Implicit sequence learning despite multitasking: The role of across-task predictability, serial processing and separation of representations

Inauguraldissertation

zur Erlangung des Doktorgrades
der Humanwissenschaftlichen Fakultät
der Universität zu Köln
nach der Promotionsordnung vom 18.12.2018
vorgelegt von

Eva Röttger
aus
Minden

29. Juli 2019

1. Berichterstatter: Prof. Dr. Hilde Haider (Köln)

2. Berichterstatter: Prof. Dr. Robert Gaschler (Hagen)

Tag der mündlichen Prüfung: 20.09.2019

Diese Dissertation wurde von der Humanwissenschaftlichen Fakultät der Universität zu Köln im September 2019 angenommen.

Zusammenfassung

Implizites Lernen ist einer der grundlegendsten Lernprozesse, der es dem Menschen ermöglicht, sich ohne Intention oder Anstrengung und selbst ohne das Bewusstsein, etwas zu lernen, an reguläre Strukturen in der Umwelt anzupassen. (z.B. Dienes & Berry, 1997). Ein oft replizierter Befund ist jedoch, dass implizites Sequenzlernen in einer seriellen Wahlreaktionsaufgabe (SRTT; Nissen & Bullemer, 1987) in Doppelaufgaben unter bestimmten Bedingungen gestört ist. Das Ziel der vorliegenden Arbeit war es, die Mechanismen zu untersuchen, die der Störung vs. Erhaltung des impliziten Lernens in Doppelaufgaben zu Grunde liegen.

In Studie 1 wurden zwei Ansätze gegenübergestellt: „*task integration*" (Rah, Reber & Hsiao, 2000; Schmidtke & Heuer, 1997) und „*parallel response selection*" (Schumacher & Schwarb, 2009). Die Ergebnisse deuten auf eine Konzeption von „task integration" hin, die nahe legt, dass implizites Lernen in Doppelaufgaben in dem Maße bewahrt vs. gestört ist, in dem zeitgleich auftretende Ereignisse in der Zweitaufgabe vorhersagbar sind oder nicht.

In Studie 2 wurde die Rolle zweier verschiedener Arten von „*across-task predictability*" untersucht, die als *lokal* oder *global* bezeichnet werden (in Abhängigkeit der ambigen Struktur der SRTT). Die Ergebnisse legen nahe, dass ein automatischer Vorhersagemechanismus (z.B. Broeker et al., 2017) auf die globale Vorhersagbarkeit der zeitlich nächsten Ko-Ereignisse anspricht und profitiert, wenn die lokale Vorhersagbarkeit ebenfalls hoch ist, aber Konflikt verursacht, wenn nicht, was die Reduktion des Vorhersagefehlers/das Sequenzlernen stört.

In Studie 3 wurde der Befund weiter untersucht, dass Sequenzlernen erhalten bleibt, wenn die zwei Aufgaben durch ein langes SOA getrennt sind (Schumacher & Schwarb, 2009). Außerdem wurde untersucht, in welchem Ausmaß vorhersagbar variierende SOAs genutzt werden können, um die Sequenz zu lernen. In einer Gegenüberstellung der Annahmen, dass variierende SOAs entweder eine globale serielle Verarbeitungsstrategie auslösen (Israel & Cohen, 2011) oder dass Versuchspersonen (ohne die Instruktion, eine Aufgabe zu priorisieren) eher eine moderat parallele Verarbeitungsstrategie vorziehen (Lehle & Hübner, 2009), ergab sich, dass Letzteres wahrscheinlich zutreffender ist. Lernen trat (mechanistisch) nur mit langen SOAs auf, aber nicht flexibel und strategisch ebenso mit kurzen SOAs. Es wird diskutiert, ob „task integration" vs. „separation" die Befunde besser erklären kann.

Zusammengenommen deuten die Befunde aller drei Studien darauf hin, dass, in der Gegenwart nicht vorhersagbarer Ko-Ereignisse, die Separierung der Aufgabenrepräsentationen bedeutsam ist. Nicht nur im Kontext des impliziten Sequenzlernens in Doppelaufgaben – sondern auch, um zukünftig generelle Fortschritte in der Multitasking-Forschung zu erzielen.

Abstract

Implicit learning is assumed to be one of the most fundamental learning processes enabling humans to adapt to regular structures inherent in the environment without intention or effort and even without being consciously aware *that* they learn or *what* they actually learn. (e.g., Dienes & Berry, 1997). One often replicated finding is, however, that implicit sequence learning in a serial reaction time task (SRTT; Nissen & Bullemer, 1987) is impaired in dual-task situations under certain conditions. The aim of the present research was to shed light on the mechanisms underlying the impairment vs. the preservation of dual-task sequence learning.

In the first study, mainly two accounts were contrasted: *task integration* (Rah, Reber, & Hsiao, 2000; Schmidtke & Heuer, 1997) vs. *parallel response selection* (Schumacher & Schwarb, 2009). The results strongly hint at a conception of task integration suggesting that dual-task implicit sequence learning is preserved vs. impaired to the extent that secondary task events, co-occurring with the SRTT, are predictable or not.

In the second study, the role of two different types of across-task predictability was investigated, termed *local* vs. *global* (depending on the ambiguous structure of the SRTT). The findings suggest that a supposed automatic prediction mechanism (e.g., Broeker et al., 2017) operates on the global predictability of the most contiguous co-occurrences, benefitting if the local across-task predictability is in accord but causing conflict if not, thereby disturbing the reduction of the prediction error and, thus, sequence learning.

In the third study, the finding of preserved sequence learning when the two tasks are temporally separated by long SOAs (Schumacher & Schwarb, 2009) was further investigated. It was also investigated to what extent participants can exploit predictably varying SOAs in order to learn the sequence. Pitting the assumption that varying SOAs trigger a global serial processing strategy (Israel & Cohen, 2011) against the assumption that participants (without prioritization instructions) prefer moderately parallel processing (Lehle & Hübner, 2009), it turned out that the latter assumption is probably more appropriate. Learning occurred only (mechanistically) with long SOAs but not flexibly and strategically with short SOAs as well. It is discussed whether task integration vs. separation can better explain the findings.

To sum up, the outcomes of all three series of experiments hint at the importance of the separation of task representations in the face of unpredictable across-task co-occurrences, not only in the context of dual-task implicit sequence learning – but probably also for future endeavors to come to progress in the research on multitasking in general.

Content

1 General Introduction

Whether we are aware of it or not, many action sequences in our daily lives are based on routines which we developed due to our remarkable ability to extract regularities from the environmental input. Imagine, for instance, how you get up in the morning, walk into the kitchen – still half asleep – and make coffee. Every single step of this action sequence, taking place within the (relatively) stable environment that is your kitchen, has been practiced many times and proceeds smoothly, without much effort and awareness. You might not be able to verbalize the steps within your coffee routine – or even not realize that you *have* something like a coffee routine. Nevertheless, on the day, for instance, a new roommate has placed the coffee powder somewhere else, your routine is very likely to falter – indicating that, indeed, you had perfectly adapted to the "normal" conditions in your kitchen. Now imagine you shared an apartment with five other people and your coffee procedure would every morning be accompanied by all kinds of random events. It seems intuitively likely that you would never develop a really stable routine. In other words, although the learning of sequenced information is essential to many human behaviors (Lashley, 1951), the evidence suggests that (implicit) sequence learning gets massively disturbed by temporally contiguous co-occurring events requiring one or the other response (for reviews, see Keele, Ivry, Mayr, Hazeltine, & Heuer, 2003; Schumacher & Schwarb, 2009; Schwarb & Schumacher, 2012).

Even though not being able to develop a stable morning coffee routine might already have subjectively unpleasant effects, it is obvious that an impairment of our implicit learning abilities, as a consequence of multiple simultaneous task demands, complicates operational procedures in numerous areas of human agency and, for instance, increases the risk of severe problems in working areas with high safety requirements. Nevertheless, our modern lives can virtually be characterized by the ubiquitous necessity to engage in multitasking activities – notwithstanding that these almost inevitably cause all sorts of performance costs. It is, thus, highly relevant to investigate the problem of implicit (sequence) learning in multitasking in more detail. Interestingly, so far, the sequencing of actions has drawn relatively little attention in the literature on multitasking – while multitasking (or, more specifically, dual-tasking) has occasionally been implemented in implicit sequence learning experiments, in order to fathom out its dependency on limited attentional resources, since the seminal study of Nissen and Bullemer (1987). The separateness of these two research fields might have sustained because they see the key to optimal performance within opposing, or incompatible, abilities, namely, in enabling parallelism to the extent of "virtually perfect time sharing" (Schumacher et al., 2001; multitasking) vs. avoiding parallelism in order not to confound within-task regularities (e.g., Houghton & Hartley, 1995; implicit sequence learning). However, while hundreds of dual-tasking studies reported severe problems in the endeavor of enabling parallelism leading unescapably to the assumption of a bottleneck in information processing (Pashler, 1994), some implicit learning studies reported preserved sequence learning despite dual-tasking due to successfully separating the tasks *temporally* (Schumacher & Schwarb, 2009) or *conceptually* (Halvorson, Wagschal, & Hazeltine, 2013) and, therefore, by avoiding parallelism.

In the present series of studies, it is suggested – by linking both research perspectives – that one functional characteristic of the ubiquitous bottleneck might lie in keeping the representations of two (or multiple) tasks separate and that maintaining separate vs. integrated representations might essentially (but not solely) determine whether sequence learning in a dual-task context is possible or not. Recently, two accounts have been put forward that are, in principle, both in line with the assumption that the insufficiently separated processing of simultaneously presented tasks might indeed be the main cause for impaired implicit sequence learning. Interestingly, however, these accounts can be characterized as addressing the problem (predominantly) from either one of the two research perspectives – thereby also suggesting different mechanisms by which sequence learning is affected by dual-tasking.

In very short, the *task integration account* (Schmidtke & Heuer, 1997), focusing on the mechanisms of implicit sequence learning, suggests that a tendency to integrate the two tasks hampers learning to the extent that (a) the integrated event sequence is often extraordinarily long and that (b) co-occurrences have no predictive value (Rah, Reber, & Hsiao, 2000). This account, thus, incorporates the assumption that associating sequenced information relies on the reduction of the prediction error (Rescorla & Wagner, 1972). Furthermore, that prediction proceeds automatically, is omnipresent, and operates on temporally contiguous events (see, e.g., Broeker et al., 2017).

The *parallel response selection account* on the other hand (Schumacher & Schwarb, 2009), more strongly considers the general mechanisms of dual-task processing thereby contributing to the debate whether the limited central (cognitive) capacity can be shared (e.g., Tombu & Jolicoeur, 2003) or not (e.g., Pashler, 1994). Here, it is suggested that selecting two responses simultaneously disturbs the learning of stimulus-response rules and, thus, sequence learning (see also Schwarb & Schumacher, 2012).

Interestingly, both lines of research also demonstrated an amazing flexibility of human cognitive processing. That is, parallel response selection (Schumacher & Schwarb, 2009; Experiment 2) and/or task integration (see Halvorson, Wagschal, et al., 2013) – both assumed to occur by default given temporally contiguous dual-task events – could be prevented simply by instruction. It is, thus, warranted, as also Koch, Poljac, Müller, and Kiesel (2018) suggested, that research on multitasking should investigate the fundamental aspects of our cognitive architecture not only in terms of its structure – but also in terms of its flexibility and plasticity. Implicit learning provides a profound basis for the plasticity of human behavior. Finding the conditions under which this plasticity is preserved despite dual-tasking will, thus, contribute to our knowledge about the flexibility of the involved cognitive mechanisms.

The aim of the present series of three studies was to shed more light on the basic mechanisms underlying implicit sequence learning in dual-task situations and to compare and to evaluate (predominantly) the two above mentioned accounts: the task integration account originating by Schmidtke and Heuer (1997; see also Rah et al., 2000) and the parallel response selection account of Schumacher and Schwarb (2009).

In the following sections, some fundamental assumptions within the implicit sequence learning literature and the multitasking literature will be introduced before reviewing previous theories and findings concerning implicit sequence learning in multitasking situations – from which the rationale and the hypotheses for the present experiments were derived.

Implicit sequence learning

The question why implicit sequence learning is often impaired by a simultaneously conducted secondary task – and whether it is, thus, dependent on attentional resources – is only one of several strongly debated questions within the huge body of literature on implicit learning (for recent reviews, see Abrahamse, Jiménez, Verwey, & Clegg, 2010; Keele et al., 2003; Schwarb & Schumacher, 2012).

Since the seminal study of Nissen and Bullemer (1987), researchers have used the *serial reaction time task* (SRTT) to investigate the nature of sequence learning. In this task, participants have to respond to a visual target stimulus occurring at one of (e.g.) four spatial locations on the screen by pressing the appropriate spatially mapped key. Unbeknownst to the participants, the successive target locations follow a regular sequence. Several training blocks repeating this sequence are followed (or interrupted) by a random block. Sequence knowledge is revealed, when the response times in this random block are significantly slower than in the later (or surrounding) sequence blocks. The implicit nature of this knowledge is inferred when participants are unable to verbalize the sequence or do not know that they had learned anything in the first place (e.g., Dienes & Berry, 1997). However, defining implicit learning – in contrast to explicit learning or hypothesis testing – is already the first of several theoretical challenges (for a short summary, see Frensch & Rünger, 2003). The smallest common denominator within this debate is that it is learning without awareness that occurs unintentionally (and probably automatically in the sense of being independent of attentional resources). Meanwhile, it is often assumed that implicit learning "consists of a continuous, incremental change in the associative pattern that is sensitive to the statistical features of the set of items or events encountered" (Frensch & Rünger, 2003, p. 17).

Related to this issue is the question whether implicit and explicit learning are based both on one single knowledge base (e.g., Cleeremans & Jiménez, 2002) or on two (or multiple) independent knowledge bases (e.g., Keele et al., 2003). The latter view has also tried to unify early attempts to explain why sequence learning suffers when a secondary task is added to the SRTT. This point will be considered in more detail below.

Since implicit (sequence) learning can be defined as learning without awareness of the products of learning, the question of what exactly it is that is learned implicitly – and how the acquired knowledge is represented in the brain – has received much of the attention in recent research (Abrahamse et al., 2010; Schwarb & Schumacher, 2012). This research has focused mainly on the dichotomy of purely stimulus-based and purely response-based learning. For instance, by demonstrating the effector independence of sequence knowledge, the findings of Cohen, Ivry, and Keele (1990) can be seen as evidence for stimulus-based learning. Transfer of sequence knowledge from one- to a slightly different stimulus-response (S-R) mapping while keeping the response locations constant (e.g., Willingham, Wells, Farrell, & Stemwedel, 2000), on the other hand, suggest that implicit motor sequence learning is represented in the form of successive response locations.

However, other alternatives have also been suggested, that is, learning of response-effect associations (e.g., Ziessler & Nattkemper, 2001) or of stimulus-response (S-R) rules (e.g., Schwarb & Schumacher, 2010) – the latter being the basis for the parallel response selection account of impaired sequence learning in dual-task contexts (see below). According to the S-R rule hypothesis, sequence knowledge is acquired when task relevant S-R pairs, as defined by the S-R rule, remain active in working memory across several trials and begin to form cross-temporal associations. Schwarb and Schumacher (2010), for instance, showed that sequence knowledge transferred to novel S-R mappings even when the response locations changed – given that these changes were simple "spatial transformations" of the original S-R rules (e.g., always one key to the left). Both, the finding of effector independence (Cohen et al., 1990) as well as many findings in line with response based theories (e.g., Willingham et al., 2000) can also be explained by the S-R rule hypothesis because, for instance, changing the effector does not change the S-R rule. However, findings of perceptual sequence learning with uncorrelated responses (e.g., Haider, Eberhardt, Esser, & Rose, 2014; Haider, Eberhardt, Kunde, & Rose, 2012) are hard to reconcile with it.

To summarize, most researchers agree that implicit learning is based on mechanisms that associate selectively attended, predictive pieces of information being relevant for behavior. Implicit knowledge remains unaware to the participants (at least) in the sense that they cannot verbalize it – and/or perform poorly in recognition tests, generation tasks, inclusion/exclusion tasks, and other established testing methods (see Haider, Eichler, & Lange, 2011).

Multitasking

Two of the main questions in the literature on multitasking – or, more specifically, dual-tasking – have been whether the ubiquitous finding of dual-task costs can be attributed to an assumed bottleneck in information processing that is either structural or strategic in nature and, thus, whether parallel processing at this stage is, in principle, possible or not (for a recent review, see Koch et al., 2018).

Two different dual-task paradigms are employed in order to investigate the limits and the possibilities of the human cognitive architecture. Dual-task interference is either assessed by comparing the performance in dual-task vs. single-task conditions or by gradually varying the temporal overlap (*stimulus onset asynchrony*; SOA) of the two tasks. The latter has been termed PRP (*psychological refractory period*) paradigm and was introduced by Welford (1952). The SOA can be varied between two extremes, ranging from complete temporal overlap (i.e., SOA = 0 ms) up to nearly mimicking a task switching situation (e.g., SOA = 1000 ms). The classical finding is that the performance in the secondary task suffers the more the shorter the SOA (which is the so-called PRP effect) but that the performance in the primary task is rather unaffected by this manipulation (see Pashler, 1984; 1994). It is assumed that one (or more) stages in information processing might exist that can be accessed by the two tasks only serially – but not in parallel. Attempts to localize this bottleneck repeatedly pointed at the response selection stage, centrally linking perceptual and motor processes (see Donders, 1868/1969; Sternberg, 1969), which themselves, in contrast, both can run in parallel with any other process (see, e.g., Pashler & Johnston, 1989). Many researchers have tried to eliminate the PRP effect (e.g., by means of extensive practice) but only few attempts have had some success (e.g., Schumacher et al., 2001; see also Hazeltine, Teague, & Ivry, 2002) – fostering the view that the "bottleneck" represents a structural limitation (Pashler, 1984, 1994) that might possibly only become extremely shortened and, thus, "latent" (Ruthruff, Johnston, Van Selst, Whitsell, & Remington, 2003; see also Strobach & Schubert, 2017a; 2017b).

In recent years, however, several findings called the assumption of a structural central bottleneck into question. For instance, Hommel (1998) found that task 2 responses, being spatially (in)compatible to task 1 responses, affected the performance in task 1. This effect was called *backward compatibility effect*, or, more generally, *backward crosstalk effect* (BCE) because interference seemingly operated "backwards" through the bottleneck – which contradicts the assumption of its structural, single-channel nature as conceptualized within Pashler's (1984; 1994) *response selection bottleneck* (RSB) model. This assumption implies that response related task 2 processing cannot start before response selection for task 1 is finished, thus, backward crosstalk effects are not predicted. To account for this, Hommel (1998) suggested an additional processing stage of automatic response *activation* allowing parallel processing at the risk of crosstalk – which has, then, finally to be overcome within the subsequent original controlled response *selection* stage of limited capacity. This way, the RSB model was expanded but could be maintained (see also Janczyk, 2016; Janczyk, Pfister, Hommel, & Kunde, 2014).

However, other models, built on the assumption that the limited central capacity can be gradually (and probably also strategically) shared, can as well explain the BCE (Logan & Gordon, 2001; Meyer & Kieras, 1997; Navon & Miller, 2002; Tombu & Jolicoeur, 2003). Crucially, these models can, nevertheless, also account for the PRP effect – simply by assuming that, for instance, under conditions highlighting the prioritized processing of task 1, the limited central capacity is directed to 100% at task 1 first. In this case of serial processing, RT1 should be approximately as fast as in a single-task condition. In case of parallel processing on the other hand, RT1 should be slowed down to the extent that capacity is shared and RT2 is accelerated. Miller, Ulrich, and Rolke (2009) tested these predictions under the assumption that (a) the extent to which participants process two tasks serially or in parallel depends on the list-wide frequency of long vs. short SOAs, respectively, and that (b) participants choose one or the other processing strategy in order to optimize the dual-task performance in terms of minimizing the *total response time* (TRT; i.e., the sum of RT1 and RT2). Their results were mainly in accord with that.

Meanwhile, it has been shown that participants are also able to flexibly engage in a more parallel or more serial processing mode simply by instruction (Lehle & Hübner, 2009) thereby producing larger vs. smaller crosstalk effects. However, several further factors, like stress, motivation, awareness of conflict, determine if participants are indeed willing or able to engage in effortful control processes (like suppressing interfering task 2 response features)

– or whether they prefer a relaxed, moderately parallel processing mode at the expense of one or the other kind of costs (see Fischer & Plessow, 2015 for a recent review).

The core assumption of the parallel response selection account of impaired implicit sequence learning (cf. Schumacher & Schwarb, 2009) builds on capacity sharing models (e.g., Tombu & Jolicoeur, 2003) as, here, it is assumed that in a condition consistently presenting the two stimuli simultaneously (i.e., with an SOA of 0 ms), triggers a parallel response selection strategy (cf. Miller et al., 2009) which, in turn, impairs sequence learning. This point will be considered in more detail below.

Implicit sequence learning in multitasking situations

Since the introduction of the SRTT (Nissen & Bullemer, 1987), one predominant question in the research on implicit sequence learning has been whether it is dependent on attentional resources (Cohen et al., 1990; Curran & Keele, 1993; Nissen & Bullemer, 1987). One method to investigate this question was to present the SRTT together with a secondary tone-counting task. Nissen and Bullemer reported that this secondary tone-counting task entirely eliminated implicit sequence learning and they concluded that attention is indeed needed to implicitly learn a repeating sequence. Other researchers found that the extent to which implicit sequence learning was impaired under dual-task requirements interacted strongly with the specific length and structure of the sequence and they concluded that the implicit learning of sequences with unique or hybrid – in contrast to ambiguous – pairwise transitions does not depend on attention (Cohen et al., 1990; Curran & Keele, 1993).

In all further research, the question whether or not implicit learning was impaired under dual-task requirements was investigated using different learning phases (dual- or single-task or both, in different lengths and ratios) and/or different test phases (dual- or single-task or both in succession and different orders). Additionally, the SRTT sequences were of different lengths and structures (see Cohen et al., 1990). In most of the earlier studies, participants' secondary task was to count one of two tones that were randomly played during the *response-stimulus interval* (RSI) of the SRTT. Conclusions concerning the dependency of implicit sequence learning on attention (and on the complexity of the sequence structure) were drawn from comparably larger or smaller learning effects in the SRTT.

Curran and Keele (1993; Experiment 1) found learning scores in a dual-task test after single-task training that were smaller than the learning scores in the preceding single-task test (but not absent). Additionally, the learning scores after dual-task training were also small and did not differ as a function of the kind of subsequent test (single- vs. dual-task; Experiment 3).

Keele and colleagues (e.g., Curran & Keele, 1993) interpreted these and similar findings as evidence for the existence of two different sequence representation systems, with only one of them depending on attention. They suggested that counting tones during the training phase might prevent attention-dependent implicit learning – and might suppress its expression when introduced later, in the test phase.

Nevertheless, Frensch and colleagues (Frensch, Lin, & Buchner, 1998; Frensch, Wenke, & Rünger, 1999) found implicit learning effects in a single-task test after dual-task training that were larger than those in the preceding dual-task test. Frensch and colleagues concluded that implicit sequence learning takes place automatically and is generally independent of attention. In their conception, the smaller learning scores in the dual-task test reflected the suppressed expression of the acquired knowledge (due to specific interference from the tone-counting task in terms of trial-by-trial variability in task scheduling). Also in favor of a "specific interference" account, Stadler (1995) considered the point that updating the tone-count in the RSI of the SRTT is usually only required in 50% of all trials thereby separating successive SRTT-targets by irregular events disrupting the organization of the sequence.

Task integration

Adding to Stadler's point, Heuer and Schmidtke (1996) criticized the tone-counting task altogether for not allowing to decide whether implicit sequence learning gets impaired due to increased memory load or due to processing requirements on a trial-by-trial basis (classifying tones). Therefore, they introduced an auditory-motor go/no-go task (foot-pedal press in response to only one of the tones, played in the RSI of the SRT). This task required immediate decisions without increased memory load – and produced substantial interference on implicit sequence learning.

Based on this finding, Schmidtke and Heuer (1997) introduced two further novel procedures into the dual-task implicit sequence learning literature. Most importantly, they added to the random tone condition two new conditions with regular tone sequences that were (to a high or lower degree) correlated with the visual-manual SRTT sequence. Second, they not only assessed the amount of implicit sequence learning in dual- as well as in single-task tests but they also obtained learning scores for both tasks, that is, they either changed the repeating SRTT- or the repeating tone sequence (or both) in different transfer-blocks and assessed learning within- as well as across tasks. They hypothesized that impaired implicit sequence learning under dual-task requirements results from task integration, that is, from the (ineffective) "attempt" to learn an integrated bimodal (visual-auditory) sequence in which every second element is random. This implies that – with correlated sequences in both tasks – integrated learning should be as good as single-task learning.

Three experiments revealed the following main findings. In Experiment 1, a dual-task test after dual-task training revealed learning scores that were the larger the more the two sequences were correlated. Indeed, with perfectly correlated sequences, the dual-task learning effect was comparably large as the single-task learning effect of the single-task control group. The single-task scores (SRTT only) of all dual-task groups were equally sized (and smaller than in the dual-task test) replicating the finding that hybrid sequences can also be learned under dual-task requirements (Cohen et al., 1990). Experiment 2 replicated the major findings of Experiment 1 under different test conditions. These results indicate that task integration occurs per default, being either beneficial or detrimental for sequence learning depending on the extent to which co-occurring events have to be attended (i.e., have to be responded to; see Experiment 3), are of predictive value for each other (Rah et al., 2000) and that the resulting integrated sequence is not extraordinarily long.

The dual-system model of sequence representation

Up to this point, Keele et al. (2003) had been able to integrate the majority of the findings into their *dual-system model of sequence representation*. In short, the model proposes two independent sequence learning systems, the multidimensional and the unidimensional system. The multidimensional system forms associations between events that occur across different "dimensions" (a term used more or less interchangeably with "modality"), given that these events are selectively attended. Importantly, attention in the sense of capacity limitation is not part of the model. The unidimensional system, on the other hand, forms associations exclusively within dimensions. This encapsulation makes it possible to associate automatically events occurring within the same dimension – even in the presence of random events within another dimension (as long as they are not task relevant).

While learning within the unidimensional system is entirely implicit, learning within the multidimensional system can also become explicit. Additionally, it is assumed that the two systems operate in parallel in single-task sequence learning, while in dual-task situations, unidimensional modules operate exclusively. However, attended information still gains access to the multidimensional system. If this information includes correlated events, associations will be also formed across dimensions. If, however, attended events are random, sequence learning will be disrupted. These assumptions are close to the task integration hypothesis and Keele et al. (2003) also propose a quite specific mechanism. By comparing task integration with classical conditioning they suggest that associations across dimensions are formed when a signal within one dimension reliably predicts an immediately following event within another dimension (see also Rescorla & Wagner, 1972).

The model also incorporates other "specific interference" accounts by considering the observation that SRTT learning seems to be consistently only then affected by co-occurring tones when participants have to respond to these tones in any way – instead of just hearing them (see Rah et al., 2000; Schmidtke & Heuer, 1997; Stadler, 1995). Specifically, it seems as if (apart from differential working memory demands) counting 50% of the tones is not so different from pressing a foot-pedal in 50% of trials, possibly because both tasks require some sort of response (or at least a decision) on a trial-by-trial basis – suffering from random- but benefitting from predictable cross-dimensional events.

Parallel response selection

In a more recent dual-task implicit learning study, Schumacher and Schwarb (2009) focused exclusively on situations in which both tasks required a response in every trial, aiming at identifying the exact locus of the impairment of learning within the central response selection stage (cf. Donders, 1868/1969; Sternberg, 1969). To investigate this assumption, they adopted the two different dual-task paradigms (introduced above) and paired the SRTT with a (random) tone-discrimination task calling for an open (vocal) response in 100% of the trials. Additionally, the tones were no longer played in the RSI of the SRTT but occurred either simultaneously with the visual SRTT stimuli or after a long SOA (of 750 ms). Since separate input and output modalities were required for both tasks in the respectively most compatible ("standard") combination of stimuli and responses (see Hazeltine, Ruthruff, & Remington, 2006), the authors expected any impairment of implicit learning to occur due to interference within the central response selection stage, thereby adopting the assumption that central capacity can, in principle, be shared (e.g., Tombu & Jolicoeur, 2003).

To summarize, preserved learning was found only when the tasks were temporally separated by the long SOA which, in the authors' conception, prevented parallel response selection (Experiment 1; see also Miller et al., 2009). It was also found simply by instructing the participants to prioritize the SRTT (Experiment 2) despite simultaneous stimulus onset. And, finally, it was found when the SRTT was the secondary task within the PRP paradigm, separated from the tone-task by the bottleneck (Experiment 3) – even though dual-task costs (i.e., the PRP effect) were also present. This outcome suggests that not dual-task interference per se but exclusively parallel response selection disturbs sequence learning.

Schumacher and Schwarb (2009) see their findings as being inconsistent with all other accounts shortly reviewed above. Most importantly, in respect to the present studies, the authors reject both the task-integration hypothesis by Schmidtke and Heuer (1997) and the dual-system model (Keele et al., 2003) as, in their study, they consistently found sequence learning despite the presence of an unpredictable secondary task – as long as the strategy of parallel response selection was prevented. They also concluded that the additivity of learning effect and PRP effect (Experiment 3) supports the hypothesis that implicit sequence learning is generally mediated by response selection (see also Schwarb & Schumacher, 2010, 2012).

Across-task prediction

The rationale for the present series of studies was derived by considering that many earlier accounts of impaired implicit sequence learning in dual-task contexts – especially the task integration account and the parallel response selection account – are in line with the assumption that the insufficient separation of crucial processes for sequence learning (or of whole task representations) might be the main cause for its disruption (in combination with a low predictive value of across-task events). Prediction – and the step-wise reduction of the prediction error as conceptualized by Rescorla and Wagner (1972) – can be seen as such a crucial learning process. The task integration account directly builds on this conception (at least in the variant proposed by Rah et al., 2000) considering the predictability of across-task events as the crucial factor determining whether sequence learning in a dual-task context is possible or not. The finding of Schumacher and Schwarb (2009) that temporally separating the SRTT and the (random) tone-task was beneficial for sequence learning while simultaneous stimulus presentation was not, could, in principle, also count as strong evidence for the task integration/ the across-task prediction account. Crucially, however, as described above, the authors interpret their findings, instead, as evidence for the parallel response selection account. In the following, the across-task prediction account will be introduced more broadly – before three series of experiments are presented which have been conducted in order to shed more light on the causes of impaired implicit sequence learning in dual-task situations.

Already in the early decades of research on learning and serial ordering of behavior (Lashley, 1951), the importance of expectations and predictive mechanisms was emphasized (Bubic, von Cramon, & Schubotz, 2010). The reduction of the prediction error is, indeed, the central mechanism in the model of classical conditioning by Rescorla and Wagner (1972). According to the principles of the predictive coding account (Clark, 2013; Friston, 2010), prediction is an omnipresent mechanism that can also proceed automatically and implicitly operating on temporally contiguous events (see, e.g., Broeker et al., 2017). Marcus, Karatekin, and Markiewicz (2006) found that predictive eye movements accompanied sequence learning suggesting that prediction is already part of the learning process itself – and that the accuracy of prediction improves in effect (see also Dale, Duran, & Morehead, 2012). Prediction allows us "to direct our behavior towards the future, while remaining well-grounded and guided by the information pertaining to the present and the past" (Bubic et al., 2010; p. 11). Learning, in the sense of reducing the prediction error, is triggered by the exposure to non-random patterns of events in the environment allowing the brain to extract the statistical relationships between these events for later predictive use. However, the brain may also, by default, predict novel events and "attempt" to extract patterns from completely random input in order to avoid surprises (that is, to minimize free energy), ensuring that the state of a biological agent remains within its physiological bounds (Friston, 2010). Prediction is, thus, not dependent on "predictability" – but strongly supported by it (Broeker et al., 2017).

The acquisition of (implicit) knowledge about the serial order of a sequence of events in a SRTT can be seen as an instance of learning via predictive processing. Learning proceeds due to the exposure to instances of conditional dependencies of successive events – which is also the core assumption within the statistical learning approach sharing some commonalities with the implicit learning approach (Perruchet & Pacton, 2006). Accordingly, the impairment of implicit sequence learning due to the integration of a randomly sequenced secondary task can be seen as a demonstration of the omnipresence and automaticity of predictive processing showing that across-task predictions occur despite being disadvantageous in some cases. For instance, in dual-tasking, the greater temporal proximity of across-task events (occurring in the same trial) in comparison to within-task events (occurring in successive trials) might bias the predictive processes to operate on co-occurrences that are potentially of low predictive value. In sum, with integrated task representations, dual-task sequence learning should depend strongly on the predictability of across-task events (cf. Rah et al., 2000; Schmidtke & Heuer, 1997). With separate task representations, on the other hand, chances should be good that the prediction mechanism will operate on successive within-task events instead – supporting sequence learning despite the presence of a random secondary task.

The separation of representations might be induced by a potent bottom-up cue, like, for instance, the temporal separation of the two tasks (cf. Schumacher & Schwarb, 2009). It has, however, also been shown that different conceptualizations of task boundaries can be induced top-down, by instruction (e.g., Freedberg, Wagschal, & Hazeltine, 2014). Participants in the study of Halvorson, Wagschal, et al. (2013) who viewed the same tasks (of which one followed a regular- and the other a random sequence) as either two separate or one integrated task, did vs. did not learn the sequence, respectively. Indeed, the implementation of different task-sets has repeatedly proven to be a powerful instrument determining which information exactly participants extract from the environment for later predictive use (see Dreisbach & Haider, 2008, 2009; Gaschler, Frensch, Cohen, & Wenke, 2012; Haider et al., 2014).

Conceptualizing predictive processing as an omnipresent mechanism, it is warranted to consider predictability as most beneficial in multitasking situations – not only for sequence learning but also for mastering other challenges whenever multiple tasks call for appropriate responses (Broeker et al., 2017). Predictive processing provides several advantages for all kinds of behavior by saving cognitive resources, by accelerating perceptual processing and by limiting the repertoire of potential responses (Bubic et al., 2010). First evidence is available that already existing sequence knowledge (acquired in single-task blocks) – allowing the use of within-task predictability – reduces general dual-task costs (Gaschler et al., 2018; see also Gaschler, Zhao, Röttger, Panzer, & Haider, 2019). It seems, thus, that in the most common dual-task context (i.e., with two randomly sequenced tasks), a considerable amount of the ubiquitous costs can possibly be attributed to predictive processing in the absence of any opportunity to reduce the prediction error.

Another multitasking situation benefitting from predictability is task switching. It has been shown that participants perform better in switch trials (in principle associated with costs) when the tasks occur in a regular sequence of which implicit knowledge has been acquired (Koch, 2001). Very likely, this knowledge supports the advance preparation of the upcoming task set. However, recently it has been shown that other predictive cues can also be utilized. Aufschnaiter, Kiesel, Dreisbach, Wenke, and Thomaschke (2017), for instance, provided temporal cues (RSI durations) contingent with the upcoming task set to 70, 80, or 90%. In result, task-switch- as well as -repetition trials benefitted from the most frequent (and, thus, predictable) task-RSI combinations – even though, at the same time, the participants were unaware of the respective contingencies.

In line with this finding – and with recent theories suggesting that timing behavior is driven by memory traces of preceding timing experiences (Los, Kruijne, & Meeter, 2014, 2017; Taatgen & van Rijn, 2011) – Zhao et al. (in press) implemented a PRP paradigm and provided direct evidence that sequences of time intervals (here: SOAs) can (a) be learned and (b) used in a predictive way, thereby reducing (global) dual-task costs. Fischer and Dreisbach (2015) could even demonstrate a very flexible (i.e., trialwise) up- and down-regulation of task shielding activities due to an increased predictability of the SOA lengths. The BCE for items predicting short SOAs (bearing a high risk for between task interference) was smaller than for items predicting long SOAs. Wendt and Kiesel (2011) reported similar findings in a single-task flanker experiment (Eriksen & Eriksen, 1974). Predictable foreperiods (i.e. time intervals before the onset of target and flankers) were utilized as cues for flexible conflict adaptation in case of interference from incompatible flankers. Interestingly – but potentially untenably – Schmidt (2013; see also Schmidt, Lemercier, & de Houwer, 2014) even suggested that findings usually interpreted as evidence for flexible conflict adaptation (for a review, see Bugg & Crump, 2012) are nothing more than manifestations of temporal expectancies as the result of context-dependent temporal learning (of one's own response rhythms).

In sum, evidence from many fields of research suggests that prediction is indeed central for cognitive processing – and predictability beneficial for optimizing the performance. Assuming that multitasking situations provide optimal testbeds for the investigation of the capabilities and limits of human motor cognitive interaction (Broeker et al., 2017; Koch et al., 2018), the present three series of experiments aimed at (re)investigating in detail the causes for the impairment of dual-task implicit sequence learning – with particular attention to the potential role of prediction and predictability.

Overview of the present studies

The rationale for the present studies was derived by considering that many earlier accounts of impaired implicit sequence learning in dual-task contexts are in line with the assumption that the insufficient separation of crucial processes for sequence learning (or of whole task representations) might be the main cause for its disruption (in combination with a low predictive value of across-task events). Within a dual-task paradigm originally introduced by Schumacher and Schwarb (2009), holding the general dual-tasking procedure (in main parts) constant across all experiments, especially two accounts were contrasted: the task integration account by Schmidtke and Heuer (1997; see also Rah et al., 2000) and the parallel response selection account (Schumacher & Schwarb, 2009).

The aim of the first study (Chapter 2) was to reinvestigate several assumptions why implicit sequence learning might be impaired in dual-task situations that have been suggested in the literature since the seminal study of Nissen and Bullemer (1987). Keeping the (visual-manual) SRTT constant across all experiments and conditions, the stimuli and the response requirements in the additional (auditory-vocal) tone-discrimination task were manipulated. To foreshadow, in line with the assumed omnipresence of prediction, the results of study 1 most prominently indicated that the predictability of the tones (on the basis of the SRTT) is indeed the crucial factor for the impairment vs. the preservation of implicit sequence learning in dual-task contexts – at least as long as an automatic tendency to integrate the two tasks is not prevented by an appropriate manipulation.

In the second study (Chapter 3), the role of across-task predictability was investigated in more detail. Considering that, depending on the structure of the SRTT sequence – i.e., whether its transitional probabilities are unique or ambiguous (cf. Cohen et al., 1990) – the local and the global across-task predictability must be discriminated, the standard 8-element ambiguous (2^{nd} order) SRTT was combined with to-be-discriminated tones that were either locally or globally predictable. It turned out that locally predictable tones (in principle capable of disambiguating ordinal sequence positions) were less useful than globally predictable tones. Potentially, the global across-task predictability reduced the frequency of response conflicts due to wrong predictions (and the necessity to inhibit features of the SRTT) as a consequence of integrated task representations – thereby preserving sequence learning.

In the third study (Chapter 4), the parallel response selection account of Schumacher and Schwarb (2009) once again came into focus. The goal was to investigate to what extent participants in a dual-task situation can efficiently exploit predictably varying SOAs in order to optimize their processing strategies – and learn the SRTT sequence despite random tones. Pitting the assumption that PRP-like varying SOAs trigger a global serial processing strategy (Israel & Cohen, 2011) against the assumption that participants (not receiving prioritization instructions) rather prefer moderately parallel processing (Lehle & Hübner, 2009), it turned out that the latter assumption is probably more appropriate. Implicit learning only occurred together with long SOAs, that is, fully automatically and mechanistically but not flexibly and strategically with short SOAs as well. Backing away from the concept of parallel and serial processing (e.g., Miller et al., 2009) this outcome hints, again, at the importance of separate task representations in the face of co-occurrences with low predictive value – highlighting, in addition, the bottom-up nature of the temporal separation of task representations.

2 Implicit sequence learning despite multitasking: The role of across-task predictability

One often replicated finding is that implicit sequence learning is hampered in dual-task situations. Thus, one crucial question has been whether implicit learning processes require attentional resources. Meanwhile, focusing exclusively on limited attentional resources might be considered as too unspecific. Overall, the focus lies now rather on the possibility that the impairment is due to interference coming along with (a) task integration (see also Schmidtke & Heuer, 1997) – or with (b) parallel response selection (Schumacher & Schwarb, 2009). Yet, other explanations have also been put forward – and there is still no agreement.
Our goal here is to contribute to this debate by testing several constraints that have been suggested in the literature within one single paradigm, originating by Schumacher and Schwarb (2009). Therefore, we paired the same visual-manual serial reaction time task (SRTT; Nissen & Bullemer, 1987) with different auditory-vocal tone-discrimination tasks across seven dual-task conditions. We manipulated (a) its relation to the SRTT and/or (b) the difficulty of response selection. The results suggest that task integration is indeed a crucial factor for implicit sequence learning: Since the tone- task is a potential source of noisy patterns of covariation in a complex arrangement of task components, sequence learning is disrupted. In line with Rah, Reber, and Hsiao (2000), the usefulness (in terms of sequence learning) of task integration seems to depend on the predictive value of across-task stimulus and/or response events.

Implicit learning is assumed to be one of the most fundamental learning processes enabling humans to exploit regular structures inherent in the environment (see, e.g., Dienes & Berry, 1997). They do this without any intention or additional effort and even without being consciously aware that they learn or what they actually learn.

Even though implicit learning is considered a rather robust phenomenon (e.g., Reber, 1993), many findings suggest that implicit learning is diluted when participants are instructed (e.g.) to count the occurrence of one of two randomly presented tones while performing an implicit learning task (Cohen, Ivry, & Keele, 1990; Curran & Keele, 1993; Frensch, Buchner, & Lin, 1994; Frensch, Lin, & Buchner, 1998; Frensch, Wenke, & Rünger, 1999; Heuer & Schmidtke, 1996; Keele, Ivry, Mayr, Hazeltine, & Heuer, 2003; Nissen & Bullemer, 1987; Schmidtke & Heuer, 1997; Schumacher & Schwarb, 2009; Stadler, 1995). Yet, there has been no agreement about the explanation why such a secondary task impairs implicit learning. Our goal here is to contribute to this debate by testing – within one single paradigm – several constraints leading to an impairment of implicit learning in a dual-task situation.

Implicit learning in dual-task situations

One of the most frequently used tasks in the field of implicit learning is the serial reaction time task (SRTT; Nissen & Bullemer, 1987). In the standard SRTT, participants see locations on the screen which are mapped to spatially corresponding keys. They are instructed to press the appropriate response key whenever a target stimulus, e.g., an asterisk, occurs at a certain location. Unbeknownst to the participants, these target locations follow a regular sequence. After several blocks of practice, the regular sequence is replaced by a random sequence. This leads to performance decrements that disappear almost immediately when the original regularity is reintroduced. Importantly, usually participants are not able to explicate their acquired knowledge when asked to do so.

Since the introduction of the SRTT, one crucial question has been whether implicit learning processes require attentional resources (e.g., Cohen et al., 1990; Curran & Keele, 1993; Nissen & Bullemer, 1987). In order to investigate this question, many researchers presented the SRTT together with a secondary tone-counting task. In the most frequently used setup, participants respond with a manual key press to the target location on the screen. Shortly after the key press [i.e., in the response-stimulus interval (RSI)] a high- or a low-pitched tone is randomly presented and the participants are instructed to count, for instance, only the high tones. Then, the next trial starts with the asterisk occurring at a different location. At the end of each block, the participants have to report the total number of counted tones.

Overall, the results obtained within this paradigm seem to show that the processes involved in implicit sequence learning are disturbed under such dual-task conditions suggesting that these processes, indeed, depend – to some degree – on attentional resources (for excellent overviews, see Keele et al., 2003; Schumacher & Schwarb, 2009).

However, explaining the impairment of implicit sequence learning by merely focusing on limited attentional resources might be considered as too unspecific. Many alternative explanations have been proposed but the debate on how to best account for these findings is still going on. For instance, Frensch and colleagues (1998; 1999) have argued to differentiate between effects that the secondary task might exert on sequence learning vs. on the impact of sequence knowledge on performance. The reaction time difference between blocks following the practiced sequence vs. containing randomly sequenced target stimuli (i.e., the measure of implicit learning) was present under single-task conditions but reduced when participants had to concurrently perform the secondary task. Therefore, the authors proposed that only the expression of learning is impaired, not the learning process itself (*suppression hypothesis*). Stadler (1995) assumed that implicit sequence learning in the earlier dual-task experiments was reduced due to the randomness of events (updating the tone-count or not) separating successive elements of the SRTT, thereby disturbing the organization of the sequence (*organizational hypothesis*). More extremely, Rah, Reber, and Hsiao (2000) suggested that, essentially, the "duality" of the standard combination of the SRTT and a tone-counting task is "illusory". The tone-counting task degrades the SRTT performance "not because it diverts attention, reduces short-term memory capacity, suppresses performance, and/or disrupts organization, but simply because it introduces a set of co-occurrences that have no predictive value" (p. 310). In a similar vein, Schmidtke and Heuer (1997) subsumed that task integration might be the reason why implicit sequence learning is impeded. They refrained from using the tone-counting task and instead instructed the participants to press a foot-pedal in response to one of the two tones (go/no-go task). Furthermore, in some of their experiments the tones were not presented randomly, but either followed a 6-elements or a 5-elements sequence. Thus, the tones were correlated with the 6-elements SRTT sequence to a high or to a lower degree. Schmidtke and Heuer found larger amounts of sequence learning with the 6-elements tone-sequence than with the 5-elements tone-sequence in a dual-task test. From this finding, they concluded that the participants had integrated the tone-task into the SRTT resulting in an easy to learn 12-elements sequence in the former and a more difficult 60-elements sequence in the latter case (*task integration hypothesis*).

In an attempt to integrate the findings and assumptions in the field of dual-task implicit learning, Keele et al. (2003) proposed the *dual-system model of sequence representation*. Here, the assumption is that implicit sequence learning relies on two independent representational systems – the unidimensional and the multidimensional system. Learning in the unidimensional system is thought to represent associations within single dimensions. This system works independently of attention. It is sufficient as a selection criterion that an event in the environment belongs to one dimension. By contrast, the multidimensional system is thought to form associations across different dimensions and therefore requires attention to select information in the environment. With regard to dual-task learning, the crucial point in the dual-system model is that the secondary tone-task is thought to impede learning in the multidimensional system, whereas learning in the unidimensional system is preserved. Thus, occasional observations of implicit sequence learning in dual-task paradigms should result exclusively from (residual) learning within the unidimensional system.

Albeit this model has largely contributed to our understanding of implicit learning, two potential weaknesses should be mentioned: First, Keele et al. had only loosely defined what the term "dimension" means. The findings of Eberhardt, Esser, and Haider (2017) suggest that this term "dimension" refers to single feature codes (e.g., location, color, shape etc.) irrespectively of whether these codes belong to the stimulus or to the response. Other researchers, however, assume that stimuli or responses constitute different dimensions (e.g., Abrahamse, Jiménez, Verwey, & Clegg, 2010). Second, the assumption of residual learning within the unidimensional system might also be ambiguous. As detailed below, the participants in all experiments reported so far were asked to respond to only one of the two presented tones. That is, in approximately 50% of the trials, they experienced a single-task situation (at least under the assumption that merely presenting a secondary stimulus does not already disrupt learning in the multidimensional system). Thus, it is conceivable that the "dual-task" learning had simply been preserved during the single-task trials.

More recently, Schumacher and Schwarb (2009) reported dual-task experiments in which the participants were instructed to respond to both stimuli in every trial (i.e., to respond manually to the visually presented SRTT stimuli and verbally to the tones). However, they also presented both stimuli simultaneously and not, as was done in most of the former experiments, within the RSI of the SRTT. Their findings suggest that under this condition, implicit sequence learning is absent – at least when participants treat both tasks with equal priority. They surmise that it is the central capacity sharing (Tombu & Jolicoeur, 2003, 2005) – or, in other words, the demand for *parallel response selection* that impedes implicit sequence learning.

Overall, this short overview reveals that the research focusing on implicit learning in dual-task situations does not provide a consistent picture – neither on the empirical nor on the theoretical side. On the empirical side, even subtle changes in the experimental setups and research designs might have provoked differences in the task representations (cf. Abrahamse et al., 2010). This, in turn, could have contributed to the divergent findings and complicates comparisons across studies. For instance, in many experiments, the participants had to count (or to respond to) only one of the tones (e.g., Cohen et al., 1990; Curran & Keele, 1993; Frensch et al., 1994; 1998; 1999; Heuer & Schmidtke, 1996; Nissen & Bullemer, 1987; Schmidtke & Heuer, 1997; Stadler, 1995), whereas in other experiments a response to every tone was required (e.g., Schumacher & Schwarb, 2009). These differences in the experimental procedures make it difficult to decide whether any preservation of implicit sequence learning under dual-task conditions was obtained because learning in the unidimensional system (Keele et al., 2003) was left intact or because participants had experienced a single-task situation in about 50% of the trials. Furthermore, even though many researchers had used the tone-counting task (with the tones occurring in the RSI of the SRTT), they had used sequences that differed in complexity (see, e.g., Cohen et al., 1990). Thus, it is not clear whether the complexity of the sequence might have affected the amount of implicit learning in dual-task conditions. Larger changes concern the requirements of the secondary tone-task. Some researchers refrained from using the tone-counting task. Instead, they instructed the participants to press a foot-pedal (Schmidtke & Heuer, 1997; go/no-go task) or to respond verbally to the tones (Schumacher & Schwarb, 2009; tone-discrimination task).

Variation in methods parallels variation in theoretical accounts of the impact of dual-tasking on implicit sequence learning. On the one hand, impaired sequence learning has been attributed to interference coming along with parallel response selection (Schumacher & Schwarb, 2009). Participants face difficulties to perform response selection in parallel for two tasks. As response selection has been attributed a major role in implicit sequence learning (e.g., Willingham, Wells, Farrell, & Stemwedel, 2000), disturbing response selection might hamper sequence learning. On the other hand, it has been suggested that the sequence learning decrements under dual-task conditions are based on (partial) randomness of the responses rather than on the requirements for simultaneous response selection. Keele et al. (2003) suggested that combining a task with a regular sequence of events and a task with a random sequence of stimuli and responses complicates the learning problem for the organism in case that the events in the two tasks are represented together. In such a compound representation the randomly sequenced stimuli and responses would reduce predictability. Integrating the two tasks can negatively affect implicit learning when events in one task are randomly sequenced and therefore have no predictive value (e.g., Rah et al., 2000; Schmidtke & Heuer, 1997).

The Present Study

The goal of the present study was to further investigate the reasons why implicit sequence learning is impeded in dual-task situations. For this purpose, we used an experimental setup similar to the variant of the dual-task paradigm used by Schumacher and Schwarb (2009; Experiment 1). While keeping the (visual-manual) SRT task constant across all experiments and conditions, we varied stimuli and response requirements in the (auditory-vocal) tone-discrimination task. Taking into account that it is still unclear whether the learning process itself or only the expression of the acquired knowledge is disturbed (Frensch et al., 1998; 1999), we generally assessed implicit learning effects under single-task conditions.

Altogether, we investigated eight experimental conditions which we grouped – according to the superordinate questions they address – into four experiments. The first three conditions (Experiment 1) aimed at replicating the finding of Schumacher and Schwarb (2009) that implicit learning is absent when the participants are asked to respond to the (randomly presented) tones in every trial. In addition, we tested if the impairment of implicit learning could be reduced when the dimensional codes of both tasks are made maximally different. In one condition, like in the experiments of Schumacher and Schwarb (2009), participants were required to say "high" vs. "low" to high vs. low pitched tones. These responses might be represented in terms of spatial codes and therefore might increase the interference between the tone-task and the (also spatially coded) SRTT (cf. Eberhardt et al., 2017; Koch, 2009; Wenke & Frensch, 2005). Therefore, we additionally tested a condition in which participants responded with arbitrary words ("blue" and "yellow") to the timbre of two tones. These two conditions were compared to a third control condition in which participants only received the SRTT (single-task condition).

The next four conditions (Experiment 2 and 3) aimed at testing more directly the task integration account proposed by Schmidtke and Heuer (1997) against the parallel response selection account of Schumacher and Schwarb (2009). In Experiment 2, we focused on factors that might preserve implicit learning in dual-tasking, whereas Experiment 3 was dedicated to the Schumacher and Schwarb assumption that facilitating the response selection process should reduce the impairment of implicit sequence learning.

In the last condition (Experiment 4), we then tested in particular if the tone-task impairs implicit learning because it introduces a set of co-occurrences that have no predictive value as suggested by Rah et al. (2000).

General Method

Apparatus and stimuli

The experiment was controlled by custom-written software (Lazarus/FreePascal, compiled for Microsoft Windows). In all conditions, the visual stimuli in the SRTT consisted of four horizontally aligned white squares (100 x 100 pixels, with a distance of also 100 pixels) on a grey background (see Figure 1). They were displayed slightly below the center of a TFT monitor (19 inch; 1280 x 1024 pixels) that was connected with a standard PC. Each square was mapped to one of four response keys (Y, X, N, M on a QWERTZ-keyboard; spatially compatible mapping). In each trial, an uppercase "X" occurred for 100 ms as the visual target in one of the four white squares signaling the participants which key had to be pressed. Unbeknownst to the participants, in all conditions the successive locations of the target followed a second order conditional 8-elements sequence (3-1-2-4-1-3-4-2).

If not otherwise described in the method sections of the experiments, the tone-task consisted of a random sequence of high (900 Hz) and low (300 Hz) tones lasting 56 ms and required a verbal response [saying "hoch" (high) in the case of a high tone or "tief" (low) in the case of a low tone]. For tone presentation and registration of verbal responses we used a head set. A sound mixer (Behringer XENYX 302USB) served as a bridge between headset and PC and integrated the tone stimuli with the verbal responses into one single wave-file per trial. The tone-task was analyzed offline, after the experiment.

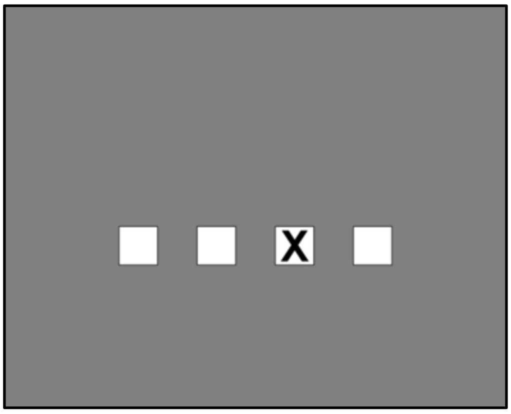

Figure 1. Screenshot of the SRT task. The target in each trial was an uppercase "X".

Procedure

All participants were introduced step by step into the dual-task training phase. They started with 20 practice trials with only the tone-discrimination task. Subsequently, they also practiced 20 trials of the SRTT and then another 20 trials of the dual-task. In all these practice trials, the stimuli of both tasks did not follow any regular sequence.

After these practice trials, the participants performed 6 dual-task training blocks of 96 trials each. In all conditions, the SRTT followed the 8-element sequence. In each block, the sequence started at a random position. A dual-task trial began with the simultaneous presentation of the visual SRTT target (the "X") and one of the two auditory stimuli of the tone-discrimination task [stimulus onset asynchrony (SOA) = 0 ms]. The participants were instructed to give both responses – the manual SRTT response and the verbal response to the tone – as fast and as accurately as possible in a freely chosen order and with "equal priority" (see Schumacher & Schwarb, 2009, Experiment 1 and 2). The response-window closed 2000 ms after the stimulus-onset and the next trial started immediately. In the single-task control condition (Experiment 1), the timing was identical, but the tones were not presented.

After the 6 dual-task blocks, the participants were transferred without further instruction to 3 single-task test blocks presenting only the SRTT. Of these test blocks, blocks 7 and 9 were (pseudo-)random blocks (i.e., the visual target locations followed a random sequence with the constraint that immediate location-repetitions were not allowed). Block 8 was a regular block in which the targets again followed the trained sequence.

At the end of the experiment, participant's explicit sequence knowledge was assessed. For this purpose, we first asked the participants whether they believed that they had been assigned to a SRTT-condition in which the stimuli followed a random or a regular sequence. Subsequently, they were informed that they had been in the regular condition and were asked to try to name the sequence. Participants were categorized as having complete explicit knowledge when they were able to name the entire sequence. Participants who could name at least six successive sequence elements were categorized as having partial explicit knowledge about the sequence.

Design

Since our main research question concerned the constraints leading to preserved implicit sequence learning in dual-task situations, we analyzed our different experimental conditions separately. By choosing this approach, we aimed at avoiding the occurrence of non-interpretable interactions. For the training blocks, we conducted one-way repeated measures ANOVAs with mean RTs as dependent variables separately for each condition and task. To assess the implicit learning effects in each condition, we conducted (two-tailed) *t*-tests with mean RTs and error rates as dependent variables between the pooled two random blocks 7 and 9 and the regular block 8. Since we found rather strong speed-accuracy trade-offs in the first half of block 7 in all dual-task conditions, we included only the second half of block 7 in these *t*-tests. This strong speed-accuracy trade-off might have been due to the fact that block 7 – the first single-task block – started without any further instruction. This might have led the participants to newly adjust their speed and accuracy.

In all analyses, trials were excluded if an error had occurred in the SRTT or if the vocal response in the tone-discrimination task could not be correctly classified. Additionally, RTs faster than 200 ms (both tasks) or slower than 1500 ms (SRT task only) were excluded. Furthermore, the data set of a participant who made more than 30% errors in at least one block of the SRTT was replaced by that of a new participant to ensure having equal numbers of participants in each condition (n = 25).[1] Whenever the assumption of sphericity was violated, Greenhouse-Geisser corrections are reported.

[1] In Experiment 2 (30% responses condition), we expanded our standard error criterion and additionally replaced the data of participants who responded to the wrong tone in more than 15% of the respective trials. We did this because a rate of 15% of this special kind of error already increases the amount of dual-task trials by one third.

Experiment 1: Is reduced implicit sequence learning in dual tasking due to code overlap within the unidimensional system?

The goal of Experiment 1 was, first, to replicate the finding of Schumacher and Schwarb (2009) that implicit learning vanished when participants responded to simultaneously presented random secondary task tones in all training trials. Such a finding seems to be at odds with the assumption of Keele et al. (2003) that conducting a secondary task disturbs sequence learning only in the multidimensional- but not in the unidimensional system. However, it is conceivable that the verbal "high"-"low" responses in the Schumacher and Schwarb experiments led the participants to represent the tone-task (like the SRT task) in terms of spatial codes – resulting in interference within the unidimensional system (cf. Eberhardt et al., 2017). To also test for this alternative account, we investigated two different dual-task conditions and one single-task condition in Experiment 1.

The first dual-task condition (*spatial condition*, hereafter) was a replication of the "equal priority" condition of Schumacher and Schwarb (2009, Experiment 1 and 2). As described in the "General Method" section, we used a high and a low pitched tone as auditory stimuli. Participants had to respond to them by saying "high" or "low". In the second dual-task condition (*arbitrary condition*), we used two tones that did not differ in pitch but in timbre - and the participants had to respond to them by saying "blue" or "yellow". Thus, the tone-task in the arbitrary condition should not activate spatial codes. If, in former studies, the code overlap had contributed to interference in the unidimensional system, the participants should show at least some implicit learning in this condition. In the *single-task condition*, participants did not receive any tones during training.

Method

Participants

75 students (16 men) of the University of Cologne (mean age 23.55, *SD* = 4.15) participated in the experiment either for monetary compensation or for course credit. They were randomly assigned to one of the three conditions. Each session lasted approximately 45 min.

Apparatus and stimuli

Apparatus and stimuli were as described in the "General Method" section. The only exception was that participants in the arbitrary condition received either a sinus-tone or the sound of a bike-bell as the auditory stimuli (both tones at approximately 300 Hz). They were asked to respond by saying “gelb” (yellow) to one sound and “blau” (blue) to the other (counterbalanced across participants). In the single-task condition, all participants received only the SRTT.

Procedure

The procedure followed the description given in the “General Method” section.

Results and Discussion

Due to our exclusion criteria, 12.2%, 13.7% and 8.0% of all trials in the spatial, the arbitrary and the single-task conditions, respectively, were excluded from the analysis.[2] Furthermore, we replaced the data of five participants in the single-task control condition. We first report the results of the training blocks, followed by the results of the test blocks.

Performance in the training blocks

Table 1 displays the mean RTs in the SRTT and the tone-discrimination task as a function of block and condition. As can be seen, in all three conditions the mean RTs in both tasks decreased across the six training blocks. Accordingly, the one-way ANOVAs with mean RTs as dependent variable (see Table 2) separately conducted for each condition and task, all revealed significant main effects of block. The only exception was the single-task control in which participants did not show any acceleration across training. There are at least two potential reasons for this finding. First, due to the rather short SRTT sequence, the learning process could have been already completed by the end of the first block. Second, the fact that the response window was fixed, may have offered less incentive for a more pronounced speed-up of responding. Additionally, the overall slower mean RTs in the tone-task suggest that participants had responded, on average, to the SRTT first.

Mean error rates in the SRTT were overall very low (1.40%, 1.43%, and 2.36% in the spatial, the arbitrary, and the control conditions, respectively). The corresponding analyses of the error rates did not reveal any significant effects.

---

[2] In the SRT task (9 blocks), 0.9% / 0.9% / 5.9% of the trials were classified as RT outliers and 2.1% / 1.7% / 7.2% of the trials were excluded due to errors in the spatial / arbitrary / single-task condition, respectively. In the tone-discrimination task (6 blocks), 0.1% / 0.1% of the trials were classified as RT outliers. In 14.9% / 17.5% of the trials the voice-key data in the spatial / arbitrary condition, respectively did not match the required response. As some trials also fulfilled multiple exclusion criteria, overall 12.2% / 13.7% / 8.0% of all trials were excluded.

Table 1. Mean RTs and SDs in the SRTT and the tone-discrimination task as a function of block and condition in Experiment 1.

Condition	SRTT Spatial		SRTT Arbitrary		SRTT Single-Task		Tone-Task Spatial		Tone-Task Arbitrary	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Block 1	606	155	593	153	416	48	749	154	791	154
Block 2	597	170	592	149	414	45	743	160	760	141
Block 3	584	160	585	140	422	47	719	154	751	147
Block 4	581	172	567	144	429	57	709	168	723	140
Block 5	558	158	563	141	415	56	688	154	721	149
Block 6	550	153	544	158	407	48	678	167	698	157
Block 7 (R)	440	81	419	64	435	55				
Block 8	433	83	416	73	411	72				
Block 9 (R)	440	73	421	65	437	66				

Table 2. Results of separate one-way ANOVAs for each condition and task as a function of the six training blocks in Experiment 1 with RTs as dependent variable.

Main effect "Block"	SRTT			Tone-Task		
	$F(5,120)$	p	η_p^2	$F(5,120)$	p	η_p^2
Spatial	8.19	< .001	.254	13.49	< .001	.360
Arbitrary	4.75	= .002	.165	9.25	< .001	.278
Single-Task	2.10	= .106	.080			

Performance in the test blocks

To assess sequence learning in the SRT task, we compared the RTs averaged across the random blocks 7 and 9 with the mean RTs in the regular block 8 (see Figure 2). The three *t*-tests revealed that only the participants in the single-task control condition showed a substantial learning effect of 26 ms, $t(24) = 3.26$, $p = .003$, $d = 0.651$. The respective differences in the two dual-task conditions were rather small (7 ms, $d = 0.236$ in the spatial condition and 5 ms, $d = 0.169$ in the arbitrary condition) and were not significant (both $|t| \approx 1$).[3] The corresponding analyses of the error rates revealed no significant effects.

[3] In Experiment 1, 9 participants reported full/partial SRTT sequence knowledge. Full sequence knowledge was reported by 1 participant in the spatial condition and 3 participants in the single-task condition. Partial sequence knowledge was reported by 4 participants in the spatial condition and 1 participant in the arbitrary condition. When these 9 participants were excluded from the test blocks analysis, the pattern of results (RTs and error rates) remained unchanged.

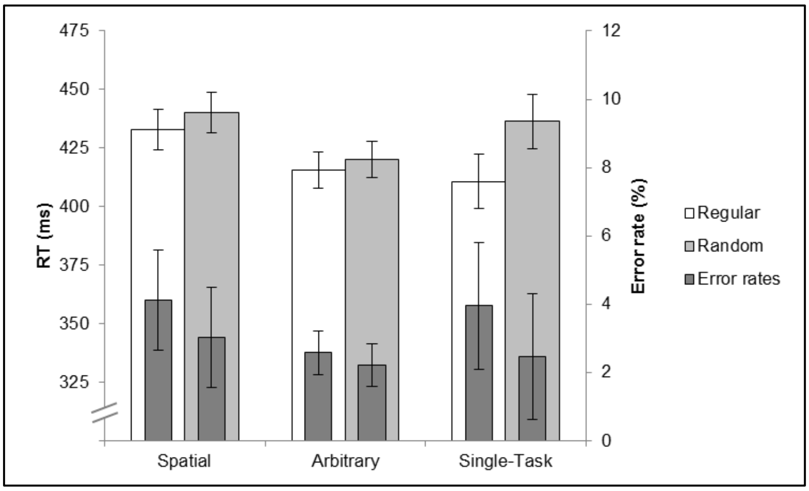

Figure 2. Mean RTs (left y-axis) and error rates (right y-axis) in the regular and the random single-task SRTT test blocks within the spatial, the arbitrary, and the single-task control condition of Experiment 1. Error bars are the 95% within-subjects confidence intervals of the learning effect calculated separately for each condition (Loftus & Masson, 1994).

Taken together, the results of Experiment 1 show implicit learning effects in the single-task condition but not in the two dual-task conditions. This pattern of results replicates the main findings of Schumacher and Schwarb (2009). Furthermore, finding no significant implicit learning effect in the arbitrary condition – in which the potential code overlap between the SRTT and the tone-task was maximally reduced – suggests that the secondary tone-task in the Schumacher and Schwarb experiments did not impair implicit learning due to an additional interference within the (spatial) unidimensional system (Keele et al., 2003). Rather, it seems that the tone-task impedes the implicit learning process on a more global level.

Contrary to the suppression hypothesis (Frensch et al., 1998; 1999), we did not find any sequence learning, albeit we assessed it under single-task conditions. The results suggest that the implicit learning process itself – and not just the usage of implicit sequence knowledge – is disturbed in dual-task situations. However, note that the participants in the studies of Frensch and colleagues had to respond to the tone-task only in about 50% of the trials whereas in our- as well as in the Schumacher and Schwarb (2009) experiments, the participants were instructed to respond to the tones in every trial. Thus, it might be that, in the earlier experiments, the trials in which no secondary task response was required were sufficient to produce small implicit learning effects. Overall, the findings of Experiment 1 seem to speak against the suppression hypothesis and cast doubt upon the assumption that the preserved sequence learning in the earlier tone-counting experiments reflected residual learning within the unidimensional system (Keele et al., 2003). Experiment 2 served to further clarify this point.

Experiment 2: What preserves implicit sequence learning in dual-tasking?

The goal of Experiment 2 was (a) to test whether we would find preserved implicit sequence learning when the participants were instructed to respond to only one of the two tones. According to Schumacher and Schwarb (2009), parallel response selection is the crucial factor that impedes dual-task implicit sequence learning. Thus, a substantial amount of trials requiring no response selection for the secondary tone-task should preserve implicit learning. To investigate this hypothesis, we reduced the number of required tone-task responses from 100% to only 30% in the *30% responses condition*.

The additional question was (b) whether implicit learning effects would be obtained if the simultaneously presented tone-task and the SRTT were correlated. Schmidtke and Heuer (1997) had found implicit learning effects under such a condition and suggested that the learning of an integrated sequence is affected by the across-task predictability of stimulus (and response) events. In a similar vein, Rah et al. (2000) suggested that sequence learning can occur when events in one task are predictive of events in the other task (which is the case if they are correlated). Thus, if task integration or predictability across the two tasks is the crucial factor, we should find implicit learning in our *correlated-tasks condition*. By contrast, if, as it is assumed by Schumacher and Schwarb (2009), parallel response selection is the key factor, it should be irrelevant whether or not both tasks follow a correlated sequence – since even correlated tasks require parallel response selection.

Method

Participants

50 students (6 men) of the University of Cologne (mean age 23.44, *SD* = 3.60) participated in the experiment either for monetary compensation or for course credit. They were randomly assigned to one of the 2 conditions. Each session lasted approximately 45 min.

Apparatus and stimuli

Apparatus and stimuli were as described in the “General Method” section.

Procedure

The procedure followed the description given in the "General Method" section. The only exceptions were (a) that in the 30% responses condition only one of the two tones per block required a response. This tone occurred in approximately 30% of the trials. Its identity alternated from block to block in order to prevent the participants from ignoring one of the tones completely. In the correlated-tasks condition (b), the two tones (both requiring a response) followed a repeating 16-elements sequence (2-1-1-2-2-2-1-1-1-2-2-1-2-2-1-1) that was correlated with the 8-elements SRTT sequence.

Results and Discussion

Due to our exclusion criteria, 12.0% of the trials in the correlated-tasks and 5.7% of the trials in the 30% responses condition were excluded from the analysis.[4] Furthermore, we replaced the data of four participants (1 participant in the correlated-tasks condition and 3 participants in the 30% responses condition) as they exceeded our error criterion. Again, we first report the results of the training phase, followed by the results of the test blocks.

Performance in the training blocks

Table 3 displays the mean RTs in the SRTT and the tone-discrimination task as a function of block and condition. In the SRTT, the participants in both conditions became faster across the six training blocks. In the tone-task, only the mean RTs of the correlated-tasks condition decreased with practice. By contrast, the mean RTs of the 30% responses condition remained rather stable across the training blocks.

Accordingly, for the SRTT the two one-way ANOVAs with RTs as dependent variable revealed significant main effects of block (see Table 4). The two one-way ANOVAs for the mean RTs in the tone-task, however, yielded only a significant block effect for the correlated-tasks condition. Probably, the block by block alternation of the imperative tone might have reduced the training effect. The error rates in the SRTT were rather low (1.35% and 1.36% in the 30% responses and the correlated-tasks condition, respectively) and did not differ across blocks.

[4] In the SRT task (9 blocks), 0.8% / 0.3% of the trials were classified as RT outliers and 2.5% / 2.0% of the trials were excluded due to errors in the correlated-tasks / 30% responses condition, respectively. In the tone-discrimination task (6 blocks), 0.2% / 0.1% of the trials were classified as RT outliers. In 14.2% / 9.7% of the trials the voice-key data in the correlated-tasks / 30% responses condition, respectively did not match the required response. Additionally, 3.9% of the "no response" trials in the 30% responses condition were excluded because participants nevertheless responded to the (wrong) tone. As some trials also fulfilled multiple exclusion criteria, overall 12.0% / 5.7% of all trials were excluded.

Table 3. Mean RTs and SDs in the SRTT and the tone-discrimination task as a function of block and condition in Experiment 2.

Condition	SRTT				Tone-Task			
	30% Responses		Correlated-Tasks		30% Responses		Correlated-Tasks	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Block 1	499	83	565	98	726	141	743	122
Block 2	513	85	557	102	751	153	740	122
Block 3	489	71	545	104	737	168	725	124
Block 4	480	71	524	91	731	154	705	120
Block 5	480	76	524	111	719	149	709	130
Block 6	469	76	512	94	729	167	701	128
Block 7 (R)	450	62	430	40				
Block 8	440	60	424	52				
Block 9 (R)	451	69	443	41				

Table 4. Results of separate one-way ANOVAs for each condition and task as a function of the six training blocks in Experiment 2 with RTs as dependent variable.

Main effect "Block"	SRTT			Tone-discrimination		
	$F(5,120)$	p	η_p^2	$F(5,120)$	p	η_p^2
30% Responses	11.29	< .001	.320	1.59	= .200	.062
Correlated-Tasks	11.98	< .001	.333	4.48	= .004	.157

Performance in the test blocks

To assess whether the participants in the 30% responses and the correlated-tasks conditions had acquired knowledge about the sequence in the SRT task, we again compared the mean RTs in the random blocks 7 and 9 with those in the regular block 8. Figure 3 depicts these mean RTs for the two conditions (for comparison, the single-task control condition of Experiment 1 is also depicted). Two separate t-tests revealed significant learning effects in the 30% responses condition (11 ms), $t(24) = 2.09$, $p = .048$, $d = 0.417$ as well as in the correlated-tasks condition (15 ms), $t(24) = 3.59$, $p = .001$, $d = 0.718$.[5] The corresponding analyses of the error rates revealed no significant effects.

[5] In Experiment 2, 7 participants reported full/partial SRTT sequence knowledge. Full sequence knowledge was reported by 1 participant in the correlated-tasks condition. Partial sequence knowledge was reported by 4 participants in the correlated-tasks condition and 2 participants in the 30% responses condition. When these 7 participants were excluded from the test blocks analysis, the pattern of results (RTs and error rates) remained unchanged.

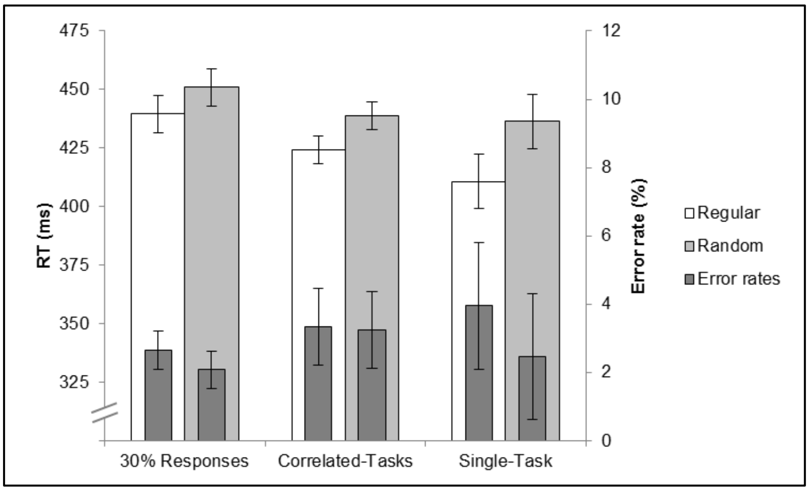

Figure 3. Mean RTs (left y-axis) and error rates (right y-axis) in the regular and the random single-task SRTT test blocks within the 30% responses and the correlated-tasks condition of Experiment 2 presented together with the single-task control condition of Experiment 1. Error bars are the 95% within-subjects confidence intervals of the learning effect calculated separately for each condition (Loftus & Masson, 1994).

Experiment 2 yielded small but significant implicit learning effects in both the 30% responses condition and the correlated-tasks condition. The finding of at least some sequence learning in the 30% responses condition suggests that the preserved implicit sequence learning in the earlier tone-counting experiments (e.g., Frensch et al., 1998; 1999; Stadler, 1995) was due to the fact that participants had to respond to the tones in only 50% of the trials. From the perspective of Schumacher and Schwarb (2009), participants might have learned the sequence because they could perform the SRTT partly under single-task requirements. However, note that a large proportion of (frequently successive) single-task SRTT trials does not only reduce parallel response selection requirements but also increases the predictive value of the respective events within the SRTT – because they are no longer separated by random secondary task (response) events. In addition, the finding of implicit learning effects in the correlated-tasks condition rather suggests that simultaneous response selection per se, as assumed by Schumacher and Schwarb (2009), is of minor importance. It replicates the results and supports the interpretation of Schmidtke and Heuer (1997) that implicit sequence learning in dual-task situations depends on whether or not the two tasks can be integrated.

Last but not least, together with the finding that eliminating potential code overlap between the two tasks did not preserve implicit sequence learning (Experiment 1), the results of the 30% responses condition (with a "spatial" tone-task) seem to speak against the assumption of Keele et al. (2003) that sequence learning in dual-task experiments reflects (residual) learning within the unidimensional system.

Experiment 3: Does facilitating the response selection process preserve implicit sequence learning?

The results of the correlated-tasks condition of Experiment 2 seem to be less in line with the account of Schumacher and Schwarb (2009) and better fit the task integration account (Schmidtke & Heuer, 1997). To again compare these two accounts, we implemented two further dual-task conditions in Experiment 3, the *ideomotor condition* and the *listen-only condition*.

In both conditions, the high and low pitched tones were replaced by the recorded spoken words "hoch" and "tief" ("high" and "low"). In the ideomotor condition, the participants' task was simply to repeat what they heard. Greenwald and Shulman (1973) already have shown that a task like this should facilitate response selection (see also Halvorson, Ebner, & Hazeltine, 2013). This, in turn, should reduce the dual-task costs – or, in terms of the Schumacher and Schwarb (2009) account – the duration of parallel response selection. Thereby, it should also reduce the impairment of implicit sequence learning. If so, we should find at least small implicit learning effects in the ideomotor condition. However, if the randomness of the tone-task is the crucial factor that disturbs the implicit learning process (Rah et al., 2000; Schmidtke & Heuer, 1997), any implicit learning effect again should be strongly reduced.

In the listen-only condition, the participants heard exactly the same auditory stimuli but did not have to respond to them. This condition served as a single-task equivalent control condition to ensure that merely hearing tones does not affect implicit learning.

Method

Participants

50 students (7 men) of the University of Cologne (mean age 23.20, *SD* = 3.03) participated in the experiment either for monetary compensation or for course credit. They were randomly assigned to one of the 2 conditions. Each session lasted approximately 45 min.

Apparatus and stimuli

Apparatus and stimuli were the same as described in the "General Method" section. The only difference concerned the stimuli in the tone-task as we replaced the sinus tones by the recorded words "hoch" (high) and "tief" (low). Fitting the gender of the participant, the words were spoken in either a male or a female voice. These voice-stimuli always lasted for 390 ms.

Procedure

Apart from the above mentioned replacements of the tone stimuli, the overall procedure followed the description given in the "General Method" section. In the listen-only condition, the participants were instructed to listen to the words without responding to them at all.

Results and Discussion

According to our exclusion criteria, overall 12.2% of the trials in the ideomotor and 6.7% of the trials in the listen-only condition were excluded.[6] Furthermore, we replaced the data of five participants (3 in the ideomotor- and 2 in the listen-only condition) as they exceeded our error criterion. Again, we first report the results of the training phase, followed by the test phase results.

Performance in the training blocks

Table 5 displays the mean RTs in the SRTT and the tone-discrimination task as a function of block and condition. Again, the participants in both conditions became faster over the course of the training. This was also true for the tone-task in the ideomotor condition. Consequently, the separate one-way ANOVAs with mean RTs as dependent variable revealed significant main effects of block in both conditions either for the SRTT or for the tone-task (see Table 6). The error rates in the SRTT were again rather low (1.67 % and 2.12% in the ideomotor- and the listen-only condition, respectively). The corresponding analyses revealed only a slight but significant difference of 1.17% (increasing from block 1 to 6) in the SRT task in the listen-only condition, $F(5,120) = 2.75, p = .038, \eta_p^2 = .103$.

[6] In the SRT task (9 blocks), 0.7% / 4.6% of the trials were classified as RT outliers and 2.5% / 6.1% of the trials were excluded due to errors in the ideomotor / listen-only condition, respectively. In the tone-discrimination task (6 blocks; ideomotor condition), 3.0% of the trials were classified as RT outliers. In 14.2% of the trials the voice-key data did not match the required response. As some trials also fulfilled multiple exclusion criteria, overall 12.2% / 6.7% of all trials in the ideomotor / listen-only condition, respectively were excluded.

To test whether the ideomotor compatible tone-task indeed facilitated response selection, we additionally computed the dual-task costs in the ideomotor condition (the difference between the mean RTs in the last training block and the regular block in the test phase). The dual-task costs were only 23 ms. Compared to the dual-task costs of the spatial condition (117 ms) and the arbitrary condition (128 ms) of Experiment 1, these dual-task costs are significantly smaller (t[48] = 3.56, p = .001, d = 1.007 and t[48] = 4.09, p < .001, d = 1.156, for the comparison between the ideomotor and the spatial condition and the ideomotor and the arbitrary condition, respectively). Thus, the ideomotor compatible task indeed reduced the response selection effort.

Table 5. Mean RTs and SDs in the SRTT and the tone-discrimination task as a function of block and condition in Experiment 3.

Condition	SRTT Ideomotor		SRTT Listen-Only		Tone-Task Ideomotor	
	Mean	SD	Mean	SD	Mean	SD
Block 1	484	79	447	78	553	88
Block 2	487	93	447	83	555	117
Block 3	478	97	436	83	538	116
Block 4	474	78	435	79	542	98
Block 5	469	81	426	78	530	112
Block 6	454	81	430	81	514	109
Block 7 (R)	443	63	442	74		
Block 8	431	61	420	79		
Block 9 (R)	434	58	436	76		

Table 6. Results of separate one-way ANOVAs for each condition and task as a function of the six training blocks in Experiment 3 with RTs as dependent variable.

Main effect "Block"	SRTT			Tone-discrimination		
	F(5,120)	p	η_p^2	F(5,120)	p	η_p^2
Ideomotor	4.39	= .007	.155	5.50	= .001	.186
Listen-Only	3.84	= .009	.138			

Performance in the test blocks

The sequence learning in the SRT task was again tested by comparing the mean RTs in the random blocks 7 and 9 with those in the regular block 8. The mean RTs are depicted in Figure 4. Two t-tests revealed a significant learning effect in the listen-only condition (18 ms), t(24) = 4.26, p < .001, d = 0.853, but not in the ideomotor condition (6 ms), t(24) =

1.46, p = .157, d = 0.293.[7] Surprisingly, the corresponding analysis of the error rates revealed in the ideomotor condition significantly less errors (difference of 1.07%) in the regular block 8 than in the two random blocks, $t(24) = 2.66$, $p = .014$, $d = 0.532$. In the listen-only condition, this difference (of 0.46%) was not significant, $|t| < 1$, $d = 0.195$.

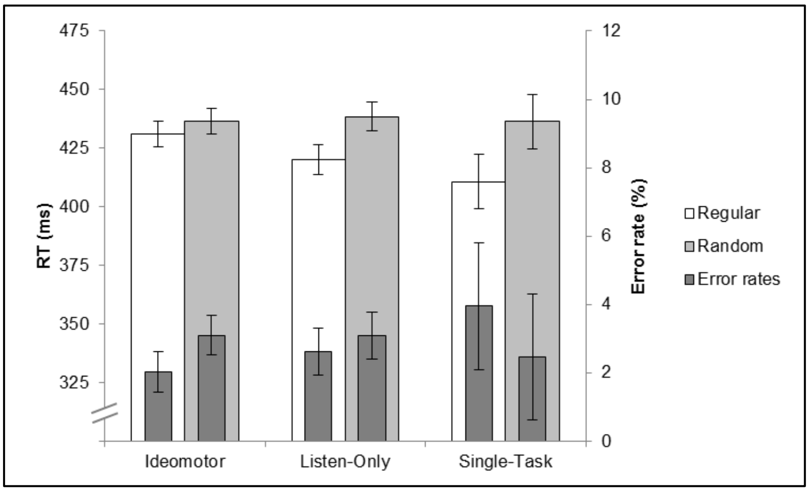

Figure 4. Mean RTs (left y-axis) and error rates (right y-axis) in the regular and the random single-task SRTT test blocks within the ideomotor and the listen-only condition of Experiment 3 presented together with the single-task control condition of Experiment 1. Error bars are the 95% within-subjects confidence intervals of the learning effect calculated separately for each condition (Loftus & Masson, 1994).

The results of Experiment 3 revealed that, as expected, the ideomotor compatible tone-task strongly reduced the dual-task costs. Nevertheless, implicit learning effects in the ideomotor condition were almost entirely absent. Only the error rates indicated a small learning effect. Thus, albeit somewhat ambiguous, it seems that facilitating the response selection process did not preserve implicit sequence learning. Since the participants in the listen-only condition showed substantial implicit learning effects, it seems as if the implicit learning process is impaired whenever participants have to produce a second response, irrespectively of how effortful it is to generate this response.

Together with the results of the correlated-tasks condition of Experiment 2, this finding suggests that the parallel response selection process per se (Schumacher & Schwarb, 2009) is not the critical factor for the impairment of implicit sequence learning. Rather, it seems to be the randomness of the verbal responses as we did find implicit learning in the

[7] In Experiment 3, 5 participants reported full/partial SRTT sequence knowledge. Full sequence knowledge was reported by 1 participant in the listen-only condition. Partial sequence knowledge was reported by 2 participants in the ideomotor condition and 2 participants in the listen-only condition. When these 5 participants were excluded from the test blocks analysis, the pattern of results (RTs and error rates) remained unchanged.

correlated-tasks condition. Thus, the entire pattern of results up to this point is fitted best by the assumption of task integration (e.g., Rah et al., 2000; Schmidtke & Heuer, 1997) leading the cognitive system to register (and to "try" to exploit) co-occurrences that have no predictive value.

Experiment 4: Does predictability of the tones affect implicit learning?

The goal of this last dual-task experiment was, once again, to investigate the role of task integration, or, more specific, the role of co-occurring (un)predictable tones on implicit sequence learning. For this purpose, 4 sequence positions of our standard SRTT were consistently presented together with one particular tone whereas the other 4 sequence positions were randomly paired with either of the two tones. Thus, only in the consistently paired trials, the SRTT response was predictive for the tone-task response or vice versa (e.g., Rah et al., 2000). It is important to note that from the consistently (or fixedly) paired SRTT positions, one position occurred in isolation and three in a short sequence (R_1-F_2-R_3-F_4-F_5-F_6-R_7-R_8; with F = fixedly paired SRTT positions, R = randomly paired positions). This enabled us to explore how within-trial predictability might affect implicit learning in dual-tasking. If the predictability between the SRTT and the tone-task is crucial for preserving implicit learning it remains an open question whether this predictability affects the association between the fixed SRTT-tone pair and the next SRTT-position (i.e., the association between F_2 and the SRTT position of R_3). Alternatively, it is also conceivable that the within-trial prediction is crucial for implicitly learning exactly this single SRTT position (i.e., learning F_2).

Method

Participants

25 students (2 men) of the University of Cologne (mean age 22.60, *SD* = 4.85) participated in the experiment either for monetary compensation or for course credit. Each session lasted approximately 45 min.

Apparatus and stimuli

Apparatus and stimuli were the same as described in the "General Method" section with the only exception that four positions of the 8-element SRTT sequence (3-1-2-4-1-3-4-2) were consistently paired with a particular tone (*fixedly paired* sequence positions) whereas the other four stimuli of the SRTT were randomly paired (*randomly paired* sequence positions;

i.e., 3*R*-1*L*-2*R*-4*H*-1*H*-3*L*-4*R*-2*R* [with *H* = fixedly paired, high tone; *L* = fixedly paired, low tone; *R* = randomly paired tone]).

Procedure

The procedure followed the description given in the "General Method" section.

Results and Discussion

According to our exclusion criteria, overall 12.8% of all trials were excluded.[8] Furthermore, we replaced the data of one participant due to our error criterion. Again, we first report the results of the training phase, followed then by the test phase results.

Performance in the training blocks

Since our main focus was on the potential difference between the fixed and the randomly paired SRTT-tone stimuli, we introduced the additional within-participants factor *type of sequence position* (fixedly vs. randomly paired sequence positions) in the analyses of results. Table 7 presents the mean RTs in the SRTT and the tone-discrimination task as a function of block and type of sequence position. As can be seen from Table 7, participants became faster over the course of the training in both the SRTT and the tone-task and with both types of sequence positions. Furthermore, the mean RTs were slower with the randomly paired than with the fixedly paired SRTT-tone stimuli. The two separate 6 (block) x 2 (type of sequence position: fixed vs. random) repeated measures ANOVAs with mean RTs in either tasks as dependent variable revealed significant main effects of block and type of sequence position – but no significant interactions (see Table 8). The difference of the mean RTs between the fixed and the randomly paired sequence positions in both tasks was already present in the first block (58 ms and 45 ms for the SRTT and the tone-task, respectively) and did not change across the training (block 6: 41 ms and 32 ms for the SRTT and the tone-task, respectively). Additionally, this difference between fixed and random SRTT-tone-task pairs occurred for each single sequence position (F_2: 37 ms; F_4: 47 ms; F_5: 49 ms; F_6: 54 ms, respectively, across the 6 training blocks in the SRTT). That is, even the responses to the isolated fixedly paired sequence position (i.e., F_2) were faster than those to the randomly paired positions.

[8] In the SRT task (9 blocks), 0.5% of the trials were classified as RT outliers and 2.3% of the trials were excluded due to errors. In the tone-discrimination task (6 blocks), 0.0% of the trials were classified as RT outliers. In 15.7% of the trials the voice-key data did not match the required response. As some trials also fulfilled multiple exclusion criteria, overall 12.8% of all trials were excluded.

The difference between fixedly and randomly paired SRTT positions was mirrored in the error rates of the SRT task [more errors in randomly- than in fixedly paired sequence positions (overall difference of 1.10%)], $F(1,24) = 7.55$, $p = .011$, $\eta_p^2 = .239$. No other effect within the analyses of error rates reached the level of significance.

Table 7. Mean RTs and SDs in the SRTT and the tone-discrimination task as a function of block and type of sequence position (fixed vs. randomly paired sequence positions) in Experiment 4.

	SRTT				Tone-Task			
Type of Sequence Position	Fixed Combinations		Random Combinations		Fixed Combinations		Random Combinations	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Block 1	542	105	600	111	725	132	770	142
Block 2	541	88	586	95	713	120	757	126
Block 3	521	102	567	103	695	114	733	116
Block 4	515	95	556	97	684	88	715	93
Block 5	511	105	559	110	673	99	709	108
Block 6	503	93	544	89	654	85	686	87
Block 7 (R)	423	56	428	45				
Block 8	413	60	456	60				
Block 9 (R)	441	59	440	51				

Table 8. Results of separate 6 (block) x 2 (type of sequence position) repeated measures ANOVAs for each task in Experiment 4 with RTs as dependent variable.

	SRTT			Tone-discrimination		
Block	$F(5,120)$	p	η_p^2	$F(5,120)$	p	η_p^2
	4.54	= .011	.159	6.55	= .001	.214
Type of Sequence Position	$F(1,24)$	p	η_p^2	$F(1,24)$	p	η_p^2
	93.58	< .001	.796	77.30	< .001	.763
Interaction	$F(5,120)$	p	η_p^2	$F(5,120)$	p	η_p^2
	1.50	= .194	.059	0.87	= .472	.035

Performance in the test blocks

In order to assess the implicit sequence learning effects in the SRTT, we compared the mean RTs in the random blocks 7 and 9 with those in the regular block 8. Again, we analyzed these learning effects separately for the two types of sequence positions; that is, the sequence positions that were – during training – either fixedly or randomly paired with the tones. The mean RTs are depicted in Figure 5. The 2 (block type: regular vs. random) x 2 (type of sequence position: fixed vs. random) repeated-measure ANOVA with mean RTs as dependent variable revealed a significant main effect of type of sequence position, $F(1,24) = 38.84$, $p < .001$, $\eta_p^2 = .618$, that was qualified by a significant interaction, $F(1,24) = 79.93$, $p <$

.001, η_p^2= .769. The main effect of block type was not significant (F < 1). Post-hoc t-tests showed that for the formerly fixedly paired sequence positions the mean RTs were significantly faster (22 ms) in the regular block 8 than in the random blocks 7 and 9, $t(24)$ = 3.59, p = .001, d = 0.717. For the randomly paired sequence positions, however, the mean RTs were significantly slower (-19 ms) in the regular block 8 than in the surrounding random blocks 7 and 9, $t(24)$ = -2.59, p = .016, d = -0.518.[9] Again, the learning effect was found for all four fixedly paired sequence positions (F_2: 23 ms; F_4: 26 ms; F_5: 17 ms, and F_6: 21 ms, respectively), but for none of the variably paired positions. The corresponding analyses of the error rates yielded a significant main effect of block type $F(1,24)$ = 6.46, p = .018, η_p^2= .212 and of type of sequence position $F(1,24)$ = 8.19, p = .009, η_p^2= .254, but no significant interaction, $F(1,24)$ = 3.42, p = .077, η_p^2= .125. Thus, participants made more errors in the random blocks than in the regular block (difference of 0.92%). In addition, they made more errors when the sequence positions were formerly randomly paired than when they were formerly fixedly paired with the tones (difference of 1.72%).

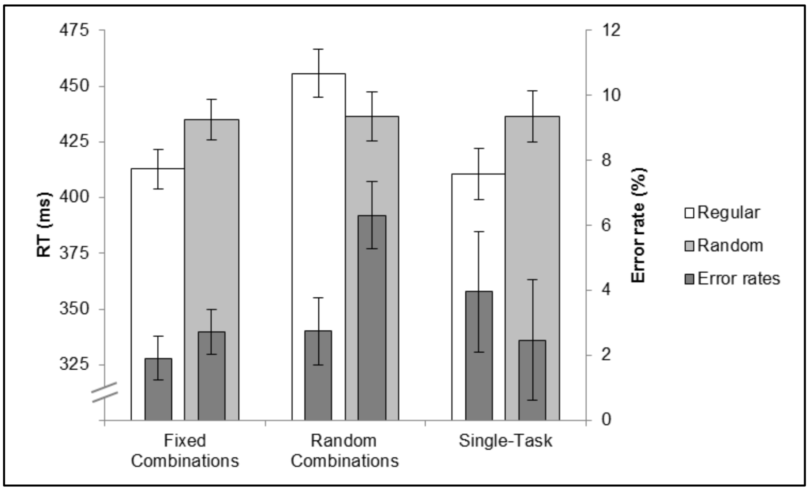

Figure 5. Mean RTs (left y-axis) and error rates (right y-axis) in the regular and the random single-task SRTT test blocks shown separately for SRTT positions that had been randomly paired versus fixedly paired with the tones during the training of Experiment 4. For means of comparison they are presented together with the single-task control condition of Experiment 1. Error bars are the 95% within-subjects confidence intervals of the learning effect calculated separately for each condition (Loftus & Masson, 1994).

Overall, the findings of this last condition revealed that the participants had implicitly learned only those sequence positions that had been consistently paired with the tones.

[9] In Experiment 4, no participant reported full/partial SRTT sequence knowledge. In our replication of Experiment 4 (see the discussion) with 10 new participants, one participant reported partial knowledge.

Basically, this finding suggests that the within-trial predictability between the SRTT and the tone-task seems to affect implicit learning. This seems to support the assumption that the crucial factor for implicit learning to occur in dual-task situations is whether or not the registered co-occurrences between the SRTT and the tone-task are predictive.

Interestingly, this within-trial predictability had not affected the associations between the SRTT response in a fixedly paired trial (e.g., F_2) and the SRTT response in a successive variably paired trial (e.g., R_3), even though the tone of this fixedly paired trial was predictive for the SRTT response of the next trial (e.g., Schmidtke & Heuer, 1997). Moreover, there are two points in the pattern of results which are not really consistent with the assumption that the participants had indeed implicitly learned the "content" of the fixedly paired SRTT sequence positions.

First, we found large performance differences between the fixedly and the randomly paired tone-SRTT stimuli already in the first block of the training phase. Implicit learning effects, however, should develop over time. Second, the mean RTs of the randomly paired sequence positions were slower in the regular block of the test phase than in the random blocks. Therefore, an alternative interpretation of our findings might be that the participants had rather learned a sequence of low versus high conflict laden trials.

The following mechanism is conceivable: First, although in each trial the tone and the SRTT-stimulus occurred simultaneously, the participants, on average, decided to respond to the SRTT-stimulus, first. As both stimuli were also presented very shortly (visual SRTT target = 100 ms; auditory stimulus = 56 ms), the participants had to maintain the tone (or the tone response) while responding to the SRTT-stimulus. In trials in which the tone- and the SRTT-stimulus are consistently paired, the SRTT-response always leads to the same tone-response. By contrast, in variably paired trials, the SRTT response might have predicted a different tone response than the tone stimulus did. This, in turn, might have produced a response conflict (reflected by slower RTs). Due to this response conflict, the learning mechanism might have been disturbed. That way, it is conceivable that participants had not learned parts of the sequence-content, but merely an abstract sequence of (e.g.) high-low-low-…-high conflict laden trials (see, e.g., Jiménez, Lupiáñez, & Vaquero, 2009).

In order to further investigate whether or not the participants had learned the content of the sequence, we replicated Experiment 4 with 10 new participants. The only difference between Experiment 4 and the replication was that we replaced the former test phase by a generation task containing two single-task blocks (see, e.g., Haider, Eichler, & Lange, 2011). In 20 of the 96 trials per test block, question marks occurred in all four white squares (instead of the usual target stimulus, the "X", in only one of the squares). The participants then had to generate (to guess) the correct response by pressing the corresponding key. These generation trials were equally distributed across all sequence positions (i.e., across the formerly fixedly or randomly paired SRTT-tone stimuli). After having pressed a key, the participants were asked to place a wager (either 1 or 50 Cent) regarding their confidence in the correctness of their response. The rationale is that participants with explicit knowledge should place high wagers when having responded correctly (e.g., Dienes & Seth, 2010).

The results of this replication showed that the participants indeed had learned the content of the formerly fixedly paired sequence positions. They generated 59.5% correct responses for the formerly fixedly paired sequence positions [including 68% for the isolated fixedly paired SRTT position (F_2)] which was significantly above the chance level of 33.33% [$t(9) = 7.76$, $p < .001$, $d = 2.455$]. By contrast, for the formerly randomly paired sequence positions the amount of correct responses was only 36% and not above chance level ($|t| < 1$, $d = 0.294$). In addition, the participants' knowledge was almost entirely implicit. With the formerly fixedly paired sequence positions, the participants placed a high vs. a low wager after having responded correctly in 63.4% vs 61.5% of cases, respectively ($|t| \approx 1$, $d = 0.064$). With the formerly randomly paired sequence positions, the participants placed a high vs. a low wager after having responded correctly in 34.7% vs 46.5% of cases, respectively ($|t| \approx 1$, $d = -0.397$).

Thus, these results suggest that the participants in Experiment 4 indeed learned exclusively the content of those sequence-positions that had been fixedly paired with the tones during training. These findings fit nicely Rah et al.'s (2000) assumption that the random tone-task degrades implicit learning simply because the participants always represent the SRTT and the (un)predictable tone-task together as one single task. They are also in line with the idea of Schmidtke and Heuer (1997) that implicit learning is preserved whenever the SRTT and the tone-task can be successfully integrated. However, one critical point appears to be that our findings suggest that this integration takes place solely within- rather than across trials (or across the entire sequence).

General Discussion

The goal of the present study was to investigate the constraints compromising implicit sequence learning in dual-task situations. In contrast to earlier dual-task implicit learning studies, we employed – in all our experiments – the same dual-task paradigm originating by Schumacher and Schwarb (2009). This enabled us to systematically test different theoretical accounts proposed in the literature to explain the reduced implicit learning effects under dual-task conditions.

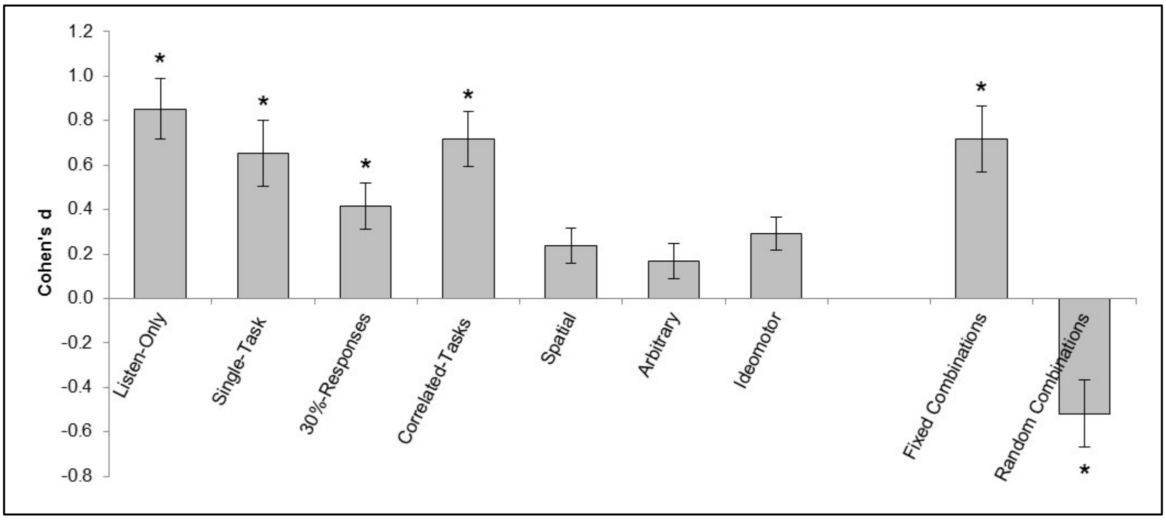

Figure 6. Cohen's d for the learning effect in each condition of the 4 Experiments in the order of being discussed in the "General Discussion" section. Error bars are the 95% confidence intervals of the effect sizes (see, e.g., Bühner & Ziegler, 2009).

Figure 6 summarizes the sizes of the implicit learning effects within the different conditions (Cohen's d). As can be seen, we found medium to large implicit learning effects when the participants received at least some single-task trials during the training (i.e., in the listen-only, single-task, 30% responses conditions, d = 0.417 to d = 0.853). Furthermore, implicit learning effects were also substantial when the tone-task and the SRTT followed different but correlated sequences (d = 0.718). By contrast, the implicit learning effects were reduced if the tone-task was presented in a random order and participants had to respond to it in all trials. This finding was independent of how time-consuming the response selection in the tone-task was. The d-values of the spatial, the arbitrary, and the ideomotor conditions are all small and of comparable size (between d = 0.169 and d = 0.293). Thus, neither reducing nor increasing the ambiguity of whether a particular stimulus (or response) belongs to task 1 or task 2 influenced the implicit learning effect (e.g., Halvorson, Ebner, et al., 2013). In Experiment 4, the effect size of the implicit learning effect for the fixedly paired sequence positions lies in the range of the effect sizes of the single-task condition (d = 0.717). Together with our replication, it seems justified to conclude that the participants in this condition had acquired implicit knowledge about those sequence positions that were consistently paired with the tones.

Overall, the pattern of results suggests that the relation between the SRTT and the tone-task is the critical factor affecting implicit learning in dual-task situations. If the tone-task was random, we found almost no implicit learning. By contrast, if there was a consistent relation between the SRTT-stimuli and the tones, as was the case in the correlated-tasks and the fixed-pair conditions, the implicit knowledge acquired during training lies in the range of single-task learning.

Since we always tested implicit learning under single-task conditions, the results are inconsistent with the suppression hypothesis (Frensch et al., 1998; 1999). They also suggest that the preserved implicit learning effects were not due to intact implicit learning in the unidimensional system as Keele et al. (2003) have proposed. We found almost no implicit learning in the spatial and the arbitrary conditions. If learning in the unidimensional system had been preserved under dual-task requirements, we should have found at least small learning effects in the arbitrary condition. Here, the difference of the codes between the SRTT and the tone-task was enlarged and hence any potential interference between the tasks should have been reduced.

In addition, albeit we could replicate the findings of Schumacher and Schwarb (2009) in our Experiment 1, the entire pattern of results seems not to be in line with their assumption that the requirement of parallel response selection per se impairs implicit sequence learning. By adding a condition in which spatial crosstalk between the tasks was not a feasible alternative explanation, we could provide stronger support for their claim that parallel response selection might cause the disruption of sequence learning in multitasking than provided in the original investigation. Yet, our further results were inconsistent with the proposition that parallel response selection causes the disruption of sequence learning in multitasking. First, we did not find clear implicit learning effects in the ideomotor condition; that is, when response selection for the tone-task was facilitated (Halvorson, Ebner, et al., 2013). Second, implicit learning should have been impaired in the correlated-tasks condition or in the fixed-paired sequence positions of Experiment 4 since also in these conditions, simultaneous response selection was inevitable. To hold for these latter findings, the Schumacher and Schwarb account requires at least the additional assumption that the concurrently selected responses only interfere if the two tasks are randomly paired. Without such an additional assumption, it appears that the pattern of results is best explained by the assumption that the impairment of implicit learning in dual-task situations is caused either by task integration (Schmidtke & Heuer, 1997) or by trying to predict events on the basis of co-occurrences that have no predictive value (e.g., Rah et al., 2000). In particular, the findings of our last experiment support this assumption. Only if the sequence position of the SRTT is consistently paired with a certain tone, implicit learning in dual-task situations is preserved.

Integration of events from two tasks might lead to activation of conflicting response tendencies as predicted responses (due to the random sequence in one of the tasks) often mismatch the response required by the stimulus actually presented in the SRTT. Such problems seem plausible as they have been documented in setups with two randomly sequenced streams of information (rather than just one stream, as in our case). For instance, work on feature binding (e.g., Dreisbach & Haider, 2009; Frings, Rothermund, & Wentura, 2007; Hommel, 1998; Moeller, Pfister, Kunde, & Frings, 2016) shows that repetition vs. alternation of irrelevant stimulus features of a prior trial affects performance in the current trial. For instance, if the irrelevant stimulus color is repeated from the last trial, the response that was due in that trial might be erroneously retrieved hampering performance in the current trial as it conflicts with the response required by the stimulus presented in the SRTT. Therefore, one conceivable explanation for the present pattern of findings is that task integration leads – in the case of variably paired SRTT-tone stimuli – to a response conflict due to incorrect predictions (see, e.g., Frings et al., 2007). This response conflict might be solved by inhibiting the activation of the SRTT response, which in turn would reduce the strengthening of associations between the successive positions of the SRTT sequence.

However, caution is needed as Experiment 4 did not provide a baseline. Hence, it is difficult to decide whether task performance has been facilitated by the fixed SRTT-tone pairings or whether indeed the integration of the variable pairings resulted in increased interference. In addition, the assumption of increased interference in the case of the variably paired SRTT-tone stimuli raises the question of how an implicit learning mechanism might work when some sequence positions are fixedly paired while others are variably paired. It is highly unlikely that the participants could have integrated the tone and the SRTT sequence into one single sequence (Schmidtke & Heuer, 1997). Currently, we suspect that the participants did not associate the successive sequence positions of the SRTT as is usually assumed in implicit SRTT learning (e.g., Cleeremans, 2011). Rather, what they might have associated is the ordinal sequence position of the certain event(s) (Schuck, Gaschler, & Frensch, 2012; Schuck, Gaschler, Kreisler, & Frensch, 2012). This would explain why they showed learning of unique sequence positions (e.g., F_2). Of course, at the time being, this is speculative and further research is needed.

The proposed explanation that participants always integrated the SRTT and the tone-task fits to several of the former findings concerning implicit learning in dual-task situations.

For instance, Schmidtke and Heuer (1997) found reduced implicit learning when presenting a 6-elements SRTT sequence together with a 5-element tone-task sequence. That is, the participants were confronted with a 60-element combined sequence. Consequently, much more trials should be necessary before the reduced activation of a single SRTT position suffices to become associated within a chain of sequence positions. Sequence learning should be impaired to the extent that there are trials leading to response conflicts due to incorrect predictions.

In former studies, dual-task implicit sequence learning was also found whenever there was a chance to keep the representations of the two tasks separate. For example, Schumacher and Schwarb (2009) found implicit learning effects when they separated the SRTT and the tone-task through long time intervals (Experiment 1: SOA = 750 ms). Additionally, it seems as if separate task representations can also be induced simply by instruction (Halvorson, Wagschal, & Hazeltine, 2013). In both cases, the tasks are probably represented as two separate tasks and are thus not integrated trialwise. As predictions in this case should only occur within-tasks, implicit sequence learning in the SRTT can be preserved. Future research should investigate whether other context manipulations are capable of preserving implicit sequence learning in multitasking by inducing separate task representations.

An interesting parallel to the proposed prediction account can be found in the *anticipative learning model* of Ziessler and Nattkemper (2001; Ziessler, Nattkemper, & Frensch, 2004). The authors assume that learning in an SRT task is essentially based on response-effect learning (the stimulus in trial n+1 is interpreted as the effect of the response to the stimulus in trial n). The authors suggest that the anticipation of this effect is an integral part of the response production. Learning is then equivalent to the reduction of the prediction error over the course of the training (Rescorla & Wagner, 1972). Importantly, Ziessler et al. (2004) could show that learning was impaired when a random tone stimulus was presented within the stimulus-response interval of the SRTT. They concluded that, in this case, the response production – and thereby the prediction mechanism – was disturbed. However, since the timing of stimulus and response events in their experiments differed from our paradigm, further research is needed to investigate whether this assumption could hold for our current findings as well.

Even though the task integration account appears to be a feasible explanation of our findings, a conceivable alternative assumption might be that task integration, at least when the two stimuli are simultaneously presented, is equivalent to the formation of a complex compound representing the two stimuli as one single stimulus. In this case, the random tones would make the whole compound random – and, thus, unpredictable. Consequently, also the assumption of such random compounds predicts reduced sequence learning in dual-task situations. However, Freedberg, Wagschal, and Hazeltine (2014) recently showed that simultaneously presented visual-auditory stimuli are not automatically bound together. Their results suggest that only if they are represented as conceptually related, the two stimuli are represented as compounds. Concerning our current results, it is not clear why the participants should have represented the task stimuli as conceptually related. In addition, we always assessed the implicit learning effects under single task conditions. Hence, if participants had learned associations between these compounds they should have shown reduced learning effects in such a single-task test. However, the implicit learning effects in the correlated condition and in the fixedly paired condition were not smaller than that found in the single-task condition.

To summarize, our findings suggest that two major factors are crucial for the impairments of implicit sequence learning in dual-task situations. The first is whether the within-trial integration results in response conflicts – due to co-occurring elements that have no predictive value (see also Rah et al., 2000; Schmidtke & Heuer, 1997). The second factor concerns the proportion of dual- to single-task trials, as single-task trials always contribute to the strengthening of the successive sequence positions within the SRTT.

3 Global – not local – across-task predictability determines the amount of implicit sequence learning in a dual-task context

When a *serial reaction time task* (SRTT; Nissen & Bullemer. 1987) is combined with a random tone-task, implicit sequence learning suffers – probably due to a tendency to integrate the two tasks, resulting in extremely long sequences and unpredictable across-task events (see Rah, Reber, & Hsiao, 2000; Röttger, Haider, Zhao, & Gaschler, 2019; Schmidtke & Heuer, 1997). In the present dual-task experiments, we investigated the role of two different types of predictability (of the tones on the basis of the SRTT) for the preservation of sequence learning. These two types were termed *local* vs. *global* (i.e., depending on the SRTT targets' sequence position vs. not). It turned out that neither high local- nor high global across-task predictability *alone* was sufficient in this respect. Nevertheless, the present findings strongly suggest that a supposed omnipresent automatic prediction mechanism (e.g., Broeker et al., 2017) operates on the global predictability of the most contiguous co-occurrences (within one trial), benefitting if the local across-task predictability is in accord but causing conflict if not – hampering the reduction of the prediction error.

One often replicated finding is that implicit sequence learning is impaired in dual-task situations (for recent reviews, see Keele, Ivry, Mayr, Hazeltine, & Heuer, 2003; Schumacher & Schwarb, 2009). Schmidtke and Heuer (1997) had suggested that this impairment is caused by task integration whenever the secondary task is random. Inserting random elements into a sequence learning task, like the *serial reaction time task* (SRTT; Nissen & Bullemer, 1987), might sham an endless sequence of unpredictable events that is impossible to learn. Similarly, Rah, Reber, and Hsiao (2000) had suggested that the "duality" of the standard combination of the SRTT and a tone-task is illusory – and that the tone-task degrades the SRTT performance "simply because it introduces a set of co-occurrences that have no predictive value" (p. 310). Crucially, even rather simple contingencies *within* the SRTT might, then, remain undetected.

In the dual-task training blocks, Schmidtke and Heuer (1997) had paired a 6-element (visual-manual) SRTT sequence with an (auditory-motor) go/no-go task that followed either also a 6-element or a 5-element or a random sequence (D-6, D-5, and D-R condition). The, resulting integrated sequences were (a) of very different length and (b) the extent to which single elements occurred predictably was also very different for the three conditions. Since the SRTT and the tone-task sequences were of the same length in the D-6 condition, the integrated sequence contained only 12 elements and the predictability of across-task events was high. In the D-5 condition, however, the sequences were of different lengths. Integrating them resulted in a 60-element sequence with much lower predictability levels, not very far from chance – as it was the case in the D-R condition.

After the training, sequence learning was assessed in dual-task as well as single-task tests (Schmidtke & Heuer, 1997; Experiment 1). In the single-task test, learning of the pure SRTT sequence was moderately present in all three conditions, in line, for instance, with the assumption that only the expression of learning is hampered by a secondary task (Frensch, Lin, & Buchner, 1998; Frensch, Wenke, & Rünger, 1999). However, in the dual-task test (with the tones present) the sizes of the learning effects were very different in the three conditions: The learning effect was very small in the D-R condition (and smaller than in the single-task test). It was intermediate (and as large as in the single-task test) in the D-5 condition. But, most importantly, it was very large (and larger than in the single-task test) in the D-6 condition. This outcome strongly suggests that, here, the participants had acquired implicit knowledge about an integrated sequence of alternating and highly predictable auditory and visual events. Schmidtke and Heuer (1997) concluded that the length and the complexity of the integrated sequence in a dual-task context most likely determines whether it can be learned or rather not.

Recently, we could add more evidence for the assumption that task integration is a crucial factor for the impairment – as well as the preservation – of implicit sequence learning in dual-tasking situations (Röttger, Haider, Zhao, & Gaschler, 2019).

Just like Schmidtke and Heuer (1997), we implemented a standard SRTT with the target occurring at one of four marked possible screen locations and the requirement to press the appropriate spatially mapped key in response. The tone-task in our experiments required the verbal responses "high" vs. "low" (in German) in response to high vs. low pitched tones (see also Schumacher & Schwarb, 2009). This task was similar to Schmidtke and Heuer's go/no-go task in that it required immediate responses. Memory load (i.e., keeping a running count of the tones; the standard procedure in earlier dual-task SRTT experiments) was not part of the task. In our *correlated tasks* condition (Röttger et al., 2019; Experiment 2) we paired an 8-element SRTT with a tone sequence that was twice as long (16 elements). Thus, the tasks were correlated to some extent – but not as perfectly as in Schmidtke and Heuer's D-6 condition. The resulting integrated sequence of manual and vocal responses had 32 elements – lying in between the D-6 (12 elements) and the D-5 (60 elements) sequence.

In contrast to Schmidtke and Heuer, we assessed learning exclusively under single-task conditions. However, our results allowed similar conclusions as we will explicate below. Our single-task test revealed that the SRTT sequence had been substantially learned in the correlated tasks condition – while exactly the same sequence in another condition (the *spatial* condition) with random tones (Röttger et al., 2019; Experiment 1) had not been learned. This pattern of results differs from that of Schmidtke and Heuer, where the learning effects in the single-task test had been more or less of the same (moderate) size for the D-6, D-5, and D-R conditions, respectively. This difference, however, is likely due to the different sequences used in both studies. Schmidtke and Heuer (1997) had used a 6-element hybrid sequence like "1-3-4-2-3-2" with unique as well as ambiguous transitions. In contrast, our 8-element SRTT sequence (3-1-2-4-1-3-4-2) was not only longer but the transitions between the successive elements were throughout ambiguous (2nd order) meaning that the prediction of the next SRTT target always required to take more than one single sequence element into account. Sequences of such higher order complexity have been found to be much more difficult to learn under dual-task conditions (e.g., Cohen, Ivry, & Keele, 1990).[1] Thus, the finding of a substantial learning effect in the single-task test in our correlated-tasks condition in comparison to the finding of a reduced effect in the spatial condition (with random tones) allows the conclusion that task integration – or across-task predictability (Rah et al., 2000) – is crucial for implicit sequence learning. Additionally, it suggests that the extent to which the tasks are correlated not only affects the learning of the integrated sequence but also the learning within the SRTT (which is what we are interested in).

Importantly, Experiment 4 of our previous study provided straightforward evidence that across-task predictability (of the tones on the basis of the SRTT) might, in fact, be the more important aspect of task integration than the length of the integrated sequence. Here, 4 of the 8 SRTT-elements had been fixedly paired with one particular tone while the other 4 elements had been randomly paired with the tones. In result, exclusively the fixedly paired elements had been learned – suggesting that frequent wrong across-task predictions due to the randomly paired elements had disrupted overall sequence learning in the sense of item-item associations or *chaining* (see, e.g., Cleeremans, 2011).

Instead, this outcome is probably best understood as *ordinal position learning* (Schuck, Gaschler, & Frensch, 2012; Schuck, Gaschler, Kreisler, & Frensch, 2012). That is, in the single-task test, the participants expressed the implicit knowledge that, e.g., the target at screen location 2 (from left), formerly fixedly paired with the low tone, always occurs at sequence position 3 (is the third event within the sequence). Such so-called position-item associations may have developed because fixedly paired SRTT items (occurring at salient local positions within the sequence[2]) had allowed an extensive local reduction of the (across-task) prediction error (e.g., Rescorla & Wagner, 1972), i.e., within the respective trial.

[1] Cohen et al. (1990) suggested that the learning of hybrid and ambiguous sequences in a dual-task context is reduced because the required attention has to be directed at the tone-task. This interpretation, however, is rather outdated. Instead, the task integration hypothesis of Schmidtke and Heuer (1997) seems to be a better candidate.

[2] In Experiment 4 of Röttger et al. (2019), the combination of SRTT- and tone-task stimuli was as follows: 3*R*-1*F*-2*R*-4*F*-1*F*-3*F*-4*R*-2*R* (with *F* = fixedly paired, *R* = randomly paired). This uneven distribution of pairing types might have offered salient anchors defining the starting point of the sequence and, thereby, its ordinal positions.

Aiming at investigating the role of across-task predictability for dual-task implicit sequence learning in more detail while using a higher order SRTT sequence like our standard 8-element 2nd order sequence (3-1-2-4-1-3-4-2) makes it necessary to pay attention to a few subtleties. First, we have to distinguish between *sequence positions* (1-8) and *target locations* (1-4). From this, it follows that two types of across-task predictability have to be defined – which in the following will be called *local* and *global*. On the one hand, sequence learning within the SRTT could depend on the extent to which each target location *locally* (depending on its sequence position) predicts the corresponding tone. On the other hand, the *global* probability that (e.g.) target location 3 predicts the high tone (independently of its sequence position) could be the key. The former is related to the assumption that the length of the integrated sequence determines the extent to which learning – in the sense of item-item associations or chaining – is possible (cf. Schmidtke & Heuer, 1997). The latter would imply that a (high) global frequency of certain co-occurrences might be the useful information reducing the prediction error not only within the respective trial(s) but potentially also, over time, across the whole SRTT sequence (e.g., due to the infrequent necessity to inhibit any feature of the SRTT after wrong predictions – allowing the simultaneous activation and, thus, association of successive SRTT elements).

A closer look at the local and the global across-task predictability levels in the D-5 and D-6 conditions of Schmidtke and Heuer (1997) reveals interesting differences.[3] While in the D-6 condition the across-task predictability was locally high (and globally also high for unique sequence elements), it turned out that both, the local and global predictability of the tones in the D-5 condition was throughout 60% – which is not much higher than chance level (50%). While this observation strongly suggests that the low across-task predictability levels in the D-5 condition had caused the reduced learning effect (rather than the length of the integrated sequence), it does not allow to decide which type of across-task predictability (i.e., global vs. local) had been crucial.

Computing the predictability of the tones also for our correlated tasks condition on the basis of the 2nd order SRTT (Röttger et al., 2019; Experiment 2), it turned out that the global predictability of the tones had been high (75%) for each of the four target locations but that the local predictability of the tones was variable. The resulting significant learning effect in our single-task test might, thus, indicate that the global predictability of the tones is

[3] The authors used a 6-element hybrid SRTT sequence like "1-3-4-2-3-2" with two unique and four ambiguous transitions The D-6 tone sequence was added by the following rules: Tones never repeated more than once. The frequent SRTT elements were followed once by the high- and once by the low tone and the two unique elements were followed by different tones. In the D-5 condition, the last tone of the D-6 sequence was omitted.

more important for dual-task sequence learning than the extent to which each SRTT element locally predicts a particular tone.

To sum up, the evidence suggests that (a) across-task predictability could be the more important aspect of task integration than the length of the integrated sequence – and that (b) global across-task predictability could be more important for implicit sequence learning in a dual-task context than local across-task predictability.

However, one major difference between our study and that of Schmidtke and Heuer (1997) makes it impossible to already draw conclusions about the mechanism(s) by which task integration affects dual-task sequence learning, namely that the differential complexity of the respectively used SRTT sequences resulted in differential outcomes in the single-task test. While Schmidtke and Heuer's 6-element hybrid SRTT sequence could be learned also in the presence of random tones, our 8-element ambiguous (2^{nd} order) sequence could not. Thus, it is necessary to vary the levels of global vs. local across-task predictability (of the tones) while keeping the underlying (higher order) SRTT sequence constant – and to compare (via single-task tests) the extent to which this SRTT sequence can be learned. In our view, single-task test results are more informative than dual-task test results because if, in a dual-task context, learning within the SRTT is preserved vs. hampered due to increased vs. reduced levels of across-task predictability, then two conclusions are justified: (a) task-integration occurs and (b) different types (global/local) and levels (high/low) of across-task predictability modulate sequence learning within the SRTT.

The present study

In the present study, we aimed at investigating the role of global vs. local across-task predictability for implicit sequence learning in a dual-task context in more detail. Therefore, we combined our standard 8-element 2^{nd} order SRTT with to-be-discriminated tones that were differentially predictable. We conceived of two different ways by which high levels of local vs. global tone-predictability could turn out to be beneficial for the strengthening of item-item associations or chaining within the SRTT. On the one hand, locally predictable tones could disambiguate transitions between successive SRTT elements. On the other hand, globally predictable tones could reduce the frequency of response conflicts due to wrong predictions for any target location (independently of its sequence position) and thereby the necessity to inhibit features of the SRTT – which could otherwise prevent chaining.

Following the approach of Rah et al. (2000), we set up three "sets of circumstances" with slightly varied types and levels of across-task predictability and present them as separate experiments to avoid the occurrence of non-interpretable interactions. Since we aimed at investigating the role of different types of across-task predictability for the extent of implicit sequence learning *within* the SRTT, our focus lies predominantly on the SRTT data (RTs and error rates). Since different levels of across-task predictability should affect the tone-task as well, we will also report the tone-task data (RTs only). In general, the tone-task should be seen mainly as a part of the predictability manipulation.

In Experiment 1, only the local predictability of the tones (on the basis of one SRTT loop) was high (75%) while the global predictability was at chance level (50%). We expected to find a substantial learning effect in the single-task test only if high levels of local across-task predictability are sufficient for sequence learning in a dual-task context – probably by means of disambiguating the transitions between successive SRTT elements (and in line with the original understanding of task integration; see Schmidtke & Heuer, 1997).

In Experiment 2, the local predictability of the tones was, again, high (75%) but now the global predictability was high (75%) as well. In case that a high level of global across-task predictability is necessary for dual-task sequence learning (as it allows an extensive reduction of the prediction error for every target location, independently of its sequence position), we expected no (strongly reduced) sequence learning in Experiment 1 but a substantial learning effect in Experiment 2.

Experiment 3 was designed similar to Experiment 4 of our previous study (Röttger et al., 2019). This time, each of the four target locations within one 8-element sequence loop was once fixedly paired with one particular tone and once randomly paired. Thus, the local across-task predictability for each target location was once high (100%) and once at chance level (50%). At the same time, the global tone-predictability was high (75%). A replication of our former finding in Experiment 4 (ordinal position learning and the absence of chaining) would now indicate that ordinal position learning can occur independently of the presence of (very) salient anchors defining a starting point of the sequence. Furthermore, this outcome would suggest that global- and local across-task predictability interact. With strong local differences in the tone-predictability, predicting the globally most likely tone must be wrong in 50% of cases for the randomly paired SRTT elements. Thus, chaining should not occur because the local tone-predictability varies too extensively.

Experiment 1

The goal of Experiment 1 was to investigate whether a high local predictability of the tones on the basis of one SRTT loop is sufficient to preserve implicit sequence learning (in the sense of chaining) in a dual-tasking situation. Therefore, we combined an 8-element 2nd order visual-manual SRTT with a two-choice auditory-vocal tone-discrimination task across six dual-task training blocks. Each element of the SRTT sequence predicted one particular tone with a probability of 75%. Subsequently, we assessed sequence learning in a single-task test (three blocks SRTT only).

Method

Participants

Twenty-five students (5 men) of the University of Cologne (mean age 22.72, *SD* = 3.41) participated in the experiment either for monetary compensation or for course credit. Each session lasted approximately 45 min.

Apparatus and stimuli

The experiment was controlled by custom-written software (Lazarus / FreePascal, compiled for Microsoft Windows). Placeholders for the visual SRTT target (an uppercase "X") were four horizontally aligned white squares on a light grey background (100 x 100 pixels, separated by gaps of also 100 pixels). They were displayed slightly below the center of a TFT monitor (19 inch; 1280 x 1024 pixels) that was connected with a standard PC. In each trial, the SRTT target occurred for 100 ms in one of the four white squares and the participants had to press a spatially mapped key in response (Y, X, N, M on a QWERTZ-keyboard). Unbeknownst to the participants, the response locations of the SRTT followed a 2nd order conditional 8-elements sequence (3-1-2-4-1-3-4-2). In the dual-task trials, a high (900 Hz) or a low (300 Hz) pitched tone, lasting 56 ms, was played simultaneously, requiring the verbal responses "hoch" vs. "tief" [high vs. low]. A sound mixer (Behringer XENYX 302USB) served as a bridge between headset and PC and integrated the tone stimuli with the verbal responses into one single wave-file per trial. The tone-task was analyzed offline, after the experiment.

Procedure

All participants were introduced step by step into the dual-task training phase. After 20 practice trials with only the tone-discrimination task and another 20 practice trials with only the SRTT, they received 20 practice trials with the dual-task. In this first phase, both tasks did not follow any regular sequence.

In the training phase, the participants performed 6 dual-task blocks of 96 trials each. Now, the SRTT followed the 8-element sequence, each block starting at a randomly drawn sequence position. A dual-task trial began with the presentation of the visual SRTT target (the "X") and the simultaneous occurrence of one of the two auditory stimuli of the tone-discrimination task. The instructions highlighted equal priority of the tasks and the response order was free. The response-window closed 2000 ms after the SRTT target onset and the next trial started immediately.

Since we implemented an 8-element 2nd order conditional sequence (3-1-2-4-1-3-4-2), the target occurred twice at each of the four possible screen locations across one sequence loop. Each target location (1-4) was once paired with the high tone and once paired with the low tone with a local probability of 75% each (i.e., depending on its sequence position). One tone was, thus, typical for a given target location at a certain sequence position – and the other tone was untypical (occurring with a local probability of 25%). The global probability that each target location was paired with one or the other tone was, thus, 50%. In other words, the resulting predictability of particular tones on the basis of one SRTT loop was locally high (75%) but globally at chance level (50%).

The dual-task training phase was followed by 3 single-task test blocks of also 96 trials presenting only the SRTT. In blocks 7 and 9, the SRTT sequence was (pseudo-)randomized (i.e., immediate repetitions were not allowed). In block 8 the originally trained sequence was reintroduced. To allow the participants a short phase of accommodation to the single-task context (and to control for initial speed-accuracy trade-offs), only the second half of block 7 entered the analysis of the single-task test.

At the end of the experiment, participant's explicit sequence knowledge was assessed (for details, see Röttger et al., 2019). Since it turned out that infrequent signs of partly explicit knowledge did not modulate any effect, the respective results will not be reported.

Results and Discussion

Trials were excluded due to SRTT errors (1.8%) or RTs < 200 ms or > 1500 ms in the SRTT (0.4%). As some trials fulfilled multiple exclusion criteria, overall 1.9% of the trials were excluded. We will first report the results of the dual-task training phase and, second, the results of the single-task test phase.

Performance in the training blocks

Table 1 displays the mean RTs in the SRTT and in the tone-discrimination task for locally typical (75% probability) vs. non-typical (25% probability) SRTT-tone combinations as a function of block. As can be seen, the participants became generally faster across the six training blocks in both tasks. However, they were also faster (in both tasks) together with the locally typical, that is, with the locally highly predictable tones.

Accordingly, two 6 (block) x 2 (local predictability of the tones) repeated measures ANOVAs (one for each task[4]) with RTs as dependent variable revealed a significant main effect of block in the SRTT $F(5,120) = 19.57$, $p < .001$, $\eta_p^2 = .449$, and in the tone-task as well, $F(5,120) = 10.94$, $p < .001$, $\eta_p^2 = .313$. Additionally, the RTs were significantly faster with the locally highly predictable tones in both the SRTT (14 ms), $F(1,24) = 24.50$, $p < .001$, $\eta_p^2 = .505$, and also in the tone-task (23 ms), $F(1,24) = 41.95$, $p < .001$, $\eta_p^2 = .636$. However, in both tasks, the effect of the tone-predictability was additive to the block effect (Fs < 1 for the respective two-way interactions).

Table 1. Mean RTs and SDs in the SRTT and the tone-discrimination task for locally typical (75% probability) vs. locally non-typical (25% probability) SRTT-tone combinations as a function of block. in Experiment 1.

	SRTT				Tone-Task			
Predictability	Local 75%		Local 25%		Local 75%		Local 25%	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Block 1	552	104	568	111	717	111	746	107
Block 2	540	96	551	104	719	100	742	103
Block 3	521	99	534	108	702	103	726	100
Block 4	499	81	517	91	678	109	693	108
Block 5	496	87	515	90	674	102	697	105
Block 6	480	73	488	81	663	107	688	113
Regular Block 8	410	53						
Random Blocks 7/9	415	39						
Learning Effect	4	20						

The SRTT error rates were similarly low (1.44% and 1.33% together with the locally typical vs. the untypical tone, respectively) and did not differ across the blocks (all Fs < 1.18).

Performance in the test blocks

To assess sequence learning in the SRTT single-task test, we compared the mean RTs (and error rates) of the collapsed random blocks 7 (2nd half) and 9 with those of the regular block 8. Figure 1 reveals that the participants responded only 4 ms faster in the regular than

[4] Whenever the sphericity assumption was violated, Greenhouse-Geisser corrected p-values are reported, along with the original degrees of freedom.

in the random blocks suggesting that the SRTT sequence had not been learned. Accordingly, the respective (two-tailed) t-test revealed that this difference was not significant, $t(24) = 1.08$, $p = .289$, $d = 0.217$.

In addition, we conducted a Bayes test (see Dienes, 2014) to assess whether this small and non-significant effect indicates evidence for the Null hypothesis (no sequence learning). Based on the effect of 26 ms for the single-task condition in our previous study (Röttger et al., 2019; Experiment 1), which we specified as maximum expected learning effect, the Bayes factor was $BF = 0.48$ indicating insensitivity of the data for making a clear decision.

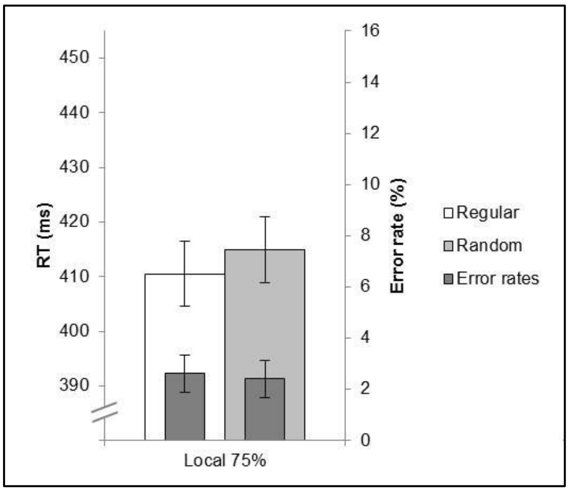

Figure 1. Mean RTs (left y-axis) and error rates (right y-axis) in the regular and the random single-task SRTT test blocks in Experiment 1. Error bars represent the 95% within-subjects confidence interval of the learning effect (Loftus & Masson, 1994).

Figure 1 also shows that the error rates were only slightly different in the regular- vs. the collapsed random test blocks (2.63% vs. 2.42%, respectively). The corresponding t-test (two-tailed) revealed that this difference was not significant ($|t| < 1$).

To summarize, the findings in Experiment 1 suggest that the high local predictability of the tones (75%) – and, thus, the disambiguation of transitions between successive SRTT elements – was not sufficient for the development of implicit sequence knowledge (within the SRTT) during the six training blocks. Additionally, the participants responded slower in both tasks at presentation of the locally non-typical tones – indicating response conflicts due to a discrepancy between the predicted and the actually required tone-task response. Both findings will be discussed in more detail after presenting the results of Experiment 2. Here, the local predictability of the tones was still high (75%) – but the global tone-predictability was now raised to 75% as well.

Experiment 2

In Experiment 2, 25 new participants were trained with the same combination of an 8-element 2nd order SRTT and a two-choice tone-task as in Experiment 1 across six dual-task blocks. Each SRTT target location (1-4) now predicted not only locally but also globally one respective tone with a probability of 75% each. If global across-task predictability should be necessary – or more important than local across-task predictability – for dual-task sequence learning to occur our single-task test should now reveal a significant learning effect.

Method

Participants

Twenty-five students (8 men) of the University of Cologne (mean age 21.92, *SD* = 2.08) participated in the experiment either for monetary compensation or for course credit. Each session lasted approximately 45 min.

Apparatus and stimuli

Apparatus, stimuli and the 2nd order SRTT sequence (3-1-2-4-1-3-4-2) were the same as in Experiment 1. The only difference concerned the across-task predictability manipulation as described below.

Procedure

The overall procedure was the same as in Experiment 1. Again, both tones occurred overall equally frequently across the dual-task training blocks. Crucially, each of the four SRTT target locations (1-4) now predicted one particular tone with a probability of 75% – independently of its local position within one SRTT sequence loop. Thus, the across-task predictability was not only locally but also globally high (75%).

Results and Discussion

Trials were excluded due to SRTT errors (1.7%) or RTs < 200 ms or > 1500 ms in the SRTT (1.0%). As some trials fulfilled multiple exclusion criteria, overall 2.4% of the trials were excluded. We will, again, first report the results of the dual-task training phase and, second, the results of the single-task test phase.

Performance in the training blocks

Table 2 displays the mean RTs in the SRTT and in the tone-discrimination task for locally *and* globally typical (75% probability) vs. non-typical (25% probability) SRTT-tone combinations as a function of block. Again, as can be seen, the participants became generally faster across the six training blocks in both tasks – and they were also faster (in both tasks) together with the with the locally and globally highly predictable tones.

Accordingly, two 6 (block) x 2 (local and global predictability of the tones) repeated measures ANOVAs (one for each task) with RTs as dependent variable revealed significant main effects of block in the SRTT, $F(5,120) = 19.21, p < .001, \eta_p^2 = .445$, and in the tone-task as well, $F(5,120) = 3.38, p = .035, \eta_p^2 = .123$. Additionally, the predictability of the tones had a significant effect in both the SRTT (9 ms), $F(1,24) = 9.99, p = .004, \eta_p^2 = .294$, and also in the tone-task (23 ms), $F(1,24) = 37.21, p < .001, \eta_p^2 = .608$. Like in Experiment 1, the effect of the tone-predictability was additive to the block effect in both tasks (*F*s < 1 for the respective two-way interactions).

Table 2. Mean RTs and SDs in the SRTT and the tone-discrimination task for locally and globally typical (75% probability) vs. non-typical (25% probability) SRTT-tone combinations as a function of block. in Experiment 2.

	SRTT				Tone-Task			
Predictability	Global 75%		Global 25%		Global 75%		Global 25%	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Block 1	648	172	660	175	771	133	804	163
Block 2	618	160	637	161	764	157	783	149
Block 3	595	153	602	158	751	153	774	147
Block 4	591	155	596	166	747	143	765	154
Block 5	575	156	583	162	731	134	763	141
Block 6	554	135	557	143	720	139	733	156
Regular Block 8	435	69						
Random Blocks 7/9	445	61						
Learning Effect	9	19						

The SRTT error rates were similarly low (1.28% and 1.50% together with the typical vs. the untypical tone, respectively) and did not differ across the blocks (all *F*s < 1).

Performance in the test blocks

Figure 2 depicts the results of the SRTT single-task test in Experiment 2, for means of comparison together with the respective results of Experiment 1. As can be seen, the mean RTs of the collapsed random blocks 7 (2nd half) and 9 were slower (9 ms) than those of the regular block 8. The respective (two-tailed) *t*-test revealed that this learning effect was significant, $t(24) = 2.37$, $p = .026$, $d = 0.474$.

The additional Bayes test (see Dienes, 2014) revealed a Bayes factor of $BF = 4.61$ indicating clear evidence for the alternative hypothesis that sequence learning had occurred.

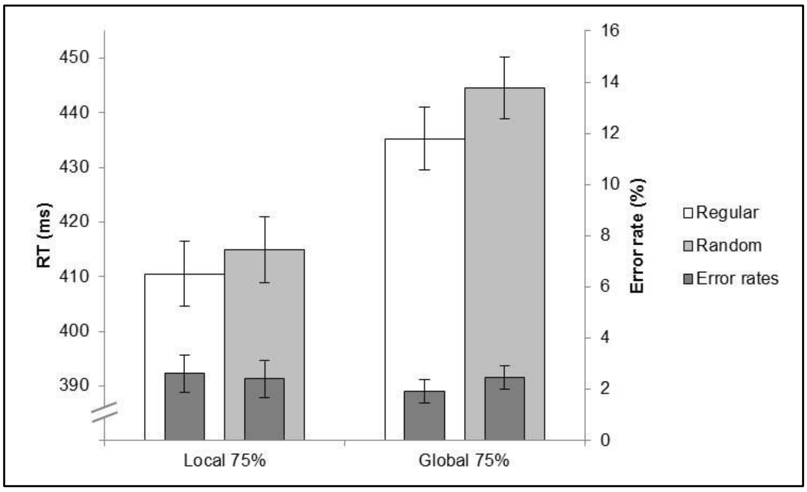

Figure 2. Mean RTs (left y-axis) and error rates (right y-axis) in the regular and the random single-task SRTT test blocks in Experiment 1 and 2. Error bars represent the 95% within-subjects confidence intervals of the learning effects in each experiment (Loftus & Masson, 1994).

Figure 2 also shows that the effect in the SRTT error rates mirrored the RT effect in Experiment 2. More errors occurred in the collapsed random test blocks than in the regular block (2.47% vs. 1.92%, respectively). However, the corresponding (two-tailed) *t*-test revealed that this difference was only marginally significant, $t(24) = 1.79$, $p = .087$, $d = 0.357$.

The findings in Experiment 2 show that increasing the global predictability of the tones while maintaining the high local predictability (now both 75%) resulted in a significant sequence learning effect in the single-task test. Nevertheless, the participants responded, again, slower in both tasks at presentation of the non-typical tones – indicating response conflicts due to a discrepancy between the predicted (typical) and the actually required (non-typical) tone-task response.

Overall, the response times were quite slow in Experiment 2, in the dual-task training phase as well as in the single task test phase. Comparing the response times between all three experiments presented in this study, the response times in Experiment 2 were overall the slowest. At the time being, we have no explanation for this finding and tend to attribute it to the between subjects nature of the experiments.

Most importantly, the differential learning outcomes in Experiments 1 vs. 2, already give a hint that the relevant across-task prediction mechanism determining the amount of sequence learning in a dual-tasking situation might *not* operate *across trials* by integrating predictable tones within associative triplets like "target in trial n – tone in trial-n – target in trial n+1" thereby potentially disambiguating the transition between the successive SRTT targets. In fact, globally highly predictable tones cannot contribute to such a disambiguation within a 2nd order SRTT sequence. The probability of (e.g.) the target occurring at location 1, given location 4 in the current trial, is the same with and without the globally typical tone, namely 50% [p(target1|target4+tone)] = [p(target1|target4)].[5] In Experiment 1, in contrast, the locally typical tone increased the predictability of the upcoming SRTT element to 75%. Nevertheless, a substantial learning effect was present only in Experiment 2, suggesting that, instead, the frequent *within-trial* co-occurrences of particular target locations and particular tones, independently of their sequence position, had been beneficial for sequence learning. We conducted Experiment 3 to further clarify this point.

Experiment 3

In Experiment 3, we kept the global tone-predictability as high as in Experiment 2 (75%) but the local across-task predictability now varied between 50% and 100%. That is, depending on its local position within one loop of the SRTT, each target location (1-4) was once fixedly and once randomly paired with the tones. This manipulation was very similar to that of Experiment 4 of our previous study (Röttger et al., 2019). In this former experiment, however, the fixed and random SRTT-tone pairs had been unevenly distributed. The tone had been always fixedly paired with the target at location 1 and always randomly paired with the target at location 2. Only the target at locations 3 and 4 had been once fixedly and once randomly paired like in the present Experiment 3. Replicating our finding of substantial (ordinal position) learning only for fixedly paired SRTT elements would indicate that neither the local- nor the global predictability of the tones *alone* is sufficient to allow for chaining.

---

[5] Across one block of 96 trials, the target occurred 24 times at any screen location: Location 1, for instance, was marked 12 times at one ordinal position across one 8-element sequence loop and 12 times at another ordinal position. Thus, the probability of the target occurring (e.g.) at position 1 in the current trial, following position 4 in the previous trial was: p(target1|target4) = 12/24 = 0.50. In Experiment 1, the locally highly predictable tone increased this transitional probability to 75%: p(target1|target4+tone) = 9/12 = 0.75. In Experiment 2, with globally highly predictable tones, this probability was still 50%: p(target1|target4+tone) = 9/18 = 0.50. Thus, the globally typical tones did not disambiguate transitions between SRTT elements.

Method

Participants

Twenty-five students (8 men) of the University of Cologne (mean age 23.08, *SD* = 3.55) participated in the experiment either for monetary compensation or for course credit. Each session lasted approximately 45 min.

Apparatus and stimuli

Apparatus and stimuli were, in principle, the same as in Experiment 1 and 2. Two slightly different 8-element 2nd order SRTT sequences were combined with the high and low tones due to certain rules as described below.

Procedure

The overall procedure was also the same as in Experiment 1 and 2. Two 8-element 2nd order SRTT sequences (1-2-4-1-3-4-2-3 / 4-3-1-4-2-1-3-2) were counterbalanced across participants. Both tones occurred equally frequently during the dual-task training blocks. Crucially, across one SRTT loop, we paired each of the four target locations once fixedly with one particular tone and once randomly with the tones. Thus, the local predictability of the tones varied between 50% and 100%. The global predictability of the tones, however, given the target at a certain location, was as high as in Experiment 2 (75%).

Results and Discussion

Trials were excluded due to SRTT errors (1.6%) or RTs < 200 ms or > 1500 ms in the SRTT (0.5%). As some trials fulfilled multiple exclusion criteria, overall 1.7% of the trials were excluded. We will first report the results of the dual-task training phase and, second, the results of the single-task test phase.

Performance in the training blocks

Table 3 displays the mean RTs in the SRTT and in the tone-discrimination task for fixedly vs. randomly paired SRTT elements as a function of block. As in Experiments 1 and 2, the participants became generally faster across the six training blocks in both tasks – and they were also faster (in both tasks) together with the with the fixedly paired SRTT elements locally predicting one particular tone with a 100% probability.

Accordingly, two 6 (block) x 2 (type of SRTT element: fixedly vs. randomly paired) repeated measures ANOVAs (one for each task) with RTs as dependent variable revealed significant main effects of block in the SRTT, $F(5,120) = 17.03, p < .001, \eta_p^2 = .415$, and in the tone-task as well, $F(5,120) = 9.31, p < .001, \eta_p^2 = .280$. Additionally, the factor type of SRTT element had a significant effect in both the SRTT (14 ms), $F(1,24) = 18.27, p < .001, \eta_p^2 = .432$, and also in the tone-task (15 ms), $F(1,24) = 20.58, p < .001, \eta_p^2 = .462$. The latter effect of type of SRTT element was additive to the block effect in both tasks (Fs < 1.56 for the respective two-way interactions).

Table 3. Mean RTs and SDs in the SRTT and the tone-discrimination task as a function of block and type of SRTT element (fixedly vs. randomly paired with the tones) in Experiment 3.

Type of SRTT element	SRTT				Tone-Task			
	Fixed		Random		Fixed		Random	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Block 1	554	108	560	106	744	114	754	120
Block 2	524	82	542	88	719	129	731	132
Block 3	506	73	515	70	685	104	710	122
Block 4	489	74	507	70	692	127	708	124
Block 5	477	77	494	74	679	133	690	127
Block 6	461	82	477	74	670	132	684	134
Regular Block 8	410	70	427	54				
Random Blocks 7/9	431	50	431	50				
Learning Effect	21	35	4	23				

The SRTT error rates were lower for the fixedly paired SRTT elements (0.90%) than for the randomly paired elements (2.19%). The corresponding 6 (block) x 2 (type of SRTT element) repeated measures ANOVA with SRTT error rates as dependent variable revealed that this difference was significant, $F(1,24) = 19.64, p < .001, \eta_p^2 = .450$ (all other Fs < 1).

Performance in the test blocks

Figure 3 depicts the results of the SRTT single-task test in Experiment 3, separately for the formerly fixedly- and for the formerly randomly paired SRTT elements. As can be seen, for the fixedly paired elements, the mean RTs of the collapsed random blocks 7 (2nd half) and 9 were slower (21 ms) than those of the regular block 8. However, for the randomly paired elements, this difference was much smaller (4 ms). The two respective (two-tailed) *t*-test revealed that the large learning effect for the fixedly paired elements was significant, $t(24) = 2.91, p = .008, d = 0.582$ – while for the randomly paired elements it was not ($|t| < 1$).

The additional Bayes test (see Dienes, 2014) revealed a Bayes factor of $BF = 26.90$ for the fixedly paired SRTT elements indicating clear evidence for the alternative hypothesis that sequence learning had occurred. For the randomly paired elements, the Bayes factor was $BF = 0.36$. Although, in a strict sense, this factor indicated insensitivity of the data, it was so close to the criterion of 0.33 that we are inclined to suspect that indeed no implicit learning had occurred for the randomly paired SRTT elements.

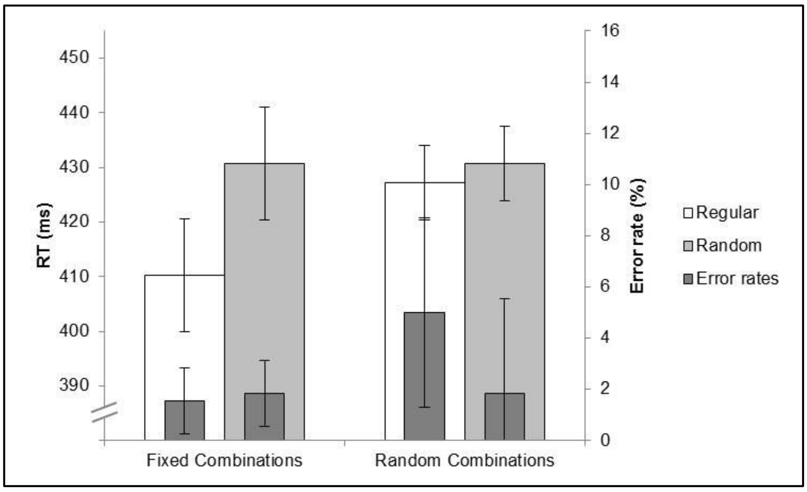

Figure 3. Mean RTs (left y-axis) and error rates (right y-axis) in the regular and the random single-task SRTT test blocks shown separately for SRTT elements that had been fixedly vs. randomly paired with the tones during the training phase of Experiment 3. Error bars represent the 95% within-subjects confidence intervals of the learning effects (Loftus & Masson, 1994).

Figure 3 also shows that the error rates were only slightly different in the regular- vs. the collapsed random test blocks for the formerly fixedly paired SRTT elements (1.56% vs. 1.83%, respectively). The corresponding (two-tailed) *t*-test revealed that this difference was not significant ($t < 1$). For the formerly randomly paired SRTT elements, the error rates were higher in the regular- (5%) than in the random blocks (1.83%) but this difference was also not significant ($|t| = 1.25$).

The findings in Experiment 3 replicate the findings of Experiment 4 of our previous study (Röttger et al., 2019). We found a substantial learning effect only for the fixedly paired SRTT elements indicating ordinal position learning instead of chaining. Additionally, during training, the participants responded slower in both tasks at presentation of the random tones indicating, again, response conflicts due to incorrect predictions.

Interestingly, we found ordinal position learning although no sequence position had been especially salient. Obvious anchors defining the ordinal positions of the SRTT sequence had not been provided as every target location was once fixedly- and once randomly paired with the tones across one sequence loop. Nevertheless, in the single-task test, the participants responded faster to any target location occurring at a sequence position that had formerly indicated a fix pairing (i.e., RTs were smaller in the regular block than in the collapsed two random blocks). It is, thus, conceivable that the 8-element sequence had been parsed into two 4-element sequences with the target occurring at each location only once (see, e.g., Cohen et al., 1990) – making it easier to represent the respective ordinal positions.

Most importantly, the finding of substantial learning only for the fixedly paired SRTT elements strongly suggests that a high global predictability of the tones *alone* (in the presence of strongly varying local predictabilities) is not sufficient to allow for chaining. In fact, always predicting the globally most likely tone in Experiment 3 could not result in more "hits" than predicting the tone by chance for the randomly paired SRTT elements.

Also, at a closer look, it becomes obvious that the 100% local predictability of the tones for the fixedly paired elements had been rather useless for disambiguating at least some transitions in the SRTT. The fixedly paired tones increased the predictability of the respective next SRTT element from 50% to only 67%, which is less than in Experiment 1 (constantly 75%) where, however, chaining had been also absent. [6]

A first conclusion might, thus, be warranted. Implicit sequence learning in a dual-task context, in the sense of item-item associations or chaining, neither depends solely on a high local across-task predictability (in principle capable of disambiguating transitions within the SRTT) nor solely on a high global across-task predictability (in principle allowing increasingly correct predictions of the tone event). The present results strongly suggest that both types of predictability interact. Whether the crucial prediction mechanism nevertheless might rather operate on the global probabilities of certain within-trial co-occurrences – and whether this tendency might depend also on other factors than the structure of the SRTT sequence – will be discussed in the "General Discussion".

General Discussion

In the present study, we investigated the role of across-task predictability, as one aspect of task integration, for the preservation as well as the impairment of implicit sequence learning in a dual-task context. Originally, Schmidtke and Heuer (1997) had suggested that a tendency to integrate sequences of events belonging to two different tasks – of which at least one follows an inherent regularity – impairs learning to the extent that the two sequences are uncorrelated. Then, on the one hand, the integrated sequence can become extraordinary long

[6] As in Experiments 1 and 2, target location 1, for instance, was marked 12 times at one ordinal position across one 8-element sequence loop and 12 times at another ordinal position. Thus, e.g., p(target1 | target4) = 12/24 = 0.50. In Experiment 3, the fixedly paired tone increased this transitional probability to only 67% (instead of 75% in Experiment 1): p(target1 | target4+tone) = 12/18 = 0.67.

(Schmidtke & Heuer, 1997) and, on the other hand, the co-occurrences lose predictive value (Rah et al., 2000). Our own findings (Röttger et al., 2019) confirmed the importance of task integration for dual-task sequence learning. Additionally, they suggested that across-task predictability might be the more important aspect of task integration than the length of the integrated sequence (although, naturally, the former is an effect of the latter).

Depending on the complexity of the sequence in one task (e.g., an SRTT), two types of across-task predictability must be distinguished which we call *local* and *global*. These two types arise because, given that the SRTT has a higher order structure, also sequence positions (e.g., positions 1-8) and possible target locations (e.g., locations 1-4) must be discriminated. Then, the local predictability of a tone-event given a certain target location (i.e., depending on its position within the sequence) is potentially different from the global tone-predictability (i.e., independently of the targets' sequence position) – and both might also have different effects. In three experiments, we varied the levels of local vs. global across-task predictability independently of each other. Therefore, we paired an 8-element 2nd order SRTT with a tone-discrimination task (see also Röttger et al., 2019; Schumacher & Schwarb, 2009) allocating the tones to the target locations in different proportions per experiment.

In Experiment 1, the local tone-predictability was high (75%) while the global tone-predictability was at chance level (50%). We hypothesized that, by way of disambiguating the transitions between successive SRTT elements, the locally highly predictable tones could turn out to be beneficial for sequence learning. This mechanism would operate *across trials* and, thus, be more in line with the assumption that the length of the integrated sequence is crucial (Schmidtke & Heuer, 1997). However, we found no significant learning effect.

In Experiment 2, the local tone-predictability remained high (75%) and the global predictability was increased to 75% as well. We hypothesized that, by allowing increasingly better predictions of the tones based on the target locations (independently of their sequence position), the globally highly predictable tones could be more beneficial than the locally highly predictable tones. This mechanism would operate *within trials*, possibly by decreasing the frequency of response conflicts as a consequence of the extensive reduction of the prediction error (Rah et al., 2000; Röttger et al., 2019). This conflict reduction may have allowed the simultaneous activation of successive SRTT elements, thereby strengthening the associations between them. Indeed, we found a substantial learning effect in Experiment 2.

In Experiment 3, the global tone-predictability remained high (75%) but the local predictability of the tones varied extensively and was either very high (100%) or low (50%). We hypothesized that if the prediction mechanism operated rather on the global across-task predictability by focusing on SRTT-tone contingencies within a given trial, we should find substantial implicit learning only for the fixedly paired SRTT elements. Here, the 100% tone-predictability allows the reduction of the prediction error. For the randomly paired elements, however, inevitably frequent wrong across-task predictions must lead to response conflicts thereby preventing the development of item-item associations or chaining within the SRTT. Indeed, replicating our former results (Röttger et al., 2019; Experiment 4), we found ordinal position learning instead (position-item associations for the fixedly paired elements). That is, the participants expressed implicit knowledge about the ordinal sequence positions of fixedly paired SRTT elements.

Based on this observation, some new and important suggestions concerning implicit sequence learning in dual-task situations might be warranted. First, and basically, the present results, again, confirm the importance of task integration – or across-task predictability – for the formation of associations within the SRTT as measured by our single-task test. Second, and more importantly, our results give a hint at the crucial route on which the supposed prediction mechanism might operate in contexts similar to the present dual-task situation, i.e., with a 2nd order sequence in the SRTT and differentially predictable secondary tone-task events. We suggest that some helpful fundamental thoughts can be derived from the literature on the *predictive coding account* (e.g., Bubic, von Cramon, & Schubotz, 2010; Clark, 2013) and the literature on *statistical learning* (e.g., Perruchet & Pacton, 2006).

According to the predictive coding account, predictions of “whatever next” (Clark, 2013) are omnipresent and do also occur implicitly (for a short review, see Broeker et al., 2017). Learning the regularities within a SRTT, might require the progressive improvement of predictions via statistical learning (Hunt & Aslin, 2001). The authors showed that implicit learning in a SRTT can be based on more than one statistic extracted from the distribution of possible events within the learning context, ranging from simple element frequency over conditional probabilities of element pairs up to the complex joint probability of exact event patterns out of all possible combinations within this context. Given a tendency to integrate the two streams of events in a dual-task (Schmidtke & Heuer, 1997), it is, thus, important to investigate, which statistical dependencies might be most informative – and, therefore, might be operated on by the prediction mechanism.

The results of Experiment 1 suggest that the prediction mechanism did not focus the increased conditional or transitional probabilities of successive SRTT elements due to locally highly predictable tones (in principle capable of disambiguating these transitions). One idea why this might have been the case can possibly be derived from findings like that of Gómez

(2002). She investigated, in the context of (artificial) language learning, the conditions under which so-called nonadjacent dependencies can be learned (conditional probabilities between the first and the third "word" separated by a more or less variable middle element in a three element string). It turned out that these nonadjacent dependencies were only learned if the variable middle element was drawn from a large set of 24 items – but not if it was drawn from smaller sets. In other words, as long as the variability of the middle element was low, the prediction mechanism seemed to focus rather on adjacent elements (e.g., the first and the middle element) missing the strong dependencies between the nonadjacent elements. These, however, were detected as soon as the variability of the middle element was high and, thus, made the nonadjacent dependencies literally stand out of the crowd.

Attempting to relate this finding to our dual-task context, the tones can be conceived of as the varying middle element separating successive elements of the SRTT. It is possible that these SRTT dependencies had not been learned in Experiment 1 because, with a set size of two, the tone-variability could have been too limited to direct the prediction mechanism to the SRTT dependencies. The "failure" to learn the SRTT sequence strongly suggests that the prediction mechanism had focused other relations, namely the within-trial predictability of the tones on the basis of the SRTT elements. Unfortunately, due to our manipulation, this within-trial predictability depended on the (unknown) SRTT's ordinal positions across-trials – precluding any reduction of the prediction error.

Increasing the global predictability of the tones from 50% to 75% in Experiment 2, offered a way out of this vicious circle. The focus on the within-trial SRTT-tone relations (now being independent of the SRTT's ordinal positions) allowed to progressively improve the respective predictions and to reduce the likelihood of response conflicts. Otherwise these response conflicts possibly would have had to be solved by inhibiting the activation of SRTT features, which, in turn, should have hampered the strengthening of associations between the successive SRTT elements. The substantial learning effect in Experiment 2 might count as evidence for this assumption, as it most probably indicates strong item-item associations or chaining. In Experiment 3, in contrast, where the global predictability of the tones was also high (75%) but the local predictability of the tones varied, chaining was absent – very likely because the temporally overlapping activation of successive SRTT elements had frequently needed to be inhibited.

Yet, assuming a prediction mechanism which, by default, focuses on the spatially and temporally most contiguous – within-trial or adjacent – dependencies (e.g., Gómez, 2002), can also explain the outcome in Experiment 3. This way, the prediction error can extensively be reduced for the fixedly paired elements – but not at all for the randomly paired elements. As a result, we observed that responses to targets occurring at sequence positions indicating a (formerly) fix pairing in the regular single-task test block were faster than the respective responses in the random test blocks. Thus, the participants expressed implicit knowledge of the ordinal positions of the fixedly paired SRTT elements. Responses to the randomly paired elements were slow and their speed did not differ between the test blocks.

As already mentioned above, the finding of position-item associations in Experiment 3 is, at first sight, a bit surprising because the distribution of the pairing types (each target location within the SRTT had been once fixedly and once randomly paired with the tones) did not provide salient anchors defining the starting point (and, thus, the ordinal positions) of the sequence (see Schuck, Gaschler, & Frensch, 2012; Schuck, Gaschler, Kreisler, et al., 2012). We suspect that the possibility to divide the 8-element 2nd order sequence into two 4-element 1st order sequences (containing each target location once) might have been quite obvious and offered a way to extract the ordinal SRTT positions nevertheless. This process might have been supported by the locally slightly increased predictability of successive SRTT elements due to the locally highly predictable (fixedly paired) tones.

To summarize, the outcomes of the present three experiments are indeed suitable to shed more light on the crucial mechanisms by which task integration might affect implicit sequence learning in a dual-task context. Assuming an omnipresent prediction mechanism (see, e.g., Broeker et al., 2017; Bubic et al., 2010; Clark, 2013) that operates on the principles of statistical learning (see, e.g., Hunt & Aslin, 2001; Perruchet & Pacton, 2006), our findings suggest that the predictability of the most contiguous upcoming event determined whether sequence learning had been possible or not. With simultaneous stimulus onset and serially produced responses, the highest contiguity of successive events could be found within-trials – and the present results strongly suggest that within-trial events (belonging to both tasks) had been focused by the prediction mechanism (see also, e.g., Gómez, 2002).

Interestingly, Gómez (2002) also showed that by increasing the variability of adjacent events, the focus of the prediction mechanism could be moved to the dependencies of nonadjacent events, meaning that this mechanism is, in principle, open for modifications. Another such modification might be triggered by separating the tasks temporally, that is, by inserting long intervals between the onsets of the stimuli (*stimulus onset asynchrony*; SOA). Schumacher and Schwarb (2009; Experiment 1) found that implicit sequence learning was preserved in such a condition despite the presence of a random tone-discrimination task (see also Röttger, Haider, Zhao, & Gaschler, in prep.). In our view, temporally separating the two tasks might have separated also the task representations. Representing the SRTT as one independent task might bring out its inherent statistical relations and, in turn, allows an extensive reduction of the prediction error.

While such an SOA manipulation might operate automatically, on a bottom-up route, the findings of Hazeltine and his colleagues (Freedberg, Wagschal, & Hazeltine, 2014; Halvorson, Wagschal, & Hazeltine, 2013) suggest that separate task representations – or task files (Hazeltine & Schumacher, 2016; Schumacher & Hazeltine, 2016) – can also be established top-down, i.e., by instruction (see also Schumacher & Schwarb, 2009; Experiment 2). Moreover, since human actions are almost always goal-directed and embedded in hierarchical sequential structures (e.g., Schiffer, Waszak, & Yeung, 2015), the extent to which the content of the two tasks is distinguishable and belongs to separate goals might determine whether the prediction mechanism focuses the respectively relevant rather than the most contiguous – but irrelevant – dependencies. Related questions are currently investigated in our lab.

To conclude, the present three dual-task sequence learning experiments added to the existing research the finding that task integration or, more specifically, across-task prediction seems to operate, per default, on the most contiguous dependencies, namely those between across-task events within the same trial. In our paradigm, given an underlying higher order SRTT sequence, it seems to be the global predictability of the tone that determines whether sequence learning is possible or not – unless some cue might trigger the establishment of separate task representations and thereby a move of the predictive focus away from the most contiguous to the most (goal-) relevant dependencies.

4 Implicit sequence learning as an indicator of efficient dual task processing?

Implicit sequence learning often suffers when a *serial reaction time task* (SRTT; Nissen & Bullemer, 1987) is presented simultaneously with a random secondary task. Schumacher and Schwarb (2009) demonstrated, however, that sequence learning is preserved when the tasks are consistently separated by long *stimulus onset asynchronies* (SOAs) – potentially due to serial- instead of parallel processing (cf. Miller, Ulrich, and Rolke, 2009). Evidence suggests that, with *varying* SOAs, like in the *psychological refractory period* (PRP) paradigm (Welford, 1952), one processing mode is globally preferred: serial processing (Israel & Cohen, 2011) or parallel processing (Lehle & Hübner, 2009). As implicit sequence learning should be preserved in the former case and impaired in the latter, we suggest that the amount of learning can serve as an indicator of the dual-task processing mode participants adopt when experiencing varying SOAs. In the present study, we combined a SRTT and a random tone-discrimination task and paired high proportions of short vs. long SOAs with certain SRTT-items within two PRP experiments. Learning occurred, purely mechanistically, only together with long SOAs suggesting that the PRP context did not trigger a global serial processing strategy. Rather, we observed a kind of automatic switching from moderately parallel- to serial processing whenever the SOA was actually long. As serial processing is, in principle, conceived of as being more efficient than parallel processing (cf. Miller et al., 2009), it is discussed whether this assumption holds for the present findings.

Every day, we are engaged in numerous diverse activities and very often we attempt to master more than one activity simultaneously – trying to maintain high levels of efficiency. Although it is well known that multitasking performance often suffers (e.g., Pashler, 1994), we feel as efficient multitaskers when, subjectively, we need less time to complete two tasks simultaneously than in succession (without making too many errors). Indeed, assessing efficiency in multitasking is usually based on the comparison of the time needed to complete two tasks in combination vs. in isolation and this comparison almost inevitably reveals dual-task costs. The most prominent finding is that the response time in the second of two tasks (RT2) is dramatically slowed down the shorter the interval between the onset of the stimuli is (*stimulus onset asynchrony*; SOA). This so-called *psychological refractory period* (PRP) effect (Telford, 1931; Welford, 1952) is usually attributed to a structural limitation in information processing allowing central processes (e.g., response selection) to proceed only serially and supporting the *response selection bottleneck* (RSB) model (Pashler, 1984, 1994). However, frequently RT1 also suffers from dual-tasking supporting the assumption of central capacity sharing (e.g., Navon & Miller, 2002; Tombu & Jolicoeur, 2003). If two tasks are processed in parallel, they share limited central capacity – to the benefit of RT2 but leading to costs in RT1. Also, the finding of backward crosstalk (compatibility effects in RT1 resulting from response related processes in Task 2) is more in line with capacity sharing (e.g., Mittelstädt & Miller, 2017) – unless, as suggested by Hommel (1998), the RSB model is extended by the stage of automatic response *activation* (in Task 2) proceeding in parallel to response *selection* in Task 1, influencing RT1 (see also Durst & Janczyk, 2018; Janczyk, Renas, & Durst, 2018).

Occasional findings of "virtually perfect time sharing" (Schumacher et al., 2001), that is, efficient parallel processing without any costs, constitute exceptional cases in the dual-tasking literature, keeping the debate going whether central processing can, in principle, proceed in parallel for two tasks or not (for a review, see Fischer & Plessow, 2015).

Miller, Ulrich, and Rolke (2009) suggested to define dual-task efficiency by the sum of the RTs in task 1 and task 2 (RT1 + RT2). The smaller the so-called "total response time" (TRT), the higher the multitasking efficiency. They suggested that in almost all cases, serial central processing should be the most efficient performance strategy, largely reducing, for instance, performance costs due to central capacity sharing (in task 1) and/or crosstalk (see also, e.g., Lehle & Hübner, 2009). They also demonstrated, however, that certain dual-task contexts, involving high proportions of trials with strongly temporally overlapping tasks (i.e., SOA $\approx$ 0 ms), can favor parallel over serial processing in terms of efficiency – actually, in rare cases, allowing for (virtually) perfect time sharing.

Integrating research on multitasking and research on implicit sequence learning, Schumacher and Schwarb (2009, Experiment 1) also demonstrated differences in dual-task performance in conditions presenting two stimuli (S1 and S2) either always simultaneously (SOA = 0 ms; DT-S condition) or consistently separated by a long SOA of 750 ms (DT-L condition). Only in the DT-S condition, they replicated the ubiquitous finding of impaired implicit sequence learning in dual-tasking (see, e.g., Cohen, Ivry, & Keele, 1990; Curran & Keele, 1993; Frensch, Buchner, & Lin, 1994; Frensch, Lin, & Buchner, 1998; Frensch, Wenke, & Rünger, 1999; Heuer & Schmidtke, 1996; Nissen & Bullemer, 1987; Rah, Reber, & Hsiao, 2000; Schmidtke & Heuer, 1997; Stadler, 1995). In the DT-L condition, learning was preserved. The authors attributed this preservation of implicit sequence learning to serial- and its impairment to parallel dual-task processing.

We suggest to interpret this differential learning outcome as a novel indicator of dual-tasking efficiency – in addition to (e.g.) the TRT of Miller et al. (2009). Implicit learning, as one of the most fundamental learning processes (e.g., Dienes & Berry, 1997), results, without much effort, in highly adaptive behavior. A dual-task context with consistently long SOAs (DT-L condition) seemingly allows implicit learning (and, thus, the development of this highly adaptive behavior) via serial processing. Accordingly, and as suggested by Schumacher and Schwarb (2009), the finding of impaired implicit learning in the DT-S condition adds to the majority of findings demonstrating the inferiority (in terms of efficiency) of a parallel processing mode. Thus, differentially strong implicit learning effects can possibly be seen as the outcome of more vs. less efficient dual-tasking.

In general, it is still not well understood, why implicit learning is impaired in dual-tasking (for reviews, see Keele, Ivry, Mayr, Hazeltine, & Heuer, 2003; Schumacher & Schwarb, 2009). Since it enables humans to automatically and effortlessly adapt to regular structures in the environment, its impairment in multitasking situations, requiring high levels of adaptability or flexibility, is somehow paradox. Especially in the light of a second finding of Schumacher and Schwarb (2009). In Experiment 2, they simply instructed the participants to prioritize the sequence learning task over the secondary task while the SOA was consistently short – and learning was preserved. That is, although the participants were apparently able to learn a sequence inherent in one of two temporally overlapping tasks, simply by implementing, as instructed, a serial processing mode, they failed to do so if the instructions highlighted equal task priority. In other words, the participants seemed to choose (or to lapse into) the inefficient parallel processing mode if not otherwise instructed – and if short SOAs were frequent.

A similarly paradox behavior was observed by Lehle and Hübner (2009). They turned the *Eriksen Flanker Task* (Eriksen & Eriksen, 1974) into a dual-task requiring a first response (R1) to the target and a second response (R2) to the flankers, and instructed the participants either to process the tasks serially or in parallel (see also Hübner & Lehle, 2007). Importantly, in a third condition, the participants received no specific instruction. Then, they assessed the degree of strategic central capacity sharing between the two tasks in terms of the size of the *flanker congruency effect* (FCE) in RT1 and RT2 in the three conditions. The FCEs were largest in the parallel condition reflecting high degrees of crosstalk, smallest in the serial condition – and intermediate in the condition with no specific instruction. Thus, although the participants were, in principle, able to globally adjust the degree of (inefficient) parallel processing (if instructed to do so), they chose a "moderate degree of parallel processing" in the control condition – thereby accepting large performance costs (Lehle & Hübner, 2009). The flankers became imperative by changing their color (and sometimes also their identity) after varying SOAs of 50, 150, and 350 ms. Whether this PRP-like SOA manipulation also affected the choice of the processing mode is unclear. FCEs were present with all degrees of temporal task overlap in the control condition but slightly modulated with the longest SOA (350 ms). However, since this interval was still rather short, the longer SOA of 750 ms used by Schumacher and Schwarb (2009) should have reduced the FCEs – indicating an almost inevitable switch to the serial processing mode (because this SOA is long enough that R1 can be produced before S2 occurs). It is, however, an empirical question whether such switches would happen automatically, due to the actually presented long SOA and, thus, trialwise – or whether the overall strategy would globally become (more) serial.

An observation resembling the latter outcome was made by Israel and Cohen (2011). Within eleven sessions, participants always had to perform two tasks with equal priority. The first eight sessions included alternating single- and dual-task blocks in which the SOA was always zero. Comparing single- and dual-task performance in sessions seven and eight, the authors found no dual-task costs any more. Obviously, after some training, the participants were able to perform the two tasks highly efficiently in parallel. However, in the last three sessions, the PRP procedure was introduced with SOAs varying between 0, 50, 150, and 800 ms and dual-task costs (in RT2) were back – even in trials actually presenting the extensively practiced situation with an SOA of zero milliseconds. It seemed as if the PRP timing context led the participants to involuntarily prioritize one task over the other, that is, to globally engage in an "exogenous" serial processing strategy (as the authors termed it).

To summarize, Israel and Cohen (2011) as well as Schumacher and Schwarb (2009), and also Lehle and Hübner (2009) demonstrated that participants are, in principle, able to flexibly adopt the respective most efficient global processing strategy by instruction or after some training – even if the context calls for increased effort to do so. With the exception of Israel and Cohen (2011) – who demonstrated a rare case of perfect time sharing – serial processing was considered to be the most efficient dual-tasking strategy. It reduces the TRT (Miller et al., 2009), it reduces crosstalk (Lehle & Hübner, 2009) and it preserves sequence learning (Schumacher & Schwarb, 2009).

Most importantly (and in line with Miller et al., 2009), in the absence of prioritization instructions, manipulating the SOAs had an immense effect on the participants' performance outcomes and, thus, most likely on their processing strategies in the studies of Israel and Cohen (2011) and Schumacher and Schwarb (2009). In the latter, separating a sequence learning task and a secondary task consistently by a long SOA preserved implicit sequence learning via serial processing. Presenting varying SOAs in the former apparently led to a global serial processing strategy as well. These two findings, however, are in contrast to the observation of Lehle and Hübner (2009) that participants in the control condition produced medium sized FCEs due to parallel processing – even though they had been exposed to (moderately) varying SOAs as well.

Given these inconsistent findings, the aim of the present study was to investigate which kind of (exogenous?) dual-task strategy participants would adopt when conducting a sequence learning task concurrently with a secondary task in the context of varying SOAs – and to what extent this strategy would be efficient. As a measure of efficient performance, we were interested in the amount of implicit sequence learning. We considered three outcomes as possible. If the PRP context indeed globally triggers a serial processing strategy, even though the instructions emphasize equal priority of the two tasks (Israel & Cohen, 2011), implicit sequence learning should be overall preserved (cf. Schumacher & Schwarb, 2009; Experiment 1). If, on the contrary, participants engage in a moderately parallel processing strategy when not encouraged to prioritize one task over the other (Lehle & Hübner, 2009), independently of the SOA manipulation, sequence learning should be overall impaired (cf. Schumacher & Schwarb, 2009, Experiment 1 and 2). As a third outcome, however, as we will further explicate below, we conceived it possible that the participants' processing modes depend very much on the actual length of the SOA – allowing (or forcing) them to switch from more parallel to more serial processing only when the respective SOA is long. In this case, learning should be evident exclusively (or mainly) for certain elements of the sequence – namely for those that had been frequently paired with a long SOA.

The present study

In three experiments, we investigated whether and to what extent participants in a dual-task implicit sequence learning situation can efficiently exploit predictably varying SOAs in order to optimize their dual-task processing strategies. Therefore, we were interested in the size of the learning effects per SOA level. We paired a visual-manual *serial reaction time task* (SRTT; Nissen & Bullemer, 1987) with an auditory-vocal tone-discrimination task in a design similar to that of Schumacher and Schwarb (2009). After replicating their finding of preserved vs. impaired sequence learning with consistently long vs. short SOAs in Experiment 1, we conducted two further PRP experiments.

In Experiment 2, we linked high proportions of either short (0 ms) or long (800 ms) SOAs to different elements of the SRTT sequence. This procedure resembles to some degree the *item-specific proportion* (ISP-) SOA manipulation introduced by Fischer and Dreisbach (2015).[1] In a situation with dimensional overlapping tasks and, thus, a high risk for across-task conflict, the authors found evidence for trialwise adjustments towards more serial (or rather less parallel) processing for items predominantly paired with short SOAs in terms of

[1] The ISP-SOA manipulation of Fischer and Dreisbach (2015) is related to the "proportion congruent" (PC) literature (for a review, see Bugg & Crump, 2012). The main finding, here, is that congruency effects are smaller for lists, contexts or items predicting high (in contrast to low) levels of conflict.

smaller backward crosstalk effects (BCEs). This outcome is understood as indicating a high extent of flexibility and efficiency. Participants seem to exploit the predictability of the short SOAs (and, thus, the predictability of conflict) and to intensify "on-the-fly" their levels of task shielding. For such adjustments to occur, the frequent exposure to conflict with certain items is a precondition. In our paradigm (rather lacking conflict due to dimensional overlap), a different source of conflict, especially with short SOAs, could possibly be the randomness of the tones in task 2 hampering task integration (Rah et al., 2000; Röttger, Haider, Zhao, & Gaschler, 2019; Schmidtke & Heuer, 1997). Potential item-specific conflict adaptation (in terms of more task shielding / serial processing for items predicting the short SOA) should, here, logically result in substantial learning effects for both item types. This outcome would be indistinguishable from that predicted by Israel and Cohen (2011), overall substantial sequence learning due to globally serial processing triggered by the mere presence of varying SOAs. Nevertheless, we were interested in the effect that such an ISP-like SOA manipulation would have on sequence learning in a PRP context for the following reason.

To the extent that sequence learning in a SRT task is implicit and incidental, it is conceivable that participants are unaware of conflict or "task integration confusion" due to the randomness of a secondary task – even with short SOAs. However, without even a vague feeling that responding to some SRTT elements is harder than to others (e.g., Dreisbach & Fischer, 2011) or feels more aversive (e.g., Dreisbach & Fischer, 2015; Dreisbach, Reindl, & Fischer, 2018), flexible anticipative strategy adjustments could also be simply impossible. Thus, if it is true that participants in our paradigm do not feel clear differences between the item types, they might indeed overall engage in moderately, low-effort, parallel processing as Lehle and Hübner (2009) suggested – but only until actually a long SOA occurs and provides the optimal mechanistic precondition for (a) serial processing and (b) for the development of implicit associations. Associations, for instance, between successive events within the SRTT as a consequence of their prolonged undisturbed conjoint activation. Substantial learning effects for SRTT elements that had been frequently paired with the long SOA – but weak (or absent) learning effects for elements that had been frequently paired with the short SOA should be the – completely incidental – result.

Otherwise, if participants do indeed engage globally in one or the other processing strategy, rather than passively drifting between parallel and serial processing, we should find overall substantial (Israel & Cohen, 2011; serial strategy) or overall impaired sequence learning (Lehle & Hübner, 2009; parallel strategy).

To foreshadow, since we found overall substantial learning in Experiment 2, being, at first sight, in accord with a global serial processing strategy triggered by the PRP context (Israel & Cohen, 2011) – or with flexible adjustments towards more serial processing for items predicting the short SOA (Fischer & Dreisbach, 2015) – we conducted Experiment 3. Here, we examined the probability that, in fact, the significant learning effect also for items predicting the short SOA, resulted from the small proportion of trials in which the actually occurring SOA was (untypically) long. For this purpose, we extended the design of a previous Experiment (Röttger et al., 2019; Experiment 4) in which we already had observed differential learning effects for single elements within a SRTT sequence. Elements being 100% predictive for the required secondary task response (fixedly paired elements) had been learned – while the unpredictive (randomly paired) elements had not been learned. In the present Experiment 3, the fixedly paired sequence positions were now additionally to 100% combined with the long SOA, the variably paired elements to 100% with the short SOA. We hypothesized that if the context of varying SOAs indeed triggers a global serial processing strategy, the variably paired sequence elements should now also be learned.

Since our research question concerns participants' (efficient?) adaptation to varying SOAs in a PRP context, reflected in the amount of dual-task implicit sequence learning, our focus lies on the SRTT data (RTs and error rates). That is, in the present study, we see the tone-task mainly as a part of the SOA manipulation – with its outcome being of rather marginal interest. Only for the purpose of double checking the extent of serial vs. parallel processing from the RT patterns in the dual-task training phase, we report the tone-task data (RTs only) as well. In the respective analyses, we collapsed the RTs of both tasks (separately) across all training blocks and analyzed them as a function of the SOAs (i.e., the actual SOAs as well as, in Experiment 2, the most likely SOAs). Following the predictions of Miller et al. (2009), RTs in the primary task (probably the SRTT)[2] should be generally faster the higher the extent of serial processing, that is, the higher the proportion of long SOAs per condition. At the same time, RTs in the secondary task (the tone-task, accordingly) should show a steeper PRP effect. Potentially, these RT patterns would additionally be modulated by the ISP-SOA manipulation in Experiment 2.

[2] Although we instructed the participants to give both tasks equal priority, we expected them to prioritize the visual-manual SRTT over the auditory-vocal tone-task because this freely chosen task order has been observed many times before and is, thus, very common (e.g., Liepelt, Strobach, Frensch, & Schubert, 2011; Röttger et al., 2019; Schumacher & Schwarb, 2009; Schumacher et al., 2001; Strobach, Salminen, Karbach, & Schubert, 2014). Additionally, it seems that participants prefer to respond to the easy task first – which might have been the SRTT (with spatially compatible S-R mappings) in our case (cf. Ruiz Fernández, Leonhard, Rolke, & Ulrich, 2011).

Experiment 1

The goal of Experiment 1 was to replicate the finding of Schumacher and Schwarb (2009) that dual-task implicit sequence learning is preserved in a condition with 100% long SOAs (SOA_{long} condition), but that no learning occurs in a condition with 100% short SOAs (SOA_{short} condition). Therefore, we combined a visual-manual SRTT (Nissen & Bullemer, 1987) with a two-choice auditory-vocal tone-discrimination task across six dual-task training blocks. Taking into account that only the expression of learning might be disturbed in dual-tasking (Frensch et al., 1998; 1999), we subsequently assessed sequence learning under single-task conditions (three blocks SRTT only).

Method

Participants

Sixty-two students of the University of Cologne (13 men; mean age 21.65, $SD = 3.54$) participated in Experiment 1 either for monetary compensation or for course credit. Each session lasted approximately 45 min.

Apparatus and stimuli

The experiment was controlled by custom-written software (Lazarus / FreePascal, compiled for Microsoft Windows). In both conditions, the placeholders for the visual SRTT target (an uppercase "X") were four horizontally aligned white squares on a light grey background (100 x 100 pixels, separated by gaps of also 100 pixels). They were displayed slightly below the center of a TFT monitor (19 inch; 1280 x 1024 pixels) that was connected with a standard PC. In each trial, the SRTT target occurred for 100 ms in one of the four white squares and the participants had to press a spatially mapped key in response (Y, X, N, M on a QWERTZ-keyboard). Unbeknownst to the participants, the responses in the SRTT followed a 2nd order conditional 8-elements sequence (3-1-2-4-1-3-4-2). Additionally, after an SOA of 0 ms or 800 ms, a high (900 Hz) or a low (300 Hz) pitched tone, lasting 56 ms, was played in an unpredictable sequence requiring the verbal responses "hoch" vs. "tief" [high vs. low]. The response-window closed 2000 ms after the SRTT target onset and the next trial started immediately. A sound mixer (Behringer XENYX 302USB) served as bridge between headset and PC and integrated the tone stimuli with the verbal responses into one single wave-file per trial. The tone-task was analyzed offline, after the experiment.

Procedure

All participants were introduced step by step into the dual-task training phase. After 20 practice trials with only the tone-discrimination task and another 20 practice trials with only the SRTT, they received 20 practice trials with the dual-task (SOA = 0 ms and free response order in the two conditions). In these practice trials, both tasks did not follow any regular sequence.

In the training phase, the participants performed 6 dual-task blocks of 96 trials each. Now, the SRTT followed the 8-elements sequence, each block starting at a randomly drawn sequence position. A dual-task trial began with the presentation of the visual SRTT target (the "X") and the simultaneous (SOA_{short} condition; SOA = 0 ms) vs. the deferred (SOA_{long} condition; SOA = 800 ms) onset of one of the two auditory stimuli of the tone-task. The instructions highlighted equal priority of the two tasks and the response order was free in both conditions (see also Schumacher & Schwarb, 2009; Experiment 1).

The dual-task training phase was followed by 3 single-task test blocks of also 96 trials presenting only the SRTT. In blocks 7 and 9, the SRTT sequence was (pseudo-)randomized (i.e., immediate repetitions were not allowed). In block 8 the originally trained sequence was reintroduced.

At the end of the experiment, participant's explicit sequence knowledge was assessed (for details, see Röttger et al., 2019). Since it turned out that infrequent signs of partly explicit knowledge did not modulate any effect, the respective results will not be reported.

Results and Discussion

Trials were excluded due to errors or RTs < 200 ms or > 1500 ms in the SRTT. Furthermore, the data of 2 participants were excluded completely because their SRTT error rates exceeded 30% in at least one block. Two further participants were excluded because they showed a negative learning effect (faster RTs in the random- than in the regular blocks) that deviated from the respective condition mean by more than 2 *SD*.

Additionally, we identified a subgroup of participants whose mean SRTT RTs with long SOAs (1169 ms across all training blocks compared to 440 ms in the remaining sample) exceeded by far the length of the respective SOA. That is, the participants seemed to wait until tone onset – responding only after having processed both stimuli. The data of these 8 participants are reported separately, in the Appendix.

In the data of the remaining 50 participants (n = 25 per condition), we identified 0.8% RT outliers and 2.1% SRTT errors, thus overall 2.3% of the trials were excluded. We will first report the results of the dual-task training phase and, second, the results of the single-task test phase.

Performance in the training blocks

First, we assessed which task order the participants had preferred during the training phase. The mean inter-response intervals (IRIs), computed as $RT_{tone\text{-}task}$ + SOA – RT_{SRTT}, were positive (SOA_{short} condition: 186 ms / SOA_{long} condition: 969 ms) meaning that the participants had responded, on average, to the SRTT first.

Figure 1 displays the mean RTs in the SRTT (i.e., RT1) and the tone-discrimination task (i.e., RT2), collapsed across the six dual-task training blocks as a function of SOA condition. As can be seen, the mean RTs in the SOA_{short} condition were much slower than the RTs in the SOA_{long} condition in both tasks (SRTT: 583 ms vs. 440 ms / tone-task: 763 ms vs. 608 ms, respectively). Accordingly, the two one-way ANOVAs with mean RTs as dependent variable revealed significant effects of SOA condition in the SRTT, $F(1,48) = 27.55, p < .001, \eta_p^2 = .365$, and in the tone-task as well, $F(1,48) = 30.18, p < .001, \eta_p^2 = .386$.

Mean SRTT error rates were very low in the SOA_{short} condition (0.89%). In the SOA_{long} condition, however, the very fast RTs were accompanied by increased error rates (2.88%). Thus, the corresponding one-way ANOVA revealed a significant main effect of SOA condition, $F(1,48) = 24.78, p < .001, \eta_p^2 = .340$.[3]

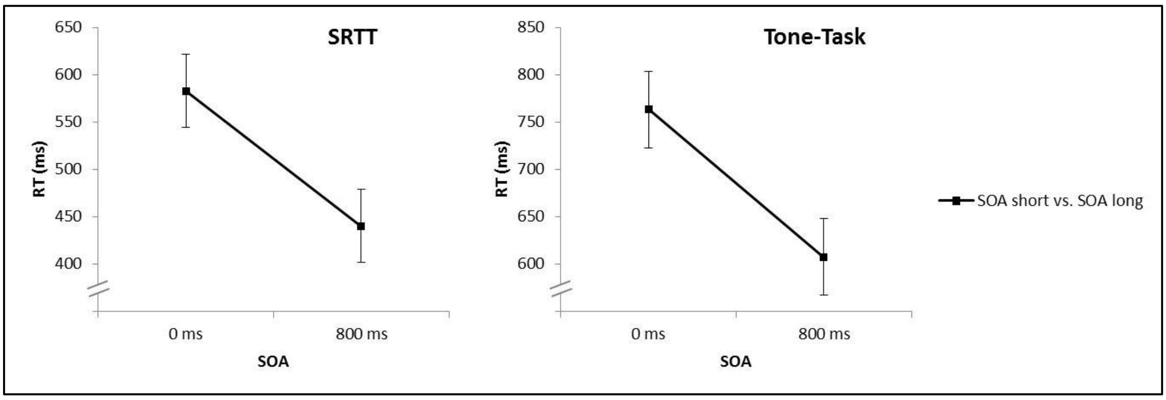

Figure 1. Mean RTs in the SRTT (left panel) and the tone-discrimination task (right panel) as a function of SOA condition in Experiment 1. Error bars represent the 95% between-subjects confidence intervals of the SOA effect (Loftus & Masson, 1994).

[3] Including the factor block in the analyses of the training phase revealed significant main effects in the SRTT, the tone-task and the SRTT error rates (all *p*s < .05). The RTs and the error rates were highest in the earlier blocks and decreased in the following. The two-way interaction with SOA condition was significant only in the SRTT, showing a slightly stronger block effect in the SOA_{long} condition; $F(5,240) = 2.45, p = .035, \eta_p^2 = .049$ (all other *F*s < 2.0; all other *p*s > .08).

Performance in the test blocks

To assess sequence learning in the SRTT single-task test, we compared the mean RTs (and error rates) of the collapsed random blocks 7 and 9 with the mean RTs of the regular block 8, separately for each SOA condition (see Figure 2). Just like in our previous study (Röttger et al., 2019), it turned out that the participants needed some trials to accommodate themselves to the single-task context, showing speed-accuracy trade-offs in the first half of the first random block (block 7). Therefore, only the second half of block 7 entered the analysis of the single-task test. The respective (two-tailed) *t*-tests revealed that the larger learning effect of 9 ms in the SOA_{long} condition was significant, $t(24) = 2.37$, $p = .026$, $d = 0.473$ – while the smaller learning effect in the SOA_{short} condition (5 ms) was not, $t(24) = 1.34$, $p = .194$, $d = 0.267$.

In addition, we conducted Bayes analyses (see Dienes, 2014) to assess whether the smaller and non-significant learning effect in the SOA_{short} condition is in accordance with the Null hypothesis (no sequence learning). Based on previous data of the single-task condition of Experiment 1 in Röttger et al. (2019), we specified a maximum expected learning effect of 26 ms if the hypothesis was true that the participants had acquired some knowledge about the sequence. For the SOA_{long} condition, the Bayes factor was $BF = 4.36$ and, thus, clearly indicated sequence learning. By contrast, in the SOA_{short} condition, the resulting Bayes factor was $BF = 0.68$ indicating insensitivity of the data for making a clear decision.

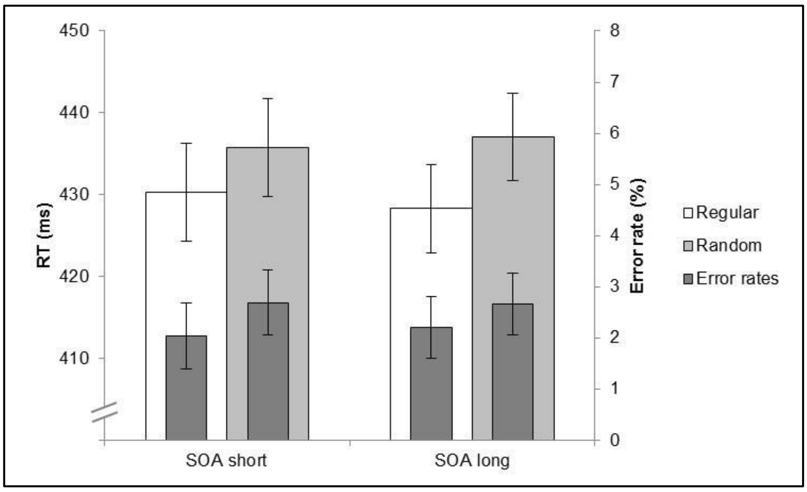

Figure 2. Mean RTs (left y-axis) and error rates (right y-axis) in the regular and the random single-task SRTT test blocks for the SOA_{short} and the SOA_{long} condition in Experiment 1. Error bars represent the 95% within-subjects confidence intervals of the learning effects calculated separately for each condition (Loftus & Masson, 1994).

As Figure 2 shows, the error rates in the collapsed random test blocks were higher than in the regular block in both conditions (2.69% vs. 2.04% in the SOA_{short} and 2.67% vs. 2.21% vs. SOA_{long} conditions, respectively). However, the two corresponding *t*-tests revealed no significant differences (both *t*s < 1.5).

To summarize, the findings in Experiment 1 replicate the results of Schumacher and Schwarb (2009; Experiment 1). We found clear evidence for sequence learning in the SOA_{long} condition, but not so in the SOA_{short} condition. The slightly less pronounced difference between the two conditions compared to the Schumacher and Schwarb study is most likely due to a shorter training phase and the application of a single-task test in our experiment. Dual-task tests, as used by Schumacher and Schwarb, i.e., with the tones still present, have been shown to reveal larger learning effects (e.g., Schmidtke & Heuer, 1997).

RTs in the SRTT (RT1) were significantly faster in the SOA_{long} condition than in the SOA_{short} condition, in line with the assumption of increased – and more efficient – serial processing with a high proportion (here 100%) of long SOAs (Miller et al., 2009). RT2 (tone-task) were also faster in the SOA_{long} condition. Accordingly, the TRT, as an independent measure of efficiency (apart from the learning effects), was smaller in the SOA_{long} condition (1048 ms) than in the SOA_{short} condition (1346 ms); $t(48) = 5.91$, $p < .001$, $d = 1.501$.

Experiment 2

Experiment 2 aimed at testing whether and how efficiently participants are able to adjust their dual-task processing strategies due to predictably varying short and long SOAs in a PRP context. If participants adopt one global processing strategy, we expected overall preserved sequence learning in case that this strategy is serial (Israel & Cohen, 2011) – but overall impaired sequence learning in case that it is parallel (Lehle & Hübner, 2009). To additionally investigate whether participants adjust their processing mode rather trialwise (due to the experience of the SOAs) we linked high proportions of short and long SOAs to different elements of the SRTT (resembling an ISP-SOA manipulation). In case that the participants' performance depends rather passively on the actually occurring SOAs, we expected to find a substantial learning effect for SRTT elements mostly paired with a long SOA – but a reduced learning effect for elements mostly paired with a short SOA. In the following, we will refer to these types of proportional SRTT-SOA pairings as *SOA types*.

Method

Participants

Sixty-two students of the University of Cologne (18 men; mean age 22.63, *SD* = 3.35) participated in Experiment 2 either for monetary compensation or for course credit. Each session lasted approximately 45 min.

Apparatus and stimuli

Apparatus, stimuli and the 2nd order conditional SRTT sequence (3-1-2-4-1-3-4-2) were the same as in Experiment 1. Short and long SOAs varied within blocks and occurred with an overall probability of 50% each. Importantly, two of the four SRTT response locations (i.e., location 1 and 3) now predicted the 800 ms SOA with a probability of 75% (SOA type 800) – and the other two (i.e., location 2 and 4) predicted the 0 ms SOA with a probability of 75% (SOA type 0). Thus, a *typical* sequence of SRTT-SOA combinations would have been 3 (long) – 1 (long) – 2 (short) – 4 (short) – 1 (long) – 3 (long) – 4 (short) – 2 (short). However, there was always a probability of 25% that the actually occurring SOA was of the *non-typical* length. The SRTT- and the tone-task events were uncorrelated.

Procedure

The procedure was also the same as in Experiment 1. Six dual-task training blocks were followed by three single-task test blocks.

Results and Discussion

Trials were excluded due to errors or RTs < 200 ms or > 1500 ms in the SRTT. Furthermore, the data of 1 participant were excluded completely because the SRTT error rate exceeded 30% in at least one block. Three further participants were excluded because they showed a negative learning effect (faster RTs in the random- than in the regular blocks) that deviated from the respective mean per SOA type by more than 2 *SD*.

As in Experiment 1, we identified a subgroup of 8 participants whose SRTT RTs with long SOAs (1064 ms compared to 537 ms in the remaining sample for SOA type 800 across all dual-task training blocks) exceeded by far the length of the respective (typical) SOA. The data of these participants will be reported separately, in the Appendix.

In the data of the remaining 50 participants we identified 0.7% RT outliers and 1.9% SRTT errors, thus overall 2.1% of the trials were excluded. Again, we will first report the results of the dual-task training phase and, second, the results of the single-task test phase.

Performance in the training blocks

As in Experiment 1, the mean IRIs were throughout positive (455 ms for SOA type 0 / 721 ms for SOA type 800, respectively) – meaning that the participants had responded, on average, to the SRTT first.

Figure 3 displays the mean RTs in the SRTT (i.e., RT1) and the tone-discrimination task (i.e., RT2), collapsed across the six dual-task training blocks as a function of actual SOA and SOA type. For means of comparison, the results of Experiment 1 are also depicted. As can be easily seen, the most crucial result in Experiment 2 was that the RTs in both tasks were exclusively affected by the actual SOAs (SRTT: 64 ms / tone-task: 208 ms across both SOA types). They did not differ due to the different SOA types (SRTT: 3 ms / tone-task: 4 ms across both actual SOAs). Furthermore, the RT pattern in the SRTT (RT1) was reversed compared to Experiment 1: RT1 was faster with actually short than with actually long SOAs (490 ms vs. 554 ms, respectively, across both SOA types). Nevertheless, the RT pattern in the tone-task (RT2) was similar to that in Experiment 1: RT2 was slower with actually short than with actually long SOAs (807 ms vs. 599 ms, respectively, across both SOA types).

Accordingly, two 2 (actual SOA) x 2 (SOA type) repeated measures ANOVAs[4] with mean RT1 and mean RT2 as dependent variables, respectively, revealed only main effects of actual SOA in the SRTT, $F(1,49) = 31.22$, $p < .001$, $\eta_p^2 = .389$, and in the tone-task as well, $F(1,49) = 291.05$, $p < .001$, $\eta_p^2 = .856$ (all other *F*s < 1.58).

The mean SRTT error rates were overall rather low and were neither affected by the actual SOA nor by the SOA type (1.83% for SOA type 0; 2.08% for SOA type 800; all Fs < 1.38 in the corresponding ANOVA).[5]

[4] Whenever the sphericity assumption was violated, Greenhouse-Geisser corrected *p*-values are reported, along with the original degrees of freedom.

[5] Including the factor block in the analyses of the training phase revealed significant main effects in the SRTT (RT1; $p < .001$) and in the tone-task (RT2; $p < .001$) but not in the SRTT error rates ($F < 1$). The two-way interaction with SOA type was significant only in RT1 ($p = .039$) with slightly faster RT1 for SOA type 800 than for SOA type 0 in the sixth block – it was, however, not significant in RT2 and in the SRTT error rates (both *F*s < 1). The two-way interaction with actual SOA was significant in RT1 ($p < .001$) and RT2 ($p = .009$) but not in the SRTT error rates ($F < 1.4$). All three-way interactions SOA type x SOA x block were not significant (all *F*s < 2.1).

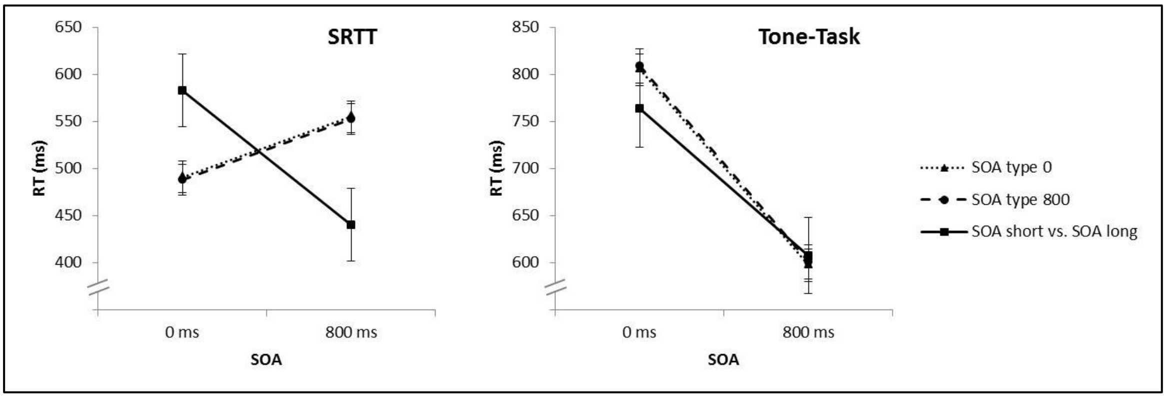

Figure 3. Mean RTs in the SRTT (left panel) and the tone-discrimination task (right panel) as a function of actual SOA and SOA type in Experiment 2. For means of comparison, they are depicted together with the results of Experiment 1. Error bars represent the 95% confidence intervals (Loftus & Masson, 1994) of the effect of the actual SOA, calculated separately for each condition (Experiment 1; between-subjects) and SOA type (Experiment 2; within-subjects).

The overall RT pattern suggests that the participants were, in principle, sensitive for the varying SOAs. Nevertheless, they showed no modulation of their overall performance due to the ISP-SOA manipulation – neither in the SRTT nor in the tone-task. Interestingly, implementing a PRP context reversed the effect of the actual SOAs on participants' manual SRTT responses (compared to Experiment 1). RT1 was slower with actually long SOAs than with actually short SOAs. The effect of the actual SOAs on the vocal tone-task RTs (slower RT2 with short SOAs; i.e., the PRP effect) was similar to that in Experiment 1 but the slope was slightly steeper. Thus, with actually short SOAs, the RT patterns in both tasks were in accordance with the predictions of Miller et al. (2009) – faster RT1 and slower RT2 in the within-subjects condition (presenting both SOAs in an overall 50:50 ratio) compared to the between-subjects condition (presenting the short SOA in 100% of the trials). However, with actually long SOAs, RT1 was too slow to meet the predictions of Miller et al. (2009). We will come back to this point after reporting the results of the test blocks.

Performance in the test blocks

To assess sequence learning in the SRTT, we compared the mean RTs (and error rates) of the collapsed random blocks 7 (2^{nd} half) and 9 with the mean RTs of the regular block 8, separately for each SOA type (i.e., for the SRTT response locations that, during the dual-task training phase, had predicted the long SOA vs. the short SOA with a probability of 75% each). Figure 4 displays the respective mean RTs and error rates.

We conducted two separate (two-tailed) *t*-tests that revealed significant learning effects of 9 ms each for SOA type 800, $t(49) = 2.47$, $p = .017$, $d = 0.349$ as well as for SOA type 0, $t(49) = 2.01$, $p = .050$, $d = 0.284$.

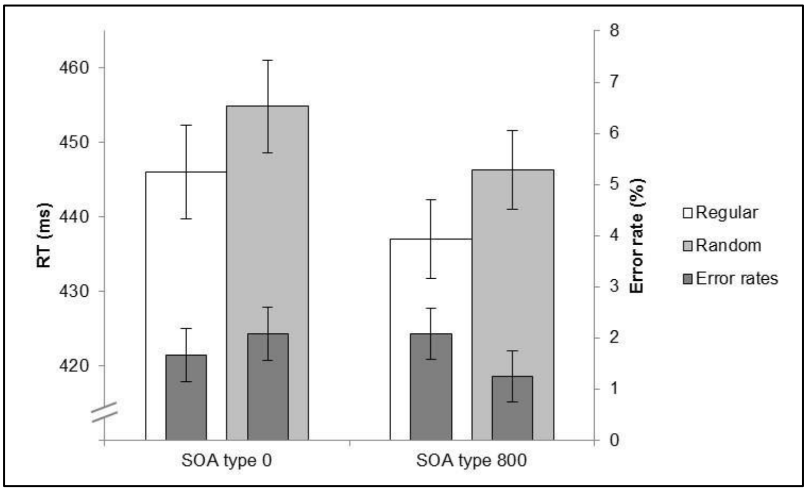

Figure 4. Mean RTs (left y-axis) and error rates (right y-axis) in the regular and the random single-task SRTT test blocks as a function of SOA type in Experiment 2. Error bars represent the 95% within-subjects confidence intervals of the learning effects calculated separately for each SOA type (Loftus & Masson, 1994).

Even though the numerical size of the learning effect was 9 ms for both SOA types, the effect sizes (Cohen's *d*) slightly differed. The additional Bayes tests confirmed this. Again, we used the size of the single-task learning effect (26 ms) from Experiment 1 of our previous study (Röttger et al., 2019) as the maximum expected learning effect. The resulting Bayes factor was BF = 5.30 for SOA type 800 indicating clear evidence for implicit learning. For the SOA type 0, the resulting Bayes factor was BF = 2.34, indicating insensitivity of the data for making a clear decision. However, this Bayes factor was numerically larger than the corresponding Bayes factor in the SOA_{short} condition in Experiment 1 (BF = 0.68) and nearly approached the criterion of 3.0 indicating learning (see Dienes, 2014).

The effect in the error rates for SOA type 0 mirrored the RT effect: more errors in the random blocks (2.08%) than in the regular block (1.67%). For SOA type 800, the effect was reversed (1.25% vs. 2.08%, respectively). Two *t*-tests (two-tailed) revealed that the reversed effect for SOA type 800 was significant, $t(49) = -2.39$, $p = .021$, $d = -0.338$, whereas the positive effect for SOA type 0 was not, $t(49) = 1.16$, $p = .253$, $d = 0.164$.

In contrast to Experiment 1 in which we replicated the findings of Schumacher and Schwarb (2009) – preserved implicit learning due to consistently long SOAs, probably via serial processing vs. impaired implicit learning due to consistently short SOAs, probably via parallel processing – Experiment 2 yielded overall rather surprising results. In the dual-task training phase, two outcomes are especially interesting.

The first interesting finding concerns the RT1 pattern (SRTT) as a function of the actual SOAs. Contrary to Experiment 1, RT1 was slower when the actual SOA was long than when it was short. This is not what one would expect given the assumption that long SOAs trigger serial processing (with faster RT1), while short SOAs trigger parallel processing (with slower RT1). However, since RT1 with long SOAs (554 ms) was still shorter than the SOA itself (800 ms), serial processing logically must have happened. Besides, the finding of increased RT1 with long SOAs in a PRP context is not unique – but currently not well understood. Miller et al. (2009) as well as Schumacher and Schwarb (2009; Experiment 3) also found slower RT1 with longer SOAs in their mixed SOA blocks. We will come back to this point in the "General Discussion".

The second interesting finding is that participants' performance was not modulated by the ISP-SOA manipulation – even though the main effect of the actual SOAs indicated that they were, in principle, sensitive to the varying time intervals. This suggests that they did not utilize the predictability of the SOAs. Potentially, because the PRP context itself already provided the relevant information determining the most efficient strategy – namely, a global serial processing strategy (cf. Israel & Cohen, 2011). In this case, however, the reversed effect of the actual SOA on RT1 (compared to Experiment 1) all the more needs an explanation since it, at first sight, hints at less efficient processing with long- compared to short SOAs. Consulting, again, the TRT as an independent measure of efficiency, reveals the opposite. The TRT was significantly smaller with actually long SOAs (1154 ms) than with actually short SOAs (1296 ms); $t(49) = 8.53$, $p < .001$, $d = 1.206$ – indicating more, instead of less, efficient processing with long SOAs.

The single-task test phase revealed substantial learning effects for both SOA types (although the evidence for learning was less clear for SOA type 0). By itself, this outcome also fits well to the assumption that the participants had globally adopted a serial processing strategy. However, one alternative interpretation is conceivable. Since the SOA types predicted a short or a long SOA with a probability of only 75% each (and occurred, thus, together with the respective other SOA in 25% of the trials), it is possible that the 25% long SOAs had been sufficient to preserve implicit learning for items of the SOA type 0. This would indicate a rather passive dependency of the participants' processing modes on the actually occurring SOAs – instead of the rather active utilization of the information provided by the PRP context. To further investigate this possibility, we conducted Experiment 3.

Experiment 3

Experiment 3 aimed at testing whether the significant learning effect for SRTT items of SOA type 0 in Experiment 2 should indeed be attributed to a serial processing strategy globally adopted by the participants in the PRP-like dual-task training phase – or whether it automatically resulted from the 25% of cases in which actually the long SOA had occurred. Therefore we reused the sequence material of Experiment 4 of our previous study (Röttger et al., 2019). Here, 4 of the 8 SRTT-elements had been fixedly paired with one particular tone whereas the other 4 elements had been randomly paired with the tones. The results indicated that exclusively the fixedly paired elements had been learned, probably because wrong, disruptive across-task predictions (inducing task integration conflicts) had occurred infrequently for these items. In the present experiment, we linked the fixedly paired elements additionally to 100% with the 800 ms SOA, and the randomly paired elements to 100% with the 0 ms SOA. We hypothesized that if the PRP context with varying SOAs triggers a global serial processing strategy, the randomly paired SRTT elements should now also be learned.

Method

Participants

Twenty-nine students of the University of Cologne (9 men; mean age 23.95, SD = 3.38) participated in Experiment 3 either for monetary compensation or for course credit. Each session lasted approximately 45 min.

Apparatus and stimuli

Apparatus and stimuli were the same as in Experiments 1 and 2. As in Experiment 4 of our previous study (Röttger et al., 2019), four positions of the 8-element SRTT sequence (3-1-2-4-1-3-4-2) were now fixedly paired with a particular tone and the other four positions were randomly paired with the tones. Importantly, the fixedly paired sequence positions now also predicted to 100% the 800 ms SOA (SOA type 800) and the randomly paired sequence positions predicted to 100% the 0 ms SOA (SOA type 0). Overall, both SOAs occurred with a probability of 50% each. In contrast to Experiment 2, now the SRTT response position 1 was always of SOA type 800, position 2 was always of SOA type 0 – positions 3 and 4, however, were each 1 x of SOA type 800 and 1 x of SOA type 0 in a 50:50 ratio. Thus, the sequence of SRTT-SOA-tone combinations was 3*R*(0)–1*F*(800)–2*R*(0)–4*F*(800)–1*F*(800)–3*F*(800)–4*R*(0)–2*R*(0); with F = fix tone; R = random tone.

Procedure

The procedure was the same as in Experiment 1 and 2. Six dual-task training blocks were followed by three single-task test blocks.

Results and Discussion

Trials were excluded due to errors or RTs < 200 ms or > 1500 ms in the SRTT. Furthermore, the data of 2 participants were excluded completely because they showed a negative learning effect (faster RTs in the random- than in the regular blocks) that deviated from the respective mean per SOA type by more than 2 *SD*.

As in Experiments 1 and 2, we identified a subgroup of 2 participants whose SRTT RTs with long SOAs (1184 ms compared to 530 ms in the remaining sample for SOA type 800 across all dual-task training blocks) exceeded by far the length of the respective SOA. The data of these participants will be reported separately, in the Appendix.

In the data of the remaining 25 participants we identified 1.1% RT outliers and 2.3% SRTT errors, thus overall 2.5% of the trials were excluded. Again, we will first report the results of the dual-task training phase and, second, the results of the single-task test phase.

Performance in the training blocks

The mean IRIs were throughout positive (312 ms for SOA type 0 / 861 ms for SOA type 800, respectively) – meaning that the participants had responded, on average, to the SRTT first.

Figure 5 displays the mean RTs in the SRTT (i.e., RT1) and the tone-discrimination task (i.e., RT2), collapsed across the six dual-task training blocks as a function of the factor SOA type (note, that "SOA type" was now equivalent to "actual SOA"). Again, for means of comparison, the results of Experiment 1 are also depicted. As in Experiment 2, the RT1 pattern due to the SOA manipulation was reversed compared to Experiment 1. RT1 was faster for SOA type 0 than for SOA type 800 (487 ms vs. 530 ms, respectively). The RT2 pattern revealed a PRP effect. RT2 was slower for SOA type 0 than for SOA type 800 (790 ms vs. 586 ms, respectively). The slope of this effect was again slightly steeper compared to the between-subjects SOA effect in Experiment 1.

Accordingly, two repeated measures ANOVAs with mean RT1 and mean RT2 as dependent variables, respectively, revealed a marginally significant effect of SOA type in the SRTT, $F(1,24) = 3.79, p = .063, \eta_p^2 = .136$, and a highly significant effect of SOA type in the tone-task, $F(1,24) = 151.78, p < .001, \eta_p^2 = .863$.

The mean SRTT error rates were overall rather low and not affected by the SOAs (1.92% for SOA type 0; 2.08% for SOA type 800; F < 1 in the corresponding ANOVA).[6]

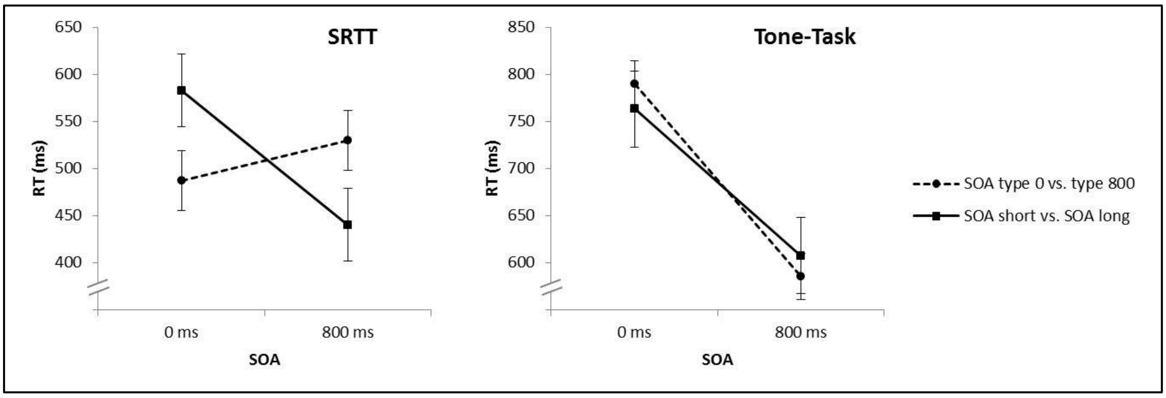

Figure 5. Mean RTs in the SRTT (left panel) and the tone-discrimination task (right panel) as a function of SOA type in Experiment 3, for means of comparison depicted together with the results of Experiment 1. Error bars represent the 95% confidence intervals (Loftus & Masson, 1994) of the SOA type effect (Experiment 3; within-subjects) / the SOA condition effect (Experiment 1; between-subjects).

Thus, the overall RT pattern was a replication of Experiment 2 and shows again that the participants were (on the one hand) sensitive for the varying SOAs but produced (on the other hand) a RT1 pattern questioning (at first sight) the assumption of serial processing due to a high proportion of long SOAs (here: 100% for SRTT elements of SOA type 800).

Performance in the test blocks

To assess sequence learning in the SRTT, we compared the mean RTs (and error rates) of the collapsed random blocks 7 (2nd half) and 9 with the mean RTs of the regular block 8, separately for each SOA type. Figure 6 displays the respective mean RTs and error rates. Two *t*-tests (two-tailed) revealed that for sequence positions of the SOA type 800, the mean RTs were significantly faster (39 ms) in the regular block 8 than in the surrounding random blocks 7 and 9, $t(24) = 10.68$, $p < .001$, $d = 2.137$. However, for sequence positions of the SOA type 0, the mean RTs were even slightly slower (-4 ms) in the regular- than in the random blocks. However, this negative effect was not significant ($|t| < 1$; $d = -0.115$). Thus, we found pronounced differences between the learning effects for the two SOA types.

[6] Including the factor block in the analyses of the training phase revealed significant main effects in the SRTT (RT1; $p = .008$) and in the tone-task (RT2; $p < .001$) but not in the SRTT error rates ($F < 1$). The two-way interaction with SOA type was marginally significant only in RT2 ($p = .064$) – but not in RT1 and in the SRTT error rates (both Fs < 1.7).

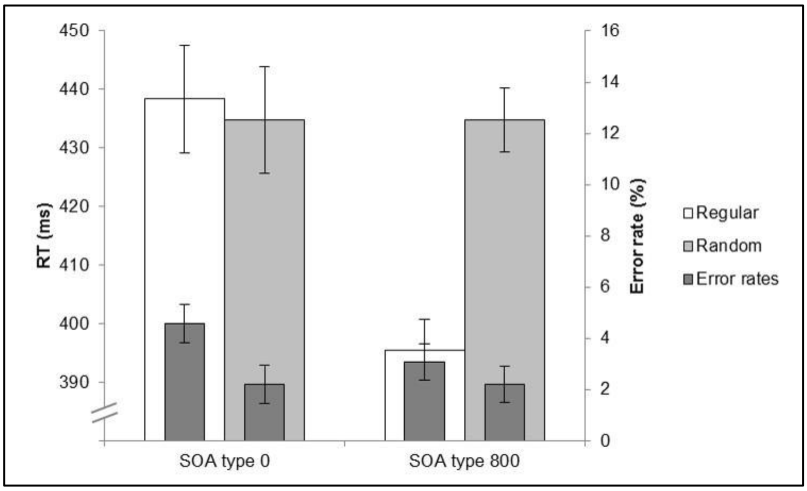

Figure 6. Mean RTs (left y-axis) and error rates (right y-axis) in the regular and the random single-task SRTT test blocks as a function of SOA type in Experiment 3. Error bars represent the 95% within-subjects confidence intervals of the learning effects calculated separately for each SOA type (Loftus & Masson, 1994).

Additional Bayes tests (see Dienes, 2014) confirmed this. Using again the size of the single-task learning effect (26 ms) from Experiment 1 of our previous study (Röttger et al., 2019) as the maximum expected learning effect, the resulting Bayes factor for SOA type 800 exceeded by far the criterion of BF =3.0 indicating clear evidence for implicit learning. For SOA type 0, on the contrary, the resulting Bayes factor was BF = 0.16, indicating clear evidence for the Null hypothesis.

For both SOA types, the error rates were slightly higher in the regular block than in the collapsed random blocks (differences of 2.36% and 0.86% for SOA type 0 and SOA type 800, respectively). Two *t*-tests (two-tailed) revealed that the negative effect for SOA type 0 was significant, $t(24) = -2.46$, $p = .021$, $d = -0.493$, whereas the negative effect for SOA type 800 was not ($|t| < 1$, $d = -0.128$).

To summarize, although the RT1 pattern in the training phase of Experiment 3 was a replication of Experiment 2 (slow RT1 with long SOAs suggesting less efficient processing), the TRT was, again, smaller for SOA type 800 (1115 ms) than for SOA type 0 (1277 ms), $t(24) = 5.00$, $p < .001$, $d = 0.999$ indicating, on the contrary, more efficient processing with long SOAs. In line with that, the single-task test phase now revealed a highly significant learning effect for SOA type 800 – but strongly reduced learning for SOA type 0. This was the case for every single item of each SOA type. Figure 7 shows the sizes of the learning effects (Cohen's d) for the 8 SRTT-SOA-tone combinations in their sequential order [3*R*(0)–1*F*(800)–2*R*(0)–4*F*(800)–1*F*(800)–3*F*(800)–4*R*(0)–2*R*(0); with *F* = fix tone; R = random tone]. The effect sizes for SOA type 800 ranged from *d* = 0.709 up to *d* = 1.389 and were, thus, very large. In contrast, the effect sizes for SOA type 0 were small and ranged from *d* = -0.254 up to *d* = 0.303. Interestingly, for response positions 3 and 4 (each 1 x fixedly paired and of SOA type 800 and 1 x randomly paired and of SOA type 0 in a 50:50 ratio), we found differential learning effects per SOA type as well – suggesting that the actual SOA determined whether learning was possible for a certain sequence element or not.

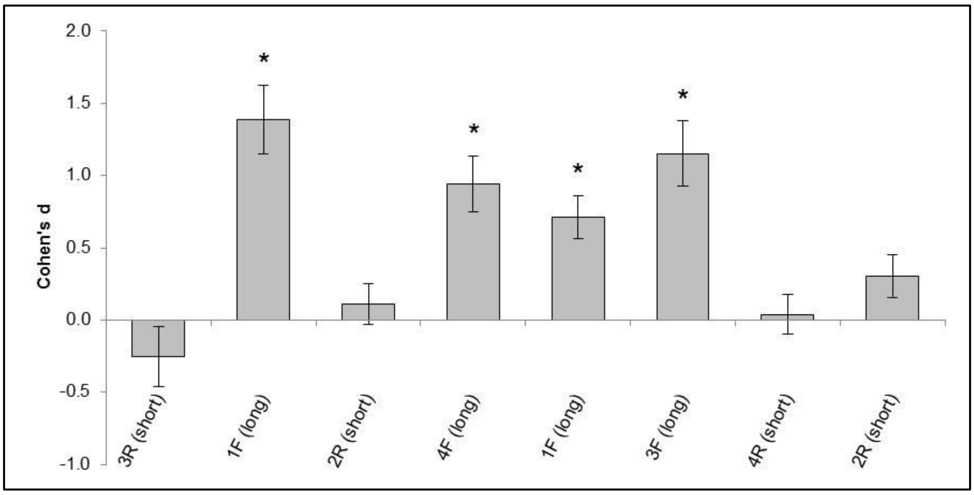

Figure 7. Cohen's d for the learning effect for the single SOA types in Experiment 3 in the order of their occurrence in the sequence. Error bars are the 95% confidence intervals of the effect sizes (see, e.g., Bühner & Ziegler, 2009).

Since we used a single-task test in which no SOAs and no tones were present any more, faster RTs for single SRTT positions of the (former) SOA type 800 occurring in the regular- compared to a random order suggest that the ordinal positions of the SOA types had been learned (Schuck, Gaschler, & Frensch, 2012; Schuck, Gaschler, Kreisler, & Frensch, 2012). This finding replicates our former results with the same stimulus- and sequence material but with SOAs of consistently 0 ms (Röttger et al., 2019, Experiment 4). Here, also exclusively the fixedly paired sequence elements (now of SOA type 800) had been learned (because they had enabled a successful within-trial task integration). In other words, implementing a PRP context in the present Experiment 3 did not change the pattern of results compared to the former Experiment 4 (Röttger et al., 2019). That is, it did not allow for learning now also the (randomly paired) SRTT elements of SOA type 0. This finding suggests that the participants had not adapted a global serial processing strategy, contrary to the predictions of Israel and Cohen (2011) – ruling out this possibility also for Experiment 2.

This finding is also at odds with the outcome of Fischer and Dreisbach (2015) who found adjustments towards more efficient (serial) dual-task processing for items predicting a short SOA (in the form of smaller BCEs). As mentioned above, the anticipative utilization of the predictable SOAs should have resulted in substantial learning (also) for elements of SOA type 0 – but the opposite was the case. Thus, the differential learning effects in the present Experiment 3 do certainly not reflect a high level of "flexibility" in the sense of (reactive) control or task shielding (see, e.g., Bugg & Crump, 2012; Fischer & Dreisbach, 2015; Fischer, Gottschalk, & Dreisbach, 2014; Gonthier, Braver, & Bugg, 2016). Rather, they indicate the passive dependency of the participants' behavior on the actually occurring SOAs. This point, as well as the question which kind of dual-task processing might have caused the observed effects will be discussed in the "General Discussion".

General Discussion

In the present study, we paired a visual-manual sequence learning task (SRTT) with an auditory-vocal tone-discrimination task and investigated whether and to what extent participants can exploit predictably varying SOAs in a PRP context in order to adjust their dual-task processing mode towards high efficiency. As a measure of efficient processing we looked at the sizes of the learning effects for SRTT positions predicting short vs. long SOAs.

We derived the conception of implicit learning as a marker for dual-task efficiency from the findings of a recent study of Schumacher and Schwarb (2009; Experiment 1). They reported substantial learning effects in a condition with consistently long SOAs (DT-L) – but reduced learning effects in a condition with consistently short SOAs (DT-S). The former was attributed to serial- the latter to parallel processing. This fits nicely to the assumption of Miller et al. (2009) that serial processing is most likely (and most efficient) in a context with a high proportion of long SOAs – while parallel processing is most likely (and *potentially* most efficient) in a context with a high proportion of short SOAs. We suggest that any dual-task processing mode allowing for implicit learning can be seen as efficient, because this kind of learning enables humans to effortlessly adapt to regularities in the environment (e.g., Dienes & Berry, 1997). Even though Israel and Cohen (2011) reported one rare case of "virtually perfect time sharing" and, thus, efficient parallel processing (see also, e.g., Schumacher et al., 2001), in the majority of cases, parallel processing turns out to be a rather inefficient strategy. It enlarges the TRT (Miller et al., 2009), it causes costs both in RT1 and RT2 due to crosstalk (e.g., Fischer & Dreisbach, 2015; Lehle & Hübner, 2009) – and it impairs implicit learning (Schumacher & Schwarb, 2009).

Interestingly, manipulating the length of the SOAs seems to have an immense impact on the participants' processing modes. The findings of Israel and Cohen (2011) even suggest that the mere existence of some long SOAs in a PRP context triggers an "exogenous" global serial processing strategy. To investigate whether varying SOAs (without explicit instructions to prioritize the SRTT) indeed trigger serial processing – or whether unspecific instructions (despite varying SOAs) rather result in "moderately parallel processing" as Lehle and Hübner (2009) suggested – we conducted three dual-task implicit sequence learning experiments and assessed the size of the learning effects due to short vs. long SOAs.

In Experiment 1, we varied the SOAs between-subjects and replicated the finding of Schumacher and Schwarb (2009), preserved learning in the SOA_{long} condition but impaired learning in the SOA_{short} condition. Additionally, the RT1 pattern (SRTT) in the training phase reflected more parallel processing in the SOA_{short} condition than in the SOA_{long} condition (slower RT1 in the former than in the latter). RT2 resembled a PRP effect.

In Experiment 2, we varied the SOAs within-subjects. Additionally, we linked high proportions (75%) of short vs. long SOAs, respectively, to different elements of the SRTT. As a result, we found significant learning effects for both SOA types, suggesting that the participants had globally adopted a serial processing strategy. Also, RT1 in the training phase was not modulated by the ISP-SOA manipulation. However, the RT1 pattern due to the actual SOAs was, surprisingly, reversed compared to Experiment 1. RT2 (also not modulated by the ISP-SOA manipulation) again revealed a PRP effect.

To test whether the varying SOAs had indeed triggered a global serial processing strategy or whether 25% actually long SOAs had been enough to also learn SRTT elements of SOA type 0, we conducted Experiment 3. Here, certain SRTT elements were consistently (to 100%) paired with either a long or a short SOA, respectively. Contrary to Experiment 2, we found substantial learning effects exclusively for elements of the SOA type 800 – but strongly reduced (even absent) learning effects for elements of the SOA type 0. Nevertheless, the RT1 pattern due to the actual SOAs (now equivalent to the factor SOA type) replicated Experiment 2 and was reversed compared to Experiment 1. RT2 again revealed a PRP effect. Thus, some aspects of our results are quite surprising and will be discussed in the following.

The most straightforward interpretation of the learning effects in Experiments 2 and 3 is that implicit learning took place automatically every time actually a long SOA occurred. In Experiment 2, for SRTT elements of SOA type 0, even the 25% of cases in which actually the long SOA occurred were sufficient in this respect. Accordingly, in Experiment 3 (with 100% SRTT-SOA contingency) learning for SOA type 0 was absent (confirmed by the Bayes factor $BF = 0.16$). This outcome suggests that merely implementing a PRP context does not trigger globally serial processing as Israel and Cohen (2011) proposed. It also implies that our

ISP-SOA manipulation (cf. Fischer & Dreisbach, 2015) did not result in flexible anticipative switches to more serial processing for elements of SOA type 0 – suggesting that, for this, at least a minor degree of conflict awareness or an (aversive) feeling of disfluency in conflict trials is required (for a short review, see Dreisbach & Fischer, 2012). Such conscious feelings might have been absent in our experiments since any "bumpiness" within the stimulus- and sequence material disturbed implicit processes.

We also found no evidence for a global parallel processing strategy (Lehle & Hübner, 2009) since implicit learning was definitely not globally impaired. Nevertheless, the kind of dual-task processing actually underlying the observed behavior did not allow for learning the whole sequence (i.e., chaining; see, e.g., Cleeremans, 2011). Instead, at least in Experiment 3, the participants seemingly had learned the ordinal positions (Schuck, Gaschler, & Frensch, 2012; Schuck, Gaschler, Kreisler, et al., 2012) of the SOA types (see also Röttger et al., 2019; Röttger, Haider, Zhao, & Gaschler, in prep.). Strong so-called position-item associations might have developed whenever, during the training, the actual presence of a long SOA at a certain position had allowed the undisturbed processing of one stimulus- and one response event, both belonging to the SRTT. With a short SOA, on the contrary, the simultaneous processing of two stimulus- and two response events belonging to separate tasks might have caused confusion and prevented strong associations. Afterwards, in the single-task test, the acquired implicit knowledge about the ordinal sequence positions of the different SOA types became manifest by facilitating the responses to SRTT elements of SOA type 800 occurring at the regular – compared to a random – ordinal sequence position.

This outcome suggests that the participants had drifted rather passively, in synchrony with the SOAs, between parallel and serial processing during the training – or, that they had preferred, in principle, a moderately parallel processing mode (cf. Lehle & Hübner, 2009), not learning anything – until actually a long SOA occurred (longer than their mean RT1) forcing them to process the tasks serially (thereby strengthening the relevant associations). Obviously, these switches to serial processing took place automatically, due to the long SOA, and required no increased levels of effortful control (as it would be necessary with strongly temporally overlapping tasks and the requirement to shield the performance against between-task interference). According to Lehle and Hübner (2009), humans prefer to avoid effortful control (see also Fischer & Plessow, 2015; Lehle, Steinhauser, & Hübner, 2008; Plessow, Schade, Kirschbaum, & Fischer, 2017) – and the observed behavior in our PRP experiments is in accord with that.

The fact that the participants had, in result, learned only parts of the SRTT sequence (the ordinal positions of SOA type 800) suggests that globally efficient (i.e., in most cases, serial) dual-task processing in the context of varying SOAs is not possible without effortful control in the sense of voluntarily prioritizing the SRTT (Schumacher & Schwarb, 2009) or keeping the task representations separate in order to prevent task integration confusion (see, e.g., Halvorson, Wagschal, & Hazeltine, 2013). The PRP context per se seems indeed to be insufficient to exogenously elicit a global serial processing strategy and to allow for chaining, contrary to the suggestion of Israel and Cohen (2011). Also, the predictability of the short SOAs, bearing the risk of task integration confusion (e.g., Röttger et al., 2019, in prep.; Schmidtke & Heuer, 1997), could, in the present dual-task context, obviously not be exploited for flexible switches to serial processing with elements of the SOA type 0 as it was demonstrated by Fischer and Dreisbach (2015). A higher degree of between-task conflict than the mere confusion due to the randomness of the secondary task – or simply the awareness of it (Dreisbach & Fischer, 2012) – seems to be a necessary precondition.

To sum up, the switches to serial processing with long SOAs that we observed in the present PRP experiments, are best described as passive instead of active and flexible. They do not indicate the implementation of an overall efficient strategy. Otherwise, we should have found substantial learning effects across both SOA types.

Another finding that probably also indicates the suboptimal nature of the observed behavior is that RT1 (SRTT) in the two PRP experiments was slow with actually long SOAs. It was slower than the corresponding RT1 in Experiment 1 (SOA_{long} condition) and it was slower than with actually short SOAs. This outcome is, at first sight, not in accord with the assumption of serial processing (cf. Miller et al., 2009). However, as already mentioned, a closer look reveals that RT1 was still shorter than the long SOA itself. Additionally, the TRT was significantly smaller with actually long than with actually short SOAs in both PRP experiments. Thus, the slow RT1 with long SOAs nevertheless must have been the result of a processing mode that was (a) serial and (b) more efficient than with short SOAs (due to the compensatory fast RT2). However, neither the RSB model (e.g., Pashler, 1994) nor models assuming central capacity sharing (e.g., Tombu & Jolicoeur, 2003) predict that RT1 should be affected by the SOA manipulation. Nevertheless, SOA effects on RT1 have been observed frequently (see also Miller et al., 2009; Schumacher & Schwarb, 2009) – but an explanation is still lacking. Response grouping (e.g., Pashler & Johnston, 1989; Ulrich & Miller, 2008) is sometimes responsible for an increase in RT1 across the SOAs meaning that participants tend to await and to process both stimuli first, in order to execute R1 and R2 then nearly simultaneously – slowing down RT1 when the SOA is long. Inter-response intervals (IRIs) smaller than 100 ms are often regarded as an indicator of grouping (e.g., Miller, 2006). In the present study, however, the respective IRIs were much larger (721 vs. 861 ms in Experiment 2 vs. 3, respectively) excluding a grouping strategy. Because, on average, R1occurred before S2-onset, it is also impossible to say whether the participants' slow RT1 were the result of withholding the already selected SRTT response shortly for some (unknown) reasons – or whether response selection itself was deferred.

Comparing RT1 with long SOAs between the experiments, the aspect that RT1 was not only slow in the PRP experiments – but also exceptionally fast in the SOA_{long} condition (Experiment 1) – should also be considered.[7] Here, the participants neither experienced any timing variability, nor the necessity to process any T2 component in parallel – favoring fast R1 on the one hand and, probably, the development of separate task representations on the other hand. The latter, in turn (and in addition to the long SOA), was most likely beneficial for chaining because it might have fostered within-SRTT- instead of across-task predictions and, thus, a reduction of the prediction error (cf. Röttger et al., 2019, in prep.). The resulting sequence knowledge might have accelerated RT1 even more. We suspect that the variable timing and, thereby, higher scheduling demands somehow must have contributed to the slowness of RT1 in Experiments 2 and 3 (and maybe as well in other PRP experiments). Equal proportions of long and short SOAs within a PRP context might, for instance, shift the point in time when participants are optimally prepared to start responding in general. Additionally, participants are possibly better prepared for the more difficult trials, with short SOAs, in which both stimuli must be processed simultaneously and then "wait" a moment for S2 if it does not occur immediately.

Interestingly, some individuals in our PRP experiments (whose data are reported in the Appendix) literally waited longer than the SOA (i.e., > 800 ms) and selected and/or executed R1 only after S2 actually occurred. Taking a closer look at the data of the rest of our participants (the regular sample), it turned out that their individual SOA effects on RT1 (computed as $RT1_{longSOA}$ – $RT1_{shortSOA}$) were all quite different. Some of the effects were negative (faster RT1 with long SOAs), some were highly positive and some were negligible – resulting in the reported mean positive SOA effect (slower RT1 with long SOAs) in both PRP experiments, suggesting that individual dual-tasking preferences might exist. Supporting

[7] In the SOA_{long} condition (Experiment 1), RT1 was very fast. In the last block of the dual-task training phase (block 6), RT1 was even 22 ms faster than the RTs in the regular single-task test block (block 8), $t(24) = -3.15$, $p = .004$, $d = 0.630$. In all other experiments and conditions, the opposite was the case.

this assumption, Brüning and Manzey (2018), identified "serial processors" and "overlapping processors" in task switching experiments always providing a preview of the upcoming stimulus in trial n+1. Only the overlapping processors made use of the preview and some of them could even turn switch costs into switch benefits. Thus, also individual dual-tasking preferences should be accounted for in future endeavors to find the causes of SOA effects on RT1 that are often found in PRP experiments. By now, admittedly, all our considerations are speculative.

However, last but not least, it must be mentioned that potential individual dual-tasking preferences did not change the overall pattern of the learning effects. To explore this possibility, we defined (post-hoc) two groups of participants each in Experiments 2 and 3 by ranking the individual SOA effects on RT1 and splitting them at the median. This procedure revealed one group with a positive mean SOA effect and one with a negative SOA effect (66 ms and 107 ms vs. -6 ms and -27 ms in Experiments 2 and 3, respectively). In Experiment 2, the learning effects (per SOA type) were not different between the groups. Accordingly, in Experiment 3, implicit learning was exclusively present (and highly significant) with SOA type 800 – but generally absent with SOA type 0 in both groups.[8] This suggests that most of the potential individual dual-tasking preferences did not favor chaining.

Taken together, the present three experiments provide additional evidence for the assumption that implicit sequence learning can be preserved in dual-task contexts via serial processing as first suggested by Schumacher and Schwarb (2009). It reduces task integration confusion (or other across-task conflicts), allows the implicit adaptation to the SRTT structure and is, thus, more efficient than parallel processing. In the SOA_{long} condition (Experiment 1), other efficiency measures (i.e., fast RT1 and a small TRT) were in accord with this classification. Thus, for the time being, the conception of implicit learning as an indicator of efficient dual-task processing can, in principle, be maintained. However, as discussed above, some of the present findings suggest a few limitations.

First, Experiments 2 and 3 revealed that serial processing due to long SOAs seems to occur automatically and rather not due to an actively chosen strategy. Substantial implicit learning effects resulted purely mechanistically. This became fully disclosed in Experiment 3, where significant learning effects exclusively occurred for SRTT elements consistently paired

[8] In Experiment 2, the learning effects for SRTT elements of the SOA type 0 as well as the learning effects for the SOA type 800 did not differ between the two groups of participants (both $|t| < 1$). In Experiment 3, the learning effects for SRTT elements of the SOA type 800 were highly significant for both groups of participants but did not differ from each other. Additionally, none of the groups showed learning for elements of the SOA type 0 (again, both $|t| < 1$).

with the long SOA – implying that also a potential "exogenous" serial processing strategy (Israel & Cohen, 2011) had not globally been applied. The resulting behavior is probably best described as passively commuting between different processing modes, investing as little effort as possible. This low-effort kind of serial processing turned out to be slow, but the TRT with long SOAs was still smaller than the TRT with short SOAs and, thus, most likely, parallel processing (cf. Miller et al., 2009). Potentially, this indicates some kind of tradeoff between different aspects (e.g., speed vs. learning) of efficient processing.

The overall outcome of our experiments suggests that choosing and maintaining a serial processing strategy in a PRP context requires the effortful implementation of cognitive control – either globally or flexibly, due to predictable risks of conflict as demonstrated by Fischer and Dreisbach (2015). However, our results strongly suggest that without obvious conflict such flexibility is not possible. Future research should investigate whether explicit instructions to process the tasks serially, as in the study of Lehle and Hübner (2009), can change the pattern of results within a PRP context – or whether it turns out that individuals have severe difficulties to stop drifting with the varying SOAs (even if they vary predictably).

Appendix:
Performance of the subgroups of participants showing particularly slow RT1 with long SOAs

In all three Experiments, we identified subgroups of participants (8 in Experiment 1, 8 in Experiment 2, and 2 in Experiment 3) whose RT1 (SRTT) with long SOAs considerably exceeded the length of the respective SOA. Obviously, these 18 participants waited until tone onset – and responded only after they had processed both stimuli. This behavior was very different from that of the regular samples. Therefore, we did not include the data of these slow participants in our main analyses.

Figure 8 displays the mean dual-task RTs of these three subgroups of participants in the SRTT and the tone-discrimination task as a function of the actual SOAs (Experiment 1; between-subjects SOA manipulation) or as a function of the item-specific SOA types (Experiment 2 and 3; within subjects SOA manipulation). For means of comparison, Figure 8 also depicts the mean RTs of the remaining participants (regular groups) in the respective conditions. As can be seen, the participants in the subgroups responded very slowly in the SRTT. This was particularly true with long SOAs / with SOA type 800. Since the number of participants within these subgroups was very small (maximal 8 participants per experiment), we refrained from conducting any statistical analyses.

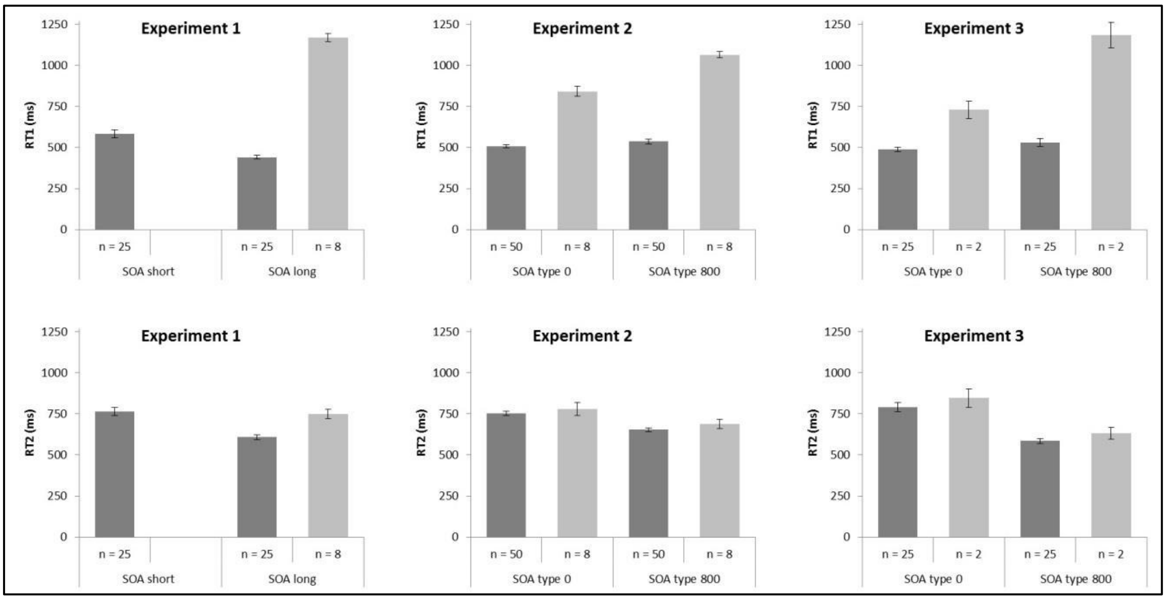

Figure 8. Mean dual-task RTs of the slow subgroups of participants in comparison to those of the regular samples in the SRTT (RT1; upper panel) and the tone-discrimination task (RT2; lower panel) as a function of the actual SOAs (Experiment 1) or the SOA types (Experiments 2 and 3). Error bars represent standard errors of the means.

Table 1 displays the learning effects for both groups of participants – the regular groups and the slow subgroups – in Experiments 1-3, respectively. In Experiment 1, the slow subgroup of participants in the SOA_{long} condition did not show sequence learning. The respective learning effect was even negative (-5 ms), meaning that these participants responded faster in the random blocks 7 and 9 than in the regular block 8. In Experiment 2, the slow subgroup of participants did not learn the SRTT response locations of the SOA type 0 – but produced a learning effect for SOA type 800 that was descriptively as large as that of the regular sample (9 ms). The two slow participants in Experiment 3 did not show sequence learning, neither with SOA type 0 nor with SOA type 800.

Table 1. Learning effects (means and standard deviations) for both groups of participants – the regular group and the slow subgroup – in Experiments 1-3, respectively, computed as the difference between the collapsed mean RTs of the random single-task test blocks 7 (2^{nd} half) and 9 and the regular single-task block 8.

Learning effect	Experiment 1				Experiment 2				Experiment 3			
	SOA short		SOA long		SOA type 0		SOA type 800		SOA type 0		SOA type 800	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Regular sample	5	20	9	18	9	31	9	26	-4	31	39	18
Subgroup			-5	26	0	28	9	25	-50	10	14	7

5 General Discussion

The aim of the present series of studies was to shed more light on the mechanisms underlying the impairment vs. preservation of implicit sequence learning in a dual-task context and to compare and evaluate (mainly) two accounts: the task integration account originating by Schmidtke and Heuer (1997; see also Rah et al., 2000) and the parallel response selection account proposed by Schumacher and Schwarb (2009). All experiments reported here hint at a conception of task integration as the crucial mechanism suggesting that sequence learning is disturbed to the extent that an omnipresent prediction mechanism operates on unpredictable across-task events occurring in close temporal contiguity, that is, within a trial. Accordingly, sequence learning should be preserved when the across-task predictability is high – or, if not, when the two tasks are represented separately, facilitating within-task predictions and, thus, learning. Nevertheless, several aspects of the proposed across-task prediction mechanism are, by now, speculative and are discussed below – as well as currently further investigated.

The role of inhibition in dual-task sequence learning

Already in the first study (Chapter 2) it was suggested that dual-task sequence learning might be disturbed to the extent that unsuccessful across-task predictions result in response conflicts – which, then, are solved by inhibiting (features of) the SRTT. This assumption seems clear-cut since the SRTT response on average preceded the tone response and, thus, served as the basis for these unsuccessful predictions. As a consequence, the simultaneous activation of successive SRTT elements (and thereby the strengthening of associations between them) might have been prevented. The results of Experiment 4 (see Chapter 2) are indicative of this assumption. Here, exclusively SRTT elements that had been fixedly paired with the tones in the training phase had been learned – while for randomly paired SRTT elements, the resulting learning effect was even negative. This finding was replicated in Experiment 3 in Chapter 3. Additionally, the finding that the response times in both tasks were slower during training for randomly- than for fixedly paired SRTT elements is in favor of the assumption that incorrect predictions had caused response conflicts (solved by inhibition). However and importantly, direct evidence for this "inhibition" assumption is lacking. Interestingly, also Koch et al. (2018) considered that, in general, processes underlying the resolution of conflict – namely, inhibition – have received relatively little attention in the dual-tasking literature, compared to the task switching research (but see Hirsch, Nolden, & Koch, 2017). In task switching, inhibition is typically seen as the most relevant conflict-resolving mechanism that supports the flexible switching between competing task sets. So-called n-2 repetition costs (larger switch costs when a recently inhibited task set must be reactivated in an "ABA" task sequence) are the marker for this "backward" inhibition occurring at the task set level (for a review, see Koch, Gade, Schuch, & Philipp, 2010).

In the present dual-task experiments, it would make little sense to look for aftereffects of inhibition also at the task set level because (in most conditions) none of the tasks had ever become irrelevant in any trial and to be abandoned. Instead, potential aftereffects of inhibition should become evident at the level of the SRTT elements in trials directly following conflict. Crucially, this consideration entails that the conflict-triggering (randomly paired) SRTT target is directly repeated. That is, if one assumes that response conflict due to a wrongly predicted tone-response in trial n is resolved by inhibiting the involved SRTT element, then the response to this element should be slowed if it is directly repeated in trial n+1. Periodically pressing the same key twice in succession is, however, a quite salient response – possibly resulting in explicit sequence knowledge because it leads the participants to engage in hypothesis testing (e.g., Frensch et al., 2003). This, in turn, would change their overall processing strategies. Hence, the usefulness of such a manipulation (implementing a SRTT sequence with direct target repetitions) strongly depends on the specific research question (e.g., whether implicit or explicit processes are in the research focus).

Furthermore, a few pilot experiments revealed that SRTT repetitions caused large costs in both tasks if the corresponding tones were not repeated as well – resembling so-called *partial repetition costs* investigated in the feature binding literature (e.g., Colzato, Raffone, & Hommel, 2006; Moeller et al., 2016). Such costs emerge if one feature of a stimulus (or a stimulus compound) is repeated while a second feature is not. As they had been bound in trial n, repeating only one feature in trial n+1 might (erroneously) re-activate also the other – causing response conflict. Observing partial repetition costs in our paradigm suggests that "task integration" might also mean that the participants represent the visual- and auditory stimuli as a compound. In the case that one part of this compound is random, a mechanism that reactivates previous- (or predicts upcoming-) compounds might also falter – hampering sequence learning. However, it turned out that, in all experiments presented here, costs due to the frequently occurring partial tone repetitions (i.e., without additional repetition of the respective SRTT item) occurred very unsystematically – suggesting that the two stimuli were rather not represented as compounds. Since the feature- (or modality-) overlap between the visual-manual SRTT and the auditory-vocal tone-task (cf. Hazeltine et al., 2006) was also negligible in the present studies, a "compound assumption" seems indeed rather inapplicable.

Thus, not across-task binding – but across-task prediction – is the most plausible mechanism causing the impairment of sequence learning in dual-tasks. Yet, since partial repetition costs sometimes occurred, it cannot be excluded that across-task binding also plays a role in the present dual-task context. It might, for instance, occur initially – but diminish as across-task predictions progressively improve with correlated tasks (Schmidtke & Heuer, 1997) or as the task representations become separated. Related questions are currently further investigated.

The role of statistical learning

The second study (Chapter 3) provided more evidence that the assumed prediction mechanism seems to focus, per default, on the statistical relationships between the most contiguous successive (adjacent) events. With simultaneous stimulus onset, these events co-occur within one trial but belong to both tasks and can, therefore, be of very low predictive value for each other. The potentially much stronger relationships of nonadjacent events, i.e., of SRTT events occurring across successive trials, separated by a tone-task event, seem to be neglected when participants maintain an integrated task representation. Impaired sequence learning is the result.

As already discussed, Gómez (2002) demonstrated, in the context of artificial language learning, that nonadjacent dependencies nevertheless can be learned if the separating middle event is highly variable, making the nonadjacent dependencies stand out of the crowd. In her study, participants had to judge whether three-element test strings were instances (or not) of an artificial language they had previously been listening to. If a language with high (instead of low) variability of the middle element had been trained, the judgements tended to be correct. This finding suggests that, in the present dual-task context, increased variability within the tone-task could have moved the predictive focus away from adjacent across-task events of low predictive value towards the most helpful (but nonadjacent) dependencies within the SRTT. In other words, high variability in the tone-task could serve as a strong bottom-up cue, triggering separate task representations and, thus, within-task predictions.[1]

In a recent study of Vuong, Meyer, and Christiansen (2016), however, participants were trained on three successive days (one hour per day) with material similar to that of Gómez (2002) – but with only a medium variability of the middle element – presented in a SRTT-like fashion. Afterwards, replicating former findings, the authors found weak knowledge about

[1] Also in other artificial language learning studies (e.g., Van den Bos, Christiansen, & Misyak, 2012), the learning of nonadjacent dependencies strongly depended on the presence of (perceptual) cues suggesting that predictive processes operate indeed, by default, on the most contiguous events – but can be moved.

the nonadjacent dependencies within the typical offline-measures (i.e. in the grammaticality judgements). In the online measures, however, (i.e., in the SRTT response times) knowledge was present. This observation adds nicely to the finding of Hunt and Aslin (2001) that implicit learning in a SRTT can be based even on the most complex joint probabilities of exact event patterns out of great numbers of possible combinations in a given context. This might simply be a matter of the number of pattern repetitions and, thus a matter of time. It is conceivable that implicit sequence learning in the presence of a temporally close random secondary task also simply (or to a certain extent) depends on the duration of the training phase. In general, it should be fruitful to take assumptions of the statistical learning literature into account for future research on dual-task sequence learning – and, thereby, on an important aspect of plasticity in multitasking per se (see also Koch et al., 2018).

The role of the separation of representations

Implicit learning is one of the most fundamental learning processes (e.g., Dienes & Berry, 1997) and contributes largely to the plasticity and adaptability of human behavior. In the third study (Chapter 4), implicit sequence learning was suggested as a novel indicator of dual-tasking efficiency. This conception was derived from the finding of Schumacher and Schwarb (2009) that sequence learning was impaired vs. preserved in the presence of a random secondary task depending on the length of the SOAs and, thereby, as suggested by the authors, on the respective dual-task processing modes. Impaired learning with short SOAs was attributed to parallel processing, preserved learning with long SOAs to serial processing – in accord with the assumptions of Miller et al. (2009) that high proportions of short vs. long SOAs trigger parallel vs. serial processing, respectively. Miller et al. investigated whether selecting one or the other processing mode is driven by the participants' goal to optimize the total reaction time (TRT) and, thus, to perform efficiently. Since serial processing is, under most circumstances, more efficient than parallel processing (in terms of the TRT; Miller et al., 2009)[2], the finding that sequence learning is preserved with long SOAs might, thus, as well indicate highly efficient – serial – processing.

Yet, in the light of the present findings – which repeatedly ruled out the (parallel/ serial) response selection account of Schumacher and Schwarb (2009) – another assumption might also be justified, namely, that preserved sequence learning with consistently long SOAs

[2] Based on mathematical simulations, Miller et al. (2009), demonstrated that serial processing is under most conditions most efficient (in terms of the TRT) – but that, under special conditions (i.e., with a high frequency of short SOAs), it can be outperformed by parallel processing.

rather indicates the (efficient) separation of task representations. Already in the "General Introduction", the parallel response selection- and the task integration hypothesis (Rah et al., 2000; Schmidtke & Heuer, 1997) were introduced as two accounts that are, in principle, *both* in line with the assumption that the insufficiently separated processing of two simultaneously presented tasks might be the cause for impaired sequence learning, suggesting, however and importantly, different processes as critical. The first and second studies (Chapter 2 and 3), then, provided strong evidence in favor of the task integration or, more precisely, the across-task prediction account, assuming that sequence learning should be impaired vs. preserved depending on the within-trial predictability of across-task events. For instance, in the correlated tasks condition (Röttger et al., 2019; Experiment 2), with regular sequences in both tasks (and, thus a high across-task predictability), learning was preserved. In Experiment 3, on the contrary, facilitating parallel response selection due to an ideomotor compatible – but still randomly sequenced – tone-discrimination task was not sufficient in order to preserve learning (see also Chapter 2). These findings can only be explained by the parallel response selection account by adding the assumption that parallel response selection disturbs sequence learning not per se but only if the two tasks are randomly paired.

In recent theoretical considerations (Hazeltine & Schumacher, 2016; Schumacher & Hazeltine, 2016) as well as in a recent study, Schumacher and colleagues also refrained from the assumption that response selection processes in the simple sense of "mental operations that associate task-related responses to current stimuli" (Schumacher et al., 2018, p. 2) are responsible for dual-task interference. They considered that adding another S-R mapping might not necessarily be equivalent with adding a "task", causing interference due to central capacity sharing (e.g., Tombu & Jolicoeur, 2003) or a response selection bottleneck (e.g., Pashler, 1984; 1994). Instead, interference between multiple task representations – or "task files" (e.g., Schumacher & Hazeltine, 2016) – could call for control processes to keep them separate (to prevent integration). Such task files do not only include sets of S-R mappings but also context information, internal goals and, importantly, sequential information belonging to these goals that should not be confounded. In a dual-task, Schumacher et al. (2018) induced integrated vs. separate task representations via different S-R mapping rules while keeping the stimulus information and response options constant (including "no response" in either of the tasks). It turned out that bimanual responses were slower than unimanual responses in the "two-task set" condition, resembling the typical dual task costs – which were absent (reversed) for the "one-task set" condition replicating the finding that task representations (i.e., whether they are integrated vs. separate) determine whether costs occur or not (see also Halvorson, Wagschal, et al., 2013).

The finding of preserved sequence learning with consistently long SOAs (Chapter 4; Experiment 1; see also Schumacher & Schwarb, 2009) is in accord with the assumption that the participants represented the tasks separately, facilitating predictions within the SRTT and allowing sequence learning. It makes, however, little sense to assume that the participants in the two PRP experiments (see Chapter 4; Experiments 2 and 3), who only acquired position-item associations for SRTT elements of SOA type 800 (see Experiment 3) or, more generally, with long SOAs, switched trialwise between integrated and separate task representations. Rather, in the wording of the "task files" framework, it seems that the participants did overall not spend much effort to keep the task files or -representations separate. Implicit learning with actually long SOAs might, then, indeed have occurred purely mechanistically due to automatic serial processing forced by the length of the SOAs.

To sum up, long SOAs might, on the one hand, trigger separate task representations (if they occur consistently), and, on the other hand, automatic serial processing (at least in a PRP context). Both conceptions of the impact of long SOAs predict that one or the other type of learning within the SRTT should occur – chaining (with consistently long SOAs) and/or ordinal position learning (at least in a PRP context; see Chapter 4). It is also plausible to assume that high proportions of short SOAs trigger integrated representations (at the risk of confounding task file features). Crosstalk as well as impaired sequence learning should be the result. The same would be predicted by capacity sharing accounts of parallel processing (e.g., Navon & Miller, 2002; Tombu & Jolicoeur, 2003). However, whether "integrated task representations" and "parallel processing" as well as "separate task representations" and "serial processing" can, in fact, be understood as two sides of the same coin, respectively, is questionable – since the whole concept "parallel processing" must be viewed critically.

As already mentioned in the "General Introduction", a debate is going on whether parallel processing at the response selection stage is, in principle, possible or not (for a recent review, see Koch et al., 2018). More confusingly, however, it seems that, in the literature, several notions of "parallel processing" coexist – and, thereby, also different assumptions about its most likely consequences (e.g., in terms of efficiency). While some researchers expected and demonstrated "virtually perfect time sharing" (e.g., Hazeltine, Teague, & Ivry, 2002; Israel & Cohen, 2011; Schumacher et al., 2001) – others demonstrated costs like, e.g., the BCE (e.g., Fischer & Dreisbach, 2015; Fischer et al., 2014; Hommel, 1998; Janczyk et al., 2014; Lehle & Hübner, 2009; Miller et al., 2009). Both classes of findings are not in accord with Pashler's (1984, 1994) RSB model[3] – and some of the former findings are also not explained by assuming central capacity sharing. Israel and Cohen (2011), for instance, draw on the Dimension Action model (Magen & Cohen, 2007) suggesting that separate (visual) modules exist, endowed with both perceptual and response selection capabilities, which are *not* shared across dimensions. This kind of parallel processing, however, is probably better described as "isochronous" (but independent) processing as it is, in fact, the opposite of task integration and/or capacity sharing – and does certainly not underlie the present findings. It is, additionally, unclear, to what degree the extent of parallel (vs. serial) processing is under strategic control and how flexible humans can switch between processing modes, depending, e.g., on individual goals or internal states or on contextual information. As described above, Miller and colleagues (2009) suggested that participants adopt a more parallel vs. more serial processing mode depending on the list-wide frequency of short vs. long SOAs in order to optimize the TRT. In their PRP experiments, they implemented blocks with either mostly short or mostly long SOAs and predicted that RT1 should be slower in the former than in the latter due to a higher extent of capacity sharing / parallel processing. At the same time, the PRP effect should be less steep because, with shared capacity, RT2 should be faster when the actual SOA is short. Otherwise, e.g., the reallocation of the full capacity to T2 after prioritized T1 processing would prolong RT2 (cf. Mittelstädt & Miller, 2017). In main parts, the findings were in accord with that.

Interestingly, Mattes et al. (subm.) found ambiguous evidence for parallel processing in an attempt to replicate the findings of Miller et al. (2009) and to additionally compare the extent of parallel vs. serial processing by using a drift-diffusion model approach[4] (see also Durst & Janczyk, 2019). Implementing conditions with different SOA distributions across three experiments, Mattes and colleagues expected that the drift rate would be lower for both tasks only with actually short SOAs in the condition with predominantly short SOAs (PS) indicating parallel processing. The non-decision time was expected to be longer only in T2 with actually short SOAs in the condition with predominantly long SOAs (PL) indicating serial processing. In other words, with actually short SOAs, the authors expected parallel processing

[3] Some observations of apparent parallel processing can be reconciled with the RSB model. The elimination of dual-task costs, for instance, can be conceived of as indicating that the bottleneck has become "latent" due to extensive training (Ruthruff et al., 2003; see also Strobach & Schubert, 2017a; 2017b). By adding a stage of automatic response activation, also the BCE can be explained within the RSB framework (Hommel, 1998).

[4] In general, two parameters of the drift diffusion model (Ratcliff & Rouder, 1998) should vary characteristically as a function of parallel vs. serial processing (cf. Mattes et al., subm.). The drift rate should be lower in both tasks with parallel than with serial processing, indicating a slower evidence accumulation process due to shared capacity. Serial processing should manifest itself in a longer non-decision time (representing perceptual and motor processes) for the secondary task at short SOAs (which is mirrored in the PRP effect).

in the PS condition and serial processing in the PL condition. Surprisingly, in the PS condition, the authors found a lower drift rate with short SOAs only for T2. Even more surprisingly, the drift rate was also lower (for both tasks) with short SOAs in the PL condition. The non-decision time was longer in T2 with short SOAs not only in the PL condition but also in the PS condition (to a lesser extent). Both findings contradict the assumption that more parallel- vs. more serial processing should be found in the in the PS- vs. the PL condition, respectively. In addition, also the RT data were overall not perfectly in line with the predictions. The PRP effect in RT2 was indeed flatter in the PS- than in the PL condition (indicating more parallel processing). However, RT1 in the PS condition increased across the actual SOAs so that the difference between the two conditions was largest with long SOAs – apparently indicating more parallel processing with long instead of short SOAs, which is not plausible. As alternative explanation, Mattes et al. (subm.) suggested that the SOA distribution might have influenced the participants' temporal expectancy (see e.g., Los et al., 2017) of S2 onset It is conceivable that participants in the PS condition learned to expect S2 immediately after S1, using S2 as an "external impulse generator" for response initiation. In this case, they should be less prepared with infrequent long- than with frequent short SOAs – slowing down RT1.

As discussed in Chapter 4, the finding of such an SOA effect on RT1 is not unique (see also, e.g. Miller et al., 2009; Schumacher & Schwarb, 2009) – and it occurred in the present PRP experiments as well (see Experiments 2 and 3; Chapter 4). By now, however, all explanations that have been proposed in the literature are speculative. In the present study, without list-wide biased SOA distributions like in the study of Mattes et al. (subm.), it was nevertheless also suggested that different extents of preparation could have caused this effect. The Participants had been possibly better prepared for more difficult trials, with short SOAs, requiring (e.g.) more inter-task coordination (e.g., Liepelt et al., 2011) – and "wait" a moment for S2 if it does not occur immediately, withholding R1.

Conclusion

Taken together, the role of parallel processing (or, more specifically, parallel response selection) in dual-tasking is still unclear. Capacity sharing models (e.g., Navon & Miller, 2002; Tombu & Jolicoeur, 2003) predict costs – which seemingly can be brought under strategic control (e.g., Lehle & Hübner, 2009; Miller et al., 2009) more or less flexibly (e.g., Fischer & Dreisbach, 2015; Fischer et al., 2014). Bottleneck models like Pashler's RSB model (1984, 1994), on the contrary, deny the possibility of parallel processing. Proponents, thus, explain occasional findings of crosstalk or "perfect time sharing" away by adding stages in the former case (e.g., Hommel, 1998) or by assuming optimized bottleneck processing in the latter case (e.g., Strobach et al., 2014). Possibly, as Hazeltine and Schumacher (2016) suggest, progress in the research on multitasking can be made by backing away from the notion that response selection is responsible for dual-task interference – and focusing on the impact of integration vs. separation of the "task files" instead. In line with that, the results of the present series of studies repeatedly ruled out a contribution of parallel response selection to the impairment of implicit sequence learning in dual-tasking. Even in Chapter 4, where the parallel response selection hypothesis of Schumacher and Schwarb (2009) was once more investigated, the outcomes were also (or even better) explained by the task integration-, or, more specifically, the across-task prediction account (Röttger et al., 2019; see also Rah et al., 2000; Schmidtke & Heuer, 1997) incorporating the assumption that implicit sequence learning requires the progressive improvement of omnipresent and automatic predictions (cf. Broeker et al., 2017) via statistical learning (cf. Perruchet & Pacton, 2006). Whether dual-task sequence learning is impaired vs. preserved, might simply depend on the extent that the prediction mechanism focuses on the respectively most predictable events. With simultaneous stimulus onset and at least one random task, any manipulation leading to a separation of representations (or task files; see Schumacher & Hazeltine, 2016) should move the predictive focus away from its default focus on the most contiguous (but unpredictable) within-trial events occurring across-tasks – towards the (predictable) within-task (SRTT) events, occurring across-trials.

In general, under which conditions sequence knowledge can be acquired in dual-task contexts – and whether it, in turn, might help to reduce several kinds of dual-task costs like, e.g., crosstalk or partial repetition costs due to across-task binding – are important questions that will be further investigated in future endeavors to better understand the limits and the possibilities of the human cognitive architecture. The present evidence ascribes a crucial role to the separation of representations. As it seems that such a separation can be induced via bottom-up cues like long SOAs or a high variability of the middle element within regular three-element strings (Gómez, 2002), it is possible that already acquired sequence knowledge (e.g., via single-task training; see Gaschler et al., 2018) might itself serve as such a separation cue, moving the focus towards predictable within-task events. As a consequence, processing in one task might be shielded against irrelevant information (see, e.g. Fischer & Plessow, 2015) from the other task, preventing that information, belonging to separate "task files", is confounded.

References

Abrahamse, E. L., Jiménez, L., Verwey, W. B., & Clegg, B. A. (2010). Representing serial action and perception. *Psychonomic Bulletin & Review, 17*(5), 603-623.

Aufschnaiter, S., Kiesel, A., Dreisbach, G., Wenke, D., & Thomaschke, R. (2017). Time-based expectancy in temporally structured task switching. *Journal of Experimental Psychology: Human Perception and Performance, 44*(6), 856-870.

Broeker, L., Kiesel, A., Aufschnaiter, S., Ewolds, H. E., Gaschler, R., Haider, H., . . . Zhao, F. (2017). Why prediction matters in multitasking and how predictability can improve it. *Frontiers in Psychology*. doi:10.3389/fpsyg.2017.02021.

Brüning, J., & Manzey, D. (2018). Flexibility of individual multitasking strategies in task-switching with preview: are preferences for serial versus overlapping task processing dependent on between-task conflict? *Psychological Research, 82*, 92-108.

Bubic, A., von Cramon, D. Y., & Schubotz, R. I. (2010). Prediction, cognition and the brain. *Frontiers in Human Neuroscience, 4*(25). doi:10.3389/fnhum.2010.00025.

Bugg, J. M., & Crump, M. C. (2012). In support of a distinction between voluntary and stimulus-driven control: A review of the literature on proportion congruent effects. *Frontiers in Psychology*. doi:10.3389/fpsyg.2012.00367.

Bühner, M., & Ziegler, M. (2009). *Statistik für Psychologen und Sozialwissenschaftler*. München: Pearson.

Clark, A. (2013). Whatever next? Predictive brains, situated agents, and the future of cognitive science. *Behavioral and Brain Sciences, 36*(3), 181-204.

Cleeremans, A. (2011). The Radical Plasticity Thesis: How the brain learns to be conscious. *Frontiers in Psychology*. doi:org/10.3389/fpsyg.2011.00086.

Cleeremans, A., & Jiménez, L. (2002). Implicit learning and consciousness: A graded, dynamic perspective. *Implicit Learning and Consciousness*, 1-40.

Cohen, A., Ivry, R. I., & Keele, S. W. (1990). Attention and structure in sequence learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 16*(1), 17-30.

Colzato, L. S., Raffone, A., & Hommel, B. (2006). What do we learn from binding features? Evidence for multilevel feature integration. *Journal of Experimental Psychology: Human Perception and Performance, 32*(3), 705-716.

Curran, T., & Keele, S. W. (1993). Attentional and nonattentional forms of sequence learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 19*(1), 189-202.

Dale, R., Duran, N. D., & Morehead, R. J. (2012). Prediction during statistical learning, and implications for the implicit/explicit divide. *Advances in Cognitive Psychology, 8*(2), 196-209.

Dienes, Z. (2014). Using Bayes to get the most out of non-significant results. *Frontiers in Psychology*. doi:10.3389/fpsyg.2014.00781.

Dienes, Z., & Berry, D. (1997). Implicit learning: Below the subjective threshold. *Psychonomic Bulletin & Review, 4*(1), 3-23.

Dienes, Z., & Seth, A. (2010). Gambling on the unconscious: A comparison of wagering and confidence ratings as measures of awareness in an artificial grammar task. *Consciousness and Cognition, 19*(2), 674-681.

Donders, F. C. (1868/1969). On the speed of mental processes (original work published 1868). *Acta Psychologica, 30*, 412-431.

Dreisbach, G., & Fischer, R. (2011). If it's hard to read… try harder! Processing fluency as signal for effort adjustments. *Psychological Research, 75*, 376-383.

Dreisbach, G., & Fischer, R. (2012). The role of affect and reward in the conflict-triggered adjustment of cognitive control. *Frontiers in Psychology*. doi:doi: 10.3389/fnhum.2012.00342

Dreisbach, G., & Fischer, R. (2015). Conflicts as Aversive Signals for Control Adaptation. *Current Directions in Psychological Science, 24*(4), 255-260.

Dreisbach, G., & Haider, H. (2008). That's what task sets are for: Shielding against irrelevant information. *Psychological Research, 72*, 355-361.

Dreisbach, G., & Haider, H. (2009). How task representations guide attention: Further evidence for the shielding function of task sets. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 35*(2), 477-486.

Dreisbach, G., Reindl, A.-L., & Fischer, R. (2018). Conflict and disfluency as aversive signals: context-specific processing adjustments are modulated by affective location associations. *Psychological Research, 82*(324-336).

Durst, M., & Janczyk, M. (2018). The Motor Locus of No-Go Backward Crosstalk. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 44*(12), 1931-1946.

Durst, M., & Janczyk, M. (2019). Two types of backward crosstalk: Sequential modulations and evidence from the diffusion model. *Acta Psychologica, 193*, 132-152.

Eberhardt, K., Esser, S., & Haider, H. (2017). Abstract feature codes: The building blocks of the implicit learning system. *Journal of Experimental Psychology: Human Perception and Performance, 43*(7), 1275-1290.

Eriksen, B. A., & Eriksen, C. W. (1974). Effects of noise letters upon the identification of a target letter in a nonsearch task. *Perception & Psychophysics, 16*, 143-149.

Fischer, R., & Dreisbach, G. (2015). Predicting high levels of multitasking reduces between-tasks interactions. *Journal of Experimental Psychology: Human Perception and Performance, 41*(6), 1482-1487.

Fischer, R., Gottschalk, C., & Dreisbach, G. (2014). Context-sensitive adjustment of cognitive control in dual-task performance. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 40*(2), 399-416.

Fischer, R., & Plessow, F. (2015). Efficient multitasking: parallel versus serial processing of multiple tasks. *Frontiers in Psychology*. doi:doi: 10.3389/fpsyg.2015.01366

Freedberg, M., Wagschal, T. T., & Hazeltine, E. (2014). Incidental learning and task boundaries. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 40*(6), 1680-1700.

Frensch, P. A., Buchner, A., & Lin, J. (1994). Implicit learning of unique and ambiguous serial transitions in the presence and absence of a distractor task. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 20*(3), 567-584.

Frensch, P. A., Haider, H., Rünger, D., Neugebauer, U., Voigt, S., & Werg, J. (2003). Verbal report of incidentally experienced environmental regularity: The route from implicit learning to verbal expression of what has been learned. In L. Jiménez (Ed.), *Attention and implicit learning* (pp. 335-366). Amsterdam: Benjamins.

Frensch, P. A., Lin, J., & Buchner, A. (1998). Learning versus behavioral expression of the learned: The effects of a secondary tone-counting task on implicit learning in the serial reaction task. *Psychological Research, 61*(2), 83-98.

Frensch, P. A., & Rünger, D. (2003). Implicit learning. *Current Directions in Psychological Science, 12*(1), 13-18.

Frensch, P. A., Wenke, D., & Rünger, D. (1999). A secondary tone-counting task suppresses expression of knowledge in the serial reaction task. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 25*(1), 260-274.

Frings, C., Rothermund, K., & Wentura, D. (2007). Distractor repetitions retrieve previous responses to targets. *The Quarterly Journal of Experimental Psychology, 60*, 1367-1377.

Friston, K. (2010). The free-energy principle: a unified brain theory? *Nature Reviews Neuroscience*. doi:doi:10.1038/nrn2787

Gaschler, R., Frensch, P. A., Cohen, A., & Wenke, D. (2012). Implicit sequence learning based on instructed task set. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 38*(5), 1389-1407.

Gaschler, R., Kemper, M., Zhao, F., Pumpe, I., Ruderisch, C.-B., Röttger, E., & Haider, H. (2018). Differential effects of cue-based and sequence knowledge-based predictability on multitasking performance. *Acta Psychologica, 191*, 76-86.

Gaschler, R., Zhao, F., Röttger, E., Panzer, S., & Haider, H. (2019). More than hitting the correct key quickly - Spatial variability in touch screen response location under multitasking in the Serial Reaction Time Task. *Experimental Psychology, 66*(3), 207-220.

Gómez, R. L. (2002). Variability and detection of invariant structure. *Psychological Science, 13*(5), 431-436.

Gonthier, C., Braver, T. S., & Bugg, J. M. (2016). Dissociating proactive and reactive control in the Stroop task. *Memory & Cognition, 44*, 778-788.

Greenwald, A. G., & Shulman, H. G. (1973). On doing two things at once: II. Elimination of the psychological refractory period effect. *Journal of Experimental Psychology, 101*, 70-76.

Haider, H., Eberhardt, K., Esser, S., & Rose, M. (2014). Implicit visual learning: How the task set modulates learning by determining the stimulus-response binding. *Consciousness and Cognition, 26*, 145-161.

Haider, H., Eberhardt, K., Kunde, A., & Rose, M. (2012). Implicit visual learning and the expression of learning. *Consciousness and Cognition, 22*(1), 82-98.

Haider, H., Eichler, A., & Lange, T. (2011). An old problem: How can we distinguish between conscious and unconscious knowledge acquired in an implicit learning task? *Consciousness and Cognition, 20*(3), 658-672.

Halvorson, K. M., Ebner, H., & Hazeltine, E. (2013). Investigating perfect timesharing: The relationship between IM-compatible tasks and dual-task performance. *Journal of Experimental Psychology: Human Perception and Performance, 39*(2), 413-432.

Halvorson, K. M., Wagschal, T. T., & Hazeltine, E. (2013). Conceptualization of task boundaries preserves implicit sequence learning under dual-task conditions. *Psychonomic Bulletin & Review, 20*(5), 1005-1010.

Hazeltine, E., Ruthruff, E., & Remington, R. W. (2006). The role of input and output modality pairings in dual-task performance: Evidence for content-dependent central interference. *Cognitive Psychology, 52*, 291-345.

Hazeltine, E., & Schumacher, E. H. (2016). Understanding central processes: The case against simple stimulus-response associations and for complex task representation. In B. Ross (Ed.), *Psychology of learning and motivation* (Vol. 64, pp. 195-245). Cambridge, MA: Elsevier.

Hazeltine, E., Teague, D., & Ivry, R. B. (2002). Simultaneous dual-task Performance reveals parallel response selection after practice. *Journal of Experimental Psychology: Human Perception and Performance, 28*(3), 527-545.

Heuer, H., & Schmidtke, V. (1996). Secondary-task effects on sequence learning. *Psychological Research, 59*(2), 119-133.

Hirsch, P., Nolden, S., & Koch, I. (2017). Higher-order cognitive control in dual tasks: Evidence from task-pair switching. *Journal of Experimental Psychology: Human Perception and Performance, 43*(3), 569-580.

Hommel, B. (1998). Automatic stimulus–response translation in dual-task performance. *Journal of Experimental Psychology: Human Perception and Performance, 24*(5), 1368-1384.

Houghton, G., & Hartley, T. (1995). Parallel models of serial behavior: Lashley revisited. *Psyche, 2*(25), 1-25.

Hübner, R., & Lehle, C. (2007). Strategies of flanker coprocessing in single and dual tasks. *Journal of Experimental Psychology: Human Perception and Performance, 33*, 103-123.

Hunt, R. H., & Aslin, R. N. (2001). Statistical learning in a serial reaction time task: Access to separable statistical cues by individual learners. *Journal of Experimental Psychology: General, 130*(4), 658-680.

Israel, M., & Cohen, A. (2011). Involuntary strategy-dependent dual task performance. *Psychological Research, 75*(6), 513-524.

Janczyk, M. (2016). Sequential modulation of backward crosstalk and task-shielding in dual-tasking. *Journal of Experimental Psychology: Human Perception and Performance, 42*(5), 631-647.

Janczyk, M., Pfister, R., Hommel, B., & Kunde, W. (2014). Who is talking in backward crosstalk? Disentangling response- from goal-conflict in dual-task performance. *Cognition, 132*(1), 30-43.

Janczyk, M., Renas, S., & Durst, M. (2018). Identifying the Locus of Compatibility-Based Backward Crosstalk: Evidence From an Extended PRP Paradigm. *Journal of Experimental Psychology: Human Perception and Performance, 44*(2), 261-276.

Jiménez, L., Lupiáñez, J., & Vaquero, J. M. (2009). Sequential congruency effects in implicit sequence learning. *Consciousness and Cognition, 18*(3), 690-700.

Keele, S. W., Ivry, R. I., Mayr, U., Hazeltine, E., & Heuer, H. (2003). The cognitive and neural architecture of sequence representation. *Psychological Review, 110*(2), 316-339.

Koch, I. (2001). Automatic and intentional activation of task sets. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 27*(6), 1474-1486.

Koch, I. (2009). The role of crosstalk in dual-task performance: Evidence from manipulating response-set overlap. *Psychological Research, 73*(3), 417-424.

Koch, I., Gade, M., Schuch, S., & Philipp, A. M. (2010). The role of inhibition in task switching: A review. *Psychonomic Bulletin & Review, 17*(1), 1-14.

Koch, I., Poljac, E., Müller, H., & Kiesel, A. (2018). Cognitive structure, flexibility, and plasticity in human multitasking - An integrative review of dual-task and task-switching research. *Psychological Bulletin, 144*(6), 557-583.

Lashley, K. S. (1951). The problem of serial order in behavior. In L. A. Jeffress (Ed.), *Cerebral mechanisms in behavior* (pp. 112-136). New York: Wiley.

Lehle, C., & Hübner, R. (2009). Strategic capacity sharing between two tasks: Evidence from tasks with the same and with different task sets. *Psychological Research, 73*(5), 707-726.

Lehle, C., Steinhauser, M., & Hübner, R. (2008). Serial or parallel processing in dual tasks: What is more effortful? *Psychophysiology, 46*, 502-509.

Liepelt, R., Strobach, T., Frensch, P. A., & Schubert, T. (2011). Improved intertask coordination after extensive dual-task practice. *The Quarterly Journal of Experimental Psychology, 64*(7), 1251-1272.

Loftus, G. R., & Masson, M. E. J. (1994). Using confidence intervals in within-subject designs. *Psychonomic Bulletin & Review, 1*(4), 476-490.

Logan, G. D., & Gordon, R. D. (2001). Executive control of visual attention in dual-task situations. *Psychological Review, 108*(2), 393-434.

Los, S. A., Kruijne, W., & Meeter, M. (2014). Outlines of a multiple trace theory of temporal preparation. *Frontiers in Psychology*. doi:10.3389/fpsyg.2014.01058.

Los, S. A., Kruijne, W., & Meeter, M. (2017). Hazard versus history: Temporal preparation is driven by past experience. *Journal of Experimental Psychology: Human Perception and Performance, 43*(1), 78-88.

Magen, H., & Cohen, A. (2007). Modularity beyond perception: Evidence from the PRP paradigm. *Journal of Experimental Psychology: Human Perception and Performance, 36*(2), 395-414.

Marcus, D. J., Karatekin, C., & Markiewicz, S. (2006). Oculomotor evidence of sequence learning on the serial reaction time task. *Memory & Cognition, 34*(2), 420-432.

Mattes, A., Tavera, F., Ophey, A., Roheger, M., Gaschler, R., & Haider, H. (subm.). Parallel and serial task processing in the PRP-paradigm: A drift diffusion model approach. *Psychological Research*.

Meyer, D. E., & Kieras, D. E. (1997). A computational theory of executive cognitive processes and multiple-task performance: Part 1. Basic mechanisms. *Psychological Review, 104*(1), 3-65.

Miller, J. (2006). Backward crosstalk effects in psychological refractory period paradigms: effects of second-task response types on first-task response latencies. *Psychological Research, 70*, 484-493.

Miller, J., Ulrich, R., & Rolke, B. (2009). On the optimality of serial and parallel processing in the psychological refractory period paradigm: Effects of the distribution of stimulus onset asynchronies. *Cognitive Psychology, 58*(3), 273-310.

Mittelstädt, V., & Miller, J. (2017). Separating limits on preparation versus online processing in multitasking paradigms: Evidence for resource models. *Journal of Experimental Psychology: Human Perception and Performance, 43*(1), 89-102.

Moeller, B., Pfister, R., Kunde, W., & Frings, C. (2016). A common mechanism behind distractor-response and response-effect binding? *Attention, Perception, & Psychophysics, 78*(4), 1074-1086.

Navon, D., & Miller, J. (2002). Queuing or sharing? A critical evaluation of the single-bottleneck notion. *Cognitive Psychology, 44*, 193-251.

Nissen, M. J., & Bullemer, P. (1987). Attentional requirements of learning: Evidence from performance measures. *Cognitive Psychology, 19*(1), 1-32.

Pashler, H. E. (1984). Processing stages in overlapping tasks: Evidence for a central bottleneck. *Journal of Experimental Psychology: Human Perception and Performance, 10*, 358-377.

Pashler, H. E. (1994). Dual-task interference in simple tasks: Data and theory. *Psychological Bulletin, 116*, 220-244.

Pashler, H. E., & Johnston, J. C. (1989). Chronometric evidence for central postponement in temporally overlapping tasks. *Quarterly Journal of Experimental Psychology, 41 A*(1), 19-45.

Perruchet, P., & Pacton, S. (2006). Implicit learning and statistical learning: One phenomenon, two approaches. *Trends in Cognitive Sciences, 10*(5), 233-238.

Plessow, F., Schade, S., Kirschbaum, C., & Fischer, R. (2017). Successful voluntary recruitment of cognitive control under acute stress. *Cognition, 168*, 182-190.

Rah, S. K., Reber, A. S., & Hsiao, A. T. (2000). Another wrinkle on the dual-task SRT experiment: It's probably not dual-task. *Psychonomic Bulletin & Review, 7*(2), 309-313.

Ratcliff, R., & Rouder, J. N. (1998). Modeling response times for two-choice decisions. *Psychological Science, 9*(5), 347-356.

Reber, A. S. (1993). *Implicit learning and tacit knowledge: An essay on the cognitive unconscious*. New York: Oxford University Press.

Rescorla, R. A., & Wagner, A. R. (1972). A theory of Pavlovian conditioning: Variations in the effectiveness of reinforcement and nonreinforcement. In A. H. Black & W. F. Prokasky (Eds.), *Classical conditioning II: Current research and theory* (pp. 64-99). New York: Appleton-Century-Crofts.

Röttger, E., Haider, H., Zhao, F., & Gaschler, R. (2019). Implicit sequence learning despite multitasking – the role of across-task predictability. *Psychological Research, 83*(3), 526-543.

Röttger, E., Haider, H., Zhao, F., & Gaschler, R. (in prep.-a). Global – not local – across-task predictability determines the amount of implicit sequence learning in a dual-task context.

Röttger, E., Haider, H., Zhao, F., & Gaschler, R. (in prep.-b). Implicit sequence learning as an indicator of efficient dual-task processing?

Ruiz Fernández, S., Leonhard, T., Rolke, B., & Ulrich, R. (2011). Processing two tasks with varying task order: Central stage duration influences central processing order. *Acta Psychologica, 137*(10-17).

Ruthruff, E., Johnston, J. C., Van Selst, M., Whitsell, S., & Remington, R. W. (2003). Vanishing dual-task interference after practice: Has the bottleneck been eliminated or is it merely latent? *Journal of Experimental Psychology: Human Perception and Performance, 29*(2), 280-289.

Schiffer, A.-M., Waszak, F., & Yeung, N. (2015). The role of prediction and outcomes in adaptive cognitive control. *Journal of Physiology - Paris, 109*, 38-52.

Schmidt, J. R. (2013). Temporal learning and list-level proportion congruency: conflict adaptation or learning when to respond? *PLoS ONE, 8*(11). doi:10.1371/journal.pone.0082320.

Schmidt, J. R., Lemercier, C., & de Houwer, J. (2014). Context-specific temporal learning with non-conflict stimuli: Proof-of-principle for a learning account of context-specific proportion congruent effects. *Frontiers in Psychology*. doi:org/10.3389/fpsyg.2014.01241.

Schmidtke, V., & Heuer, H. (1997). Task integration as a factor in secondary-task effects on sequence learning. *Psychological Research, 60*(1-2), 53-71.

Schuck, N. W., Gaschler, R., & Frensch, P. A. (2012). Implicit learning of what comes when and where within a sequence: The time-course of acquiring serial position-item and item-item associations to represent serial order. *Advances in Cognitive Psychology, 8*(2), 83-97.

Schuck, N. W., Gaschler, R., Kreisler, A., & Frensch, P. A. (2012). Position–item associations play a role in the acquisition of order knowledge in an implicit serial reaction time task. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 38*(2), 440-456.

Schumacher, E. H., Cookson, S. L., Smith, D. M., Nguyen, T. V. N., Sultan, Z., Reuben, K. E., & Hazeltine, E. (2018). Dual-task processing with identical stimulus and response sets: Assessing the importance of task representation in dual-task interference. *Frontiers in Psychology*. doi:org/10.3389/fpsyg.2018.01031

Schumacher, E. H., & Hazeltine, E. (2016). Hierarchical Task Representation: Task Files and Response Selection. *Current Directions in Psychological Science, 25*(6), 449-454.

Schumacher, E. H., & Schwarb, H. (2009). Parallel response selection disrupts sequence learning under dual-task conditions. *Journal of Experimental Psychology: General, 138*(2), 270-290.

Schumacher, E. H., Seymour, T. L., Glass, J. M., Fencsik, D. E., Lauber, E. J., Kieras, D. E., & Meyer, D. E. (2001). Virtually perfect time sharing in dual-task performance: Uncorking the central cognitive bottleneck. *Psychological Science, 12*(2), 101-108.

Schwarb, H., & Schumacher, E. H. (2010). Implicit sequence learning is represented by stimulus–response rules. *Memory & Cognition, 38*, 677-688.

Schwarb, H., & Schumacher, E. H. (2012). Generalized lessons about sequence learning from the study of the serial reaction time task. *Advances in Cognitive Psychology, 8*(2), 165-178.

Stadler, M. A. (1995). The role of attention in implicit learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 21*(3), 674-685.

Sternberg, S. (1969). The discovery of processing stages: Extensions of Donders' method. *Acta Psychologica, 30*, 276-315.

Strobach, T., Salminen, T., Karbach, J., & Schubert, T. (2014). Practice-related optimization and transfer of executive functions: A general review and a specific realization of their mechanisms in dual tasks. *Psychological Research, 78*(6), 836-851.

Strobach, T., & Schubert, T. (2017a). Mechanisms of practice-related reductions of dual-task interference with simple tasks: Data and theory. *Advances in Cognitive Psychology, 13*(1), 28-41.

Strobach, T., & Schubert, T. (2017b). No evidence for task automatization after dual-task training in younger and older adults. *Psychology and Aging, 32*(1), 28-41.

Taatgen, N., & van Rijn, H. (2011). Traces of times past: Representations of temporal intervals in memory. *Memory & Cognition, 39*(8), 1546-1560.

Telford, C. W. (1931). The refractory phase of voluntary and associative responses. *Journal of Experimental Psychology, 14*(1), 1-36.

Tombu, M., & Jolicoeur, P. (2003). A central capacity sharing model of dual-task performance. *Journal of Experimental Psychology: Human Perception and Performance, 29*(1), 3-18.

Tombu, M., & Jolicoeur, P. (2005). Testing the Predictions of the Central Capacity Sharing Model. *Journal of Experimental Psychology: Human Perception and Performance, 31*(4), 790-802.

Ulrich, R., & Miller, J. (2008). Response grouping in the psychological refractory period (PRP) paradigm: Models and contamination effects. *Cognitive Psychology, 57*(75-121).

Van den Bos, E., Christiansen, M. H., & Misyak, J. B. (2012). Statistical learning of probabilistic nonadjacent dependencies by multiple-cue integration. *Journal of Memory and Language, 67*, 507-520.

Vuong, L. C., Meyer, A. S., & Christiansen, M. H. (2016). Concurrent statistical learning of adjacent and nonadjacent dependencies. *Language Learning, 66*(1), 8-30.

Welford, A. T. (1952). The „psychological refractory period“ and the timing of high-speed performance - A review and a theory. *British Journal of Psychology, 43*(1), 2-19.

Wendt, M., & Kiesel, A. (2011). Conflict adaptation in time: Foreperiods as contextual cues for attentional adjustment. *Psychonomic Bulletin & Review, 18*, 910-916.

Wenke, D., & Frensch, P. A. (2005). The influence of task instructions on action coding: Constraint setting or direct coding? *Journal of Experimental Psychology: Human Perception and Performance, 31*(4), 803-819.

Willingham, D. B., Wells, L. A., Farrell, J. M., & Stemwedel, M. E. (2000). Implicit motor sequence learning is represented in response locations. *Memory & Cognition, 28*, 366–375.

Zhao, F., Gaschler, R., Schneider, L., Thomaschke, R., Röttger, E., & Haider, H. (in press). Sequence knowledge on when and what supports dual tasking. *Journal of Cognition*.

Ziessler, M., & Nattkemper, D. (2001). Learning of event sequences is based on response-effect learning: Further evidence from a serial reaction task. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 27*(3), 595-613.

Ziessler, M., Nattkemper, D., & Frensch, P. A. (2004). The role of anticipation and intention in the learning of effects of self-performed actions. *Psychological Research, 68*(2-3), 163-175.

Published article and contributions of the authors

Chapter 2 is based on the manuscript:

Röttger, E., Haider, H., Zhao, F., & Gaschler, R. (2019). Implicit sequence learning despite multitasking – the role of across-task predictability. *Psychological Research, 83*(3), 526-543.

HH and RG developed the rationale of the present studies and received grants from the German Research Foundation (Deutsche Forschungsgemeinschaft, DFG) within the Priority Program SPP 1772 "Multitasking"; grants HA 5447/11-1 (HH) and GA 2246/1-1 (RG). HH and ER developed the hypotheses and designs for the Experiments 1-4. ER programmed the experiments, analyzed the data and wrote the manuscript with help of HH. HH, RG and FZ revised the manuscript.

Chapter 3 (not yet published):

HH and ER developed the hypotheses and designs for the Experiments 1-3. ER programmed the experiments, analyzed the data and wrote the manuscript.

Chapter 4 (not yet published):

HH and ER developed the hypotheses and designs for the Experiments 1-3. ER programmed the experiments, analyzed the data and wrote the manuscript.