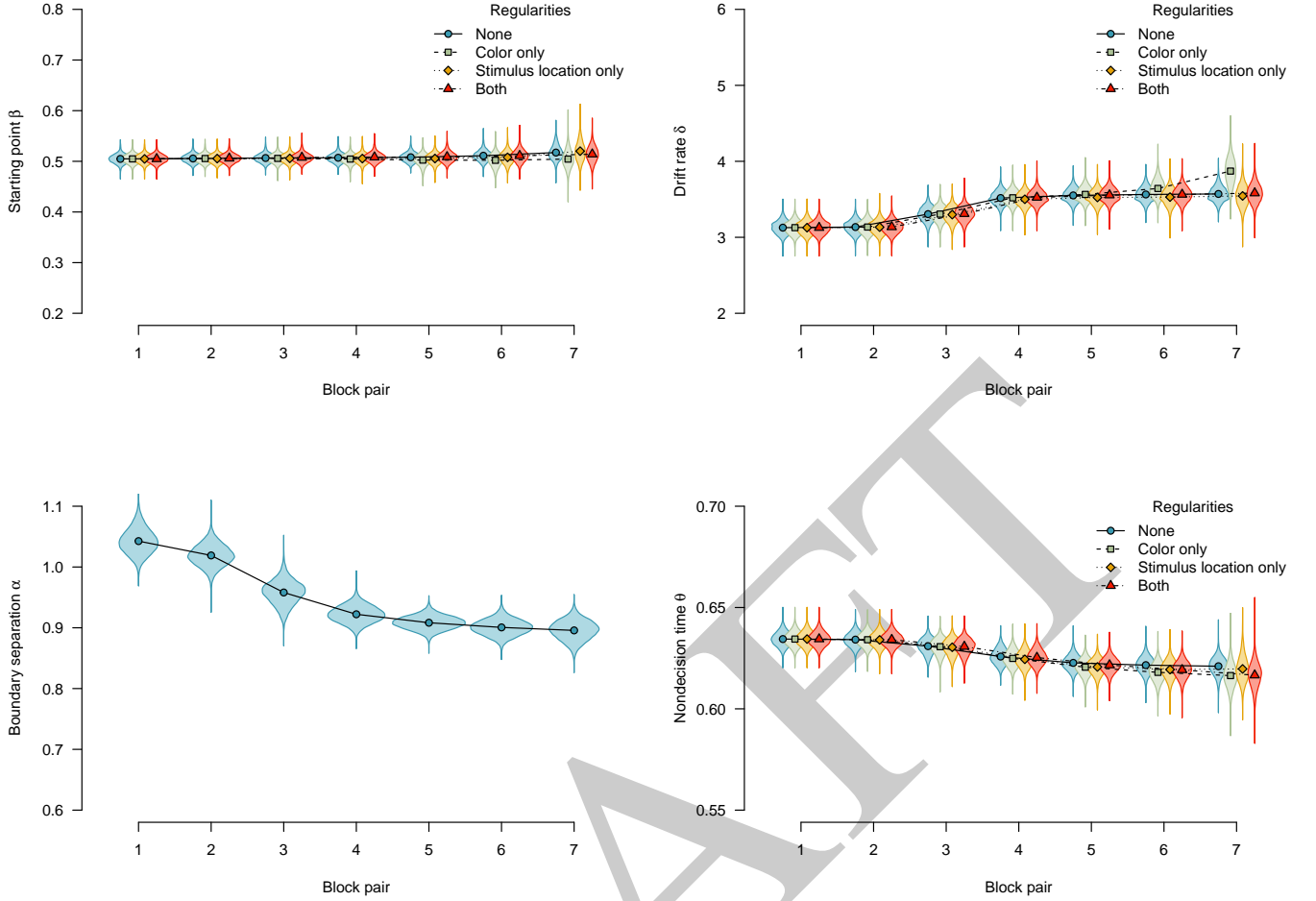
Figure 6. Parameter estimates from Experiment 3 for spatially incompatible trials. Points represent posterior means of the group-level parameters μ_{kb}, violins represent their corresponding posterior densities.

Implications

Our findings of no effects of sequences of stimulus colors or stimulus locations on SRTT performance are inconsistent with previous studies which found parallel learning of stimulus sequences and sequences of response locations (Eberhardt et al., 2017; Goschke & Bolte, 2012; Mayr, 1996). moreover, they are also inconsistent with findings of purely observational implicit learning of stimulus sequences (e.g., Howard, Mutter, & Howard, 1992; Song, Howard, & Howard, 2008; Wilts & Haider, 2023). These studies have in common that the relevant stimulus features follow simpler sequences than in our study: While we used probabilistic first-order conditional sequences where the regular stimulus was presented with a probability of .6, Eberhardt et al. (2017) used 7-item first-order conditional and 12-item second-order conditional deterministic sequences, Goschke and Bolte (2012) used 8- or 9-item sequences with both first- and second-order information where each sequence was interrupted in only approximately 5% of trials, Mayr (1996)

used 6- or 7-item first-order conditional deterministic sequences, Gheysen, Gevers, De Schutter, Van Waelvelde, and Fias (2009) used blocks of a 5-item deterministic sequence (2–4–3–1–4) interrupted by blocks of pseudorandom materials. While it is conceivable that probabilistic sequences are more difficult to learn than deterministic sequences, and it might therefore be more difficult to detect small learning effects for perceptual sequences, we deem such an explanation insufficient to explain the absence of learning effects for perceptual sequences in our experiments: First, with more than 2,000 trials, our experiments had much longer learning phases than previous studies. Second, we not only failed to find an effect of learning of perceptual sequences, which might be attributable to a lack of statistical power; instead, with the Bayesian methods we employed, we found strong evidence for the absence of such learning effects. We, therefore, conclude that a lack of practice or statistical power in our study most likely cannot explain the discrepancy between our study and previous findings. Instead, we interpret these results as indicative that deterministic sequences of stimu-

lus features such as those utilized in previous studies can be learned in the SRTT; in marked contrast, probabilistic sequences of stimulus features such as those utilized in our experiments cannot be learned in the SRTT.

It remains, however, an open question whether earlier demonstrations of learning of deterministic perceptual sequences indeed indicate that such sequences can be learned implicitly. Instead, it is also conceivable that these findings have been contaminated with explicit sequence knowledge, and that the observed learning effects were the result of such residual explicit sequence knowledge for at least three reasons: First, in the standard SRTT design, it has frequently been observed that not only performance effects are much larger for deterministic (compared with probabilistic) sequences, but also that deterministic sequences promote the development of explicit sequence knowledge (Esser & Haider, 2017; Jiménez & Méndez, 1999). Second, studies using deterministic 12-item second-order conditional sequences found learning of a perceptual sequence only for explicit—but not implicit—learners (Kelly & Burton, 2001; Kelly, Burton, Riedel, & Lynch, 2003; Willingham, 1999). Moreover, in line with our findings, Deroost and Coomans (2018) found that sequence awareness is a necessary condition for purely-perceptual sequence learning. Third, the above studies rely on an a-posteriori classification of participants into subgroups of implicit and explicit learners by some direct test of explicit sequence knowledge: Such measures have been criticized for not being sensitive enough to detect explicit sequence knowledge (Shanks & St. John, 1994; Timmermans & Cleeremans, 2015). Some of these studies (Gheysen et al., 2009; Goschke & Bolte, 2012) rely on a process-dissociation (PD) measure to classify participants as explicit learners. However, Barth, Stahl, and Haider (2019) demonstrated that in applications of the PD approach to sequence learning, explicit sequence knowledge is systematically underestimated. Therefore, these studies cannot be interpreted to provide conclusive evidence for the implicitness of the observed learning effects beyond reasonable doubt.

The extended SRTT design that we used in our study has been used to investigate the parallel learning of multiple uncorrelated sequences. Findings of such parallel learning have been interpreted as being evidential for a unidimensional learning system that is organized along dimension-specific, encapsulated processing modules. While it has been demonstrated that above-zero learning scores for both sequences can also be explained with a unitary learning system and that these findings therefore do not provide unequivocal evidence for modularization (Barth et al., 2023), the absence of interference may indeed provide convincing evidence for modularization. Vice versa, finding destructive or constructive interference between sequence would be evidential for a commen representation of both sequences.

However, if learning of perceptual sequences would indeed be restricted to explicit sequence learning, the presence or absence of interference between such learning effects and learning effects for the sequence of response locations would not indicate encapsulated processing within a unidimensional learning system that is restricted to implicit sequence learning. Instead, finding absence of interference between (explicitly learned) perceptual sequences and (implicitly learned) sequences of response locations could only indicate a separation between an explicit and an implicit learning mechanism. Conversely, finding (destructive or constructive) interference between both sequences would indicate that both implicit and explicit sequence learning both rely on shared resources.

Conclusion and Outlook

The present study was aimed at testing the assumption that implicit sequence learning proceeds in a set of dimension-specific, encapsulated processing modules. To this aim, in three experiments, we used an extended SRTT design where stimulus features and responses followed uncorrelated sequences, and intended to test whether learning of perceptual sequences is expressed via changes in perceptual processes involved in task execution, and sequences of responses are expressed via motor-related processes. However, against our expectations, we were not able to replicate learning of perceptual sequences, a surprising result that we attribute to the fact that we used probabilistic, not deterministic, perceptual sequences to avoid contamination with explicit sequence knowledge. While this surprising result hints at the possibility that perceptual sequence learning in the extended SRTT design necessitates sequence awareness, our results presented here should be considered preliminary: Future research is needed to directly assess the role of sequence awareness for the learning of deterministic versus probabilistic perceptual sequences. In a second step, it may then be possible to use the extended SRTT design to address the question whether a single mechanism or multiple independent learning mechanisms mediate sequence learning.

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Appendix
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.

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

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

$$\beta_n \sim \mathrm{N}_{.01}^{.99}\left(\zeta_{ikb}^{(\beta)} + p^{(\beta)}\kappa_{ij}^{(\beta)}, s_i^{(\beta)}\right)$$

$$\delta_n \sim \mathrm{N}\left(\zeta_{ikb}^{(\delta)} + p^{(\delta)}\kappa_{ij}^{(\delta)}, s_i^{(\delta)}\right)$$

$$\tau_n \sim \mathrm{N}_{.001}\left(\zeta_{ikb}^{(\theta)} + p^{(\theta)}\kappa_{ij}^{(\theta)} + \zeta_{il}^{(\xi)} + p^{(\xi)}\kappa_{il}^{(\xi)}, s_i^{(\tau)}\right)$$

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.

$$\zeta_{ikb}^{(\beta)} \sim \mathrm{N}\left(\mu_{kb}^{(\beta)}, \sigma^{(\beta)}\right)$$

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

$$\kappa_{ij}^{(\beta)} \sim \mathrm{N}\left(\mu_j^{\kappa^{(\beta)}}, \sigma_j^{\kappa^{(\beta)}}\right) \text{ for } j = 1, ..., 5$$

and

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

The

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

and

$$\mu_6^{\kappa^{(\beta)}} = -\sum_{j=1}^{5} \mu_j^{\kappa^{(\beta)}}$$

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

$$\sigma_j^{\kappa^{(\beta)}} \sim t_{df=I-1}^{+}$$

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 conditions means are dummy coded (with nonregular trials serving as the reference group).

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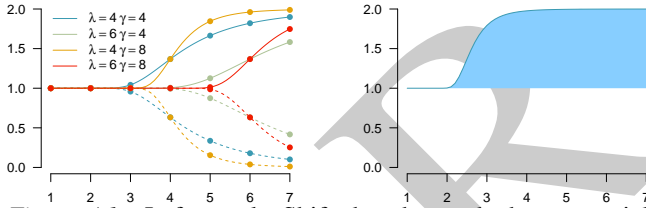
Figure A1. Left panel: Shifted and stretched exponential functions for different values of λ (location) and γ (shape), with $\upsilon = 1$ and $\iota \in \{0, 2\}$. Right panel: The average effect ψ corresponds to the area under the curve (blue) between initial limit and the function's value $f(b)$.