See discussions, stats, and author profiles for this publication at: https://www.researchgate.net/publication/335351146

## Linking task selection to task performance: Internal and predictable external processing constraints jointly influence voluntary task switching behavior

Article in Journal of Experimental Psychology Human Perception \& Performance • August 2019
DOI: 10.1037/xhp0000690

CITATIONS
0

3 authors:


Victor Mittelstädt
University of Tuebingen
12 PUBLICATIONS 63 CITATIONS
SEE PROFILE

Andrea Kiesel
University of Freiburg
141 PUBLICATIONS 4,105 CITATIONS
SEE PROFILE

Some of the authors of this publication are also working on these related projects:

Project instruction-based action control View project

Sustainable Energy Efficiency / Nachhaltige Energieeffizienz View project

# Linking Task Selection to Task Performance: Internal and Predictable External Processing Constraints Jointly Influence Voluntary Task Switching Behavior 

Victor Mittelstädt<br>University of Freiburg and University of Otago

Jeff Miller<br>University of Otago

Andrea Kiesel<br>University of Freiburg


#### Abstract

Findings from studies using the voluntary task switching (VTS) paradigm (Arrington \& Logan, 2004) suggest that task selection in multitasking can be influenced by both cognitive and environmental constraints. In the present study, we used an adaptive VTS paradigm to directly test whether and how people adapt to these 2 constraints when they are instructed to optimize their task performance. In 5 experiments, the availabilities of stimuli for 2 tasks in a trial changed predictably because the stimulus needed for a task repetition appeared with an SOA that increased linearly with the number of repetitions. Experiments 1a and 1 b demonstrated that stimulus availability did not automatically induce switching behavior. Experiment 2 showed that the predictable external constraints were accommodated in participants' switching behavior once participants overcame their reluctance to switch tasks. Experiments 3 and 4 revealed that both switch costs and switch rates were influenced by manipulating the time between trials. Moreover, switch costs and switch rates were correlated across all experiments; and when the time for advanced preparation of task selection was limited (Experiment 1a, 1b, and certain conditions of Experiments 3 and 4), the SOA in task switches approximately matched switch costs. Together, these results point to a link between task selection and performance indicating that participants adapt their task selection behavior to mutual effects of external and internal influences on task performance. We propose that both task selection and task performance can be integrated within a framework of competing multiple task-set activations.


## Public Significance Statement

In real-world multitasking, people often decide for themselves how to schedule multiple tasks in the face of both cognitive (i.e., internal) and environmental (i.e., external) constraints. In the present study, we examined how people adapted their task selection behavior to the mutual effects of internal and external influences on task performance. The results suggest that these two types of processing constraints jointly guided task selection behavior, indicating a link between task selection and performance in multitasking.

Keywords: multitasking, voluntary task-switching, switch costs

People have limited cognitive (processing) capacity and we must adapt to our limitations to perform efficiently in our dynamically changing environment (e.g., Anderson, 1990; Gray, Sims, Fu, \& Schoelles, 2006; Navon \& Gopher, 1979). Cognitive control is needed to flexibly adjust the competing flow of information arising from different external sources toward the currently relevant task goal (e.g., Abrahamse, Braem, Notebaert, \& Verguts,

2016; Miller \& Cohen, 2001; Verbruggen, McLaren, \& Chambers, 2014). This flexible reconfiguration of the flow of activations arising from multiple sources of information is especially required in multitasking situations: Multiple task sets are represented within our system and we constantly need to monitor our environment for information relevant to these tasks. We are then often required- or voluntarily decide-to perform tasks simultaneously (i.e., dual-

[^0][^1]tasking) or to switch rapidly between them (i.e., task-switching). Performance limitations in both dual-tasking (e.g., Pashler, 1984; Welford, 1952) and task-switching (e.g., Jersild, 1927; Rogers \& Monsell, 1995; for reviews, see, e.g., Kiesel et al., 2010; Meiran, 2010; Vandierendonck, Liefooghe, \& Verbruggen, 2010) reveal the internal processing constraints of the human brain (for integrative multitasking reviews, see Koch, Poljac, Müller, \& Kiesel, 2018; Pashler, 2000; Salvucci \& Taatgen, 2010).

Importantly, however, adequate task-organization behaviorthat is, which information to attend and which task(s) to perform at any given time-is often not externally specified by the environment (e.g., Kushleyeva, Salvucci, \& Lee, 2005; Payne, Duggan, \& Neth, 2007). Instead, we are required to selforganize our multitasking behavior to accommodate both cognitive and environmental constraints. How people adapt to their limitations and environments in their actual multitasking be-havior-that is, the mechanisms underpinning how voluntary selection of task sets arises in such situations-remains fairly underspecified, presumably because the most prominent experimental multitasking paradigm "inducing" voluntary task selections was not developed to tackle this question (e.g., Arrington \& Logan, 2004).

In the present study, we aim to provide some further insights into these mechanisms by investigating how people adapt their task selection behavior to cognitive and environmental constraints. Specifically, in our task environments the availabilities of stimuli for two tasks in a trial were manipulated in such a way that the stimulus of the chosen task appeared with a delay or stimulus onset asynchrony (SOA) in the subsequent trial, and this SOA increased linearly with the number of task repetitions until there was a task switch (Mittelstädt, Miller, \& Kiesel, 2018). We recently introduced this multitasking paradigm by demonstrating in two experiments that this dynamic manipulation successfully induced voluntary task switches in participants' task selection behavior without the instruction to randomly choose tasks as is done in the standard voluntary task switching paradigm (e.g., Arrington \& Logan, 2004). In the present study, we report several experiments using additional versions of this paradigm to further elaborate whether and how participants adapt their task selection behavior to internal contexts (i.e., previous task selection) as well as external contexts (i.e., stimulus availabilities).

## Determinants of Task Selection Behavior in Voluntary Task Switching

In voluntary task-switching (VTS) experiments, two stimuli associated with two independent task sets are presented in each trial. Each task is usually mapped to one hand and participants are told that they can decide which task to perform in a given trial. Without any further instructions, participants avoid task switching (e.g., mean switch rate below . 15 in Kessler, Shencar, \& Meiran, 2009). In addition, responses are slower in trials in which participants switch tasks compared to trials in which participants repeat tasks (e.g., mean switch costs above 450 ms in Kessler et al., 2009). Thus, similar to paradigms where task switching is required rather than voluntary (e.g., Rogers \& Monsell, 1995; Rubinstein, Meyer, \& Evans, 2001; Sohn \& Carlson, 2000), switching tasks results in performance costs, and these switch costs suggest that
behavior in VTS paradigms is heavily influenced by the cognitive constraints involved in multitasking.

Because participants tend to switch tasks rarely when left entirely free to choose tasks, task selection behavior has most commonly been studied in experiments where participants are specifically instructed to perform both tasks equally often and in a random sequence (Arrington \& Logan, 2004; Demanet, Verbruggen, Liefooghe, \& Vandierendonck, 2010; Vandamme, Szmalec, Liefooghe, \& Vandierendonck, 2010). Although participants typically succeed in selecting each task equally often, they quite consistently tend to repeat tasks more often than chance (e.g., Dignath, Kiesel, \& Eder, 2015; Masson \& Carruthers, 2014; Mayr \& Bell, 2006). To explain this finding, Arrington and Logan (2005) proposed that task selection results from a competition between the use of an availability heuristic and a representativeness heuristic. When participants fail to select a task based on a mentally represented random sequence (i.e., representativeness heuristic), they select tasks on the basis of the most active task set (i.e., availability heuristic)-which is typically the task set associated with a repetition.

Importantly, the specific characteristics of stimuli presented in the current trial also influence task selection behavior. First, stimulus repetitions further increase the tendency to repeat a task (e.g., Demanet et al., 2010; Mayr \& Bell, 2006). Second, stimulus-based priming effects on task selection have been observed in a study by Arrington, Weaver, and Pauker (2010): When participants performed a given task to a bivalent priming stimulus (i.e., an uninformative advance stimulus which included attributes associated with two different task sets), they were more likely to perform this task again (compared to an alternative task) when they were exposed a second time to this same priming stimulus. Third, participants are more likely to select the task that is associated with a stimulus to which the response is spatially congruent compared to incongruent (Chen \& Hsieh, 2013). Fourth and finally, stimulus availability influences task selection behavior. When two stimuli are presented with a variable SOA, participants are more likely to perform the task associated with the stimulus that appears first (e.g., Arrington, 2008; Arrington \& Weaver, 2015). The finding that this likelihood increases as SOA increases suggests that task selection can be biased by the time the system is exposed to stimulus-driven task-set activations during a trial. Clearly, like the influence of previous task selection, all of these observed external influences on task selection behavior during a trial conflict somewhat with the instruction to randomly select tasks. Consequently, these findings have also been interpreted as evidence that people select tasks based on the most active task set (i.e., availability heuristic).

Interestingly, violations of the randomness instruction in terms of guiding task selection on the basis of the most active task set influenced by both internal and external contexts might provide some indirect hints concerning adaptive task selection behavior (see also Mittelstädt, Dignath, Schmidt-Ott, \& Kiesel, 2018). Unfortunately, however, there are good reasons to assume that the randomness instruction counters or obscures participants' potential adaptive task selection behavior. For example, Liefooghe, Demanet, and Vandierendonck (2010) showed that asymmetries in switch costs-that is, the finding that switch costs are usually higher when switching from a less familiar, weaker task to a
well-practiced, stronger task (see Allport, Styles, \& Hsieh, 1994; Yeung \& Monsell, 2003)—as well as the corresponding asymmetries in switching behavior (i.e., participants perform the weaker task more often than the stronger task)-were only present in VTS conditions without randomness instructions, but not with them. ${ }^{1}$ This suggests that randomness instructions impose an additional demand that distorts the type of cognitive processing that takes place when participants choose tasks without this instruction (e.g., additional inhibitory processes, see Lien \& Ruthruff, 2008). Thus, previous findings from VTS studies suggesting that task selection (i.e., switch rate) and task performance (i.e., switch costs) at least partially result from separable cognitive processes (e.g., Arrington \& Yates, 2009; Chen \& Hsieh, 2013) might be critical because the randomness instruction might distort a possible cognitive link between these two measures.

In summary, task selection seems to be influenced by both internal contexts (e.g., previous task selection) and external contexts (e.g., stimulus availabilities). It has been difficult to study how people adapt to the mutual effects of these two types of influences, however, with previous paradigms. Without instructions to switch randomly, participants rarely switch. Unfortunately, the instruction to switch randomly basically means that participants are instructed not to adapt their switching behavior to any internal and external factors (i.e., but to respond randomly instead). Thus, the study of how people adapt to internal and external factors requires an experimental paradigm in which switching behavior can be investigated without the global randomness instruction.

## The Self-Organized Task-Switching Paradigm

Recently, we developed a version of the voluntary task switching paradigm to study the mutual influences of cognitive and external constraints on voluntary task switching without instructing participants to select tasks randomly. In our experiments, we investigated how differential stimulus availability could counteract the internal cognitive constraints favoring task repetitions (Mittelstädt et al., 2018). Specifically, in each trial we presented two stimuli associated with separate tasks, with each task requiring responses with either the index or middle finger of one hand. Participants could voluntarily select the task by responding with the corresponding hand. Crucially, we delayed in trial $n$ the onset of the stimulus of the task performed in trial $\mathrm{n}-1$ by a certain SOA. Thus, if participants wanted to repeat the previous task in trial $n$, they had to wait longer for the repetition stimulus. Moreover, the SOA increased further with each additional repetition of the task. The stimulus needed for a task switch was always presented without any delay, so the time between switch and repetition stimuli-and thus the external constraint favoring task switchesincreased with the number of consecutive task repetitions (see Figure 1). Whenever a participant switched tasks, the SOA was reset to the first SOA step size and a new sequence started.

The major finding of two experiments with different SOA increments (i.e., 50 ms vs. 33 ms ) was that this procedure induced switching behavior for all participants, yielding average switch rates of .38 and .30 , respectively-in contrast to other studies in which little or no switching behavior was observed without global randomness instructions (e.g., Arrington \& Reiman, 2015; Kessler et al., 2009). Note that the presence of a switch avoidance bias


Figure 1. Typical trial sequences in Experiments 1a, 1b, 2, 3, and 4. Stimuli were always presented within the fixation rectangle, but only the stimulus needed for a task switch was presented immediately at the end of the response stimulus interval (RSI; Experiments 1a and 1b: RSI $=0 \mathrm{~ms}$; Exp. 2: RSI $=400 \mathrm{~ms}$; Exps. 3 and 4: RSI $=100 \mathrm{~ms}$ or 700 ms ). The stimulus needed for a task repetition was presented with a stimulus onset asynchrony (SOA) that depended on a) the previous task selection history (i.e., how often this task was selected before) and b) the experimentspecific SOA step size (i.e., Experiments 1a, 1b, 3, and 4: step size $=50$ ms ; Exp. 2: step size $=50 \mathrm{~ms}$ or 100 ms ).
(i.e., switch rates $<.50$ ) suggests that cognitive differences between these transitions still heavily influenced switching behav-ior-presumably because of the average switch costs ( 118 ms and 130 ms ) observed in the two experiments.

Interestingly, switch rates increased substantially after the first blocks in these two experiments (i.e., higher switch rates after block 1 or block 2), which suggests that participants adjusted their switching behavior after learning about the external processing constraints (i.e., the delayed onsets of stimuli needed for task repetitions). Thus, the early availability of the switch stimuli did not just automatically bias the competition of task sets to influence switching behavior.

Importantly, the ability of this paradigm to capture both switching limitations and switching behavior on a common time scale allowed additional insights into how participants incorporated switch costs and stimulus availabilities into their task selection behavior. Specifically, our procedure allowed us to explore how much extra switch stimulus availability (i.e., size of SOA by which the repetition stimulus is delayed) would be necessary to elicit task switches in individual runs. Interestingly, in the two experiments the (median) size of SOA in switch trials was similar to switch costs. This suggests that internal and external processing constraints were traded off in a manner to minimize the time required to complete a trial.

## The Present Experiments

The five experiments reported here used the self-organized task switching paradigm introduced by Mittelstädt et al. (2018) to more

[^2]directly elaborate on how switch costs and external context mutually influence task switching behavior. In Experiments 1a and 1b, we explored the boundaries of inducing switching behavior with the use of our adaptive switch stimulus availability procedure. Specifically, we investigated whether increased availability of switch stimuli can also increase switch rates when preparatory processes in advance of trials have no time to operate (i.e., no response-stimulus interval) and when the potential maximum waiting time was rather low due to a small number of trials per task (i.e., 30 trials in each task). In Experiment 2, we manipulated blockwise the temporal dynamics of the stimulus availability manipulation (i.e., different SOA step sizes). In Experiments 3 and 4, we kept constant the dynamics of these external processing constraints (i.e., SOA increments) but manipulated the length of the response-stimulus interval (RSI) between trials blockwise (Experiment 3) and trialwise (Experiment 4)-to manipulate internal processing constraints (i.e., switch costs), and also to investigate the trade-off of switch cost and stimulus availability when there was less opportunity for advance preparation of task selection.

In all experiments, we report both switch costs and switch rates to assess how these measures were influenced by our experimental manipulations. In general, we expect that switching would be avoided to a greater extent when it is more detrimental to task performance. To examine switching behavior more closely, we also investigated the distribution of switches at different SOAs and compared the sizes of the SOAs in switch trials to the sizes of switch costs. By measuring both measures on the same scale, we can explicitly investigate how the external processing benefits (i.e., switch stimulus availability) are temporally pitted against the internal processing costs (i.e., switch costs) under different conditions of our predictable task environment (e.g., with more or less time for advanced preparation of task selection).

## Experiment 1a

Experiment 1a was modeled after the paradigm used by Mittelstädt et al. (2018). A letter (vowel vs. consonant) and a number (odd vs. even) categorization task were used and each task was mapped to one hand. Participants could decide voluntarily which task to perform on each trial, but the stimulus for the chosen task appeared with an SOA in the subsequent trial and this SOA increased by 50 ms for each consecutive task repetition until a task switch reset it to 50 ms .

We implemented several modifications of the Mittelstädt et al. (2018) paradigm to investigate whether participants' switching behavior was still influenced by switch stimulus availabilities when the possibility of preparatory task selection in advance of trials (and blocks) was minimized. First, a response-stimulusinterval (RSI) of 0 ms was used to avoid preparatory task selection processes in advance of a trial and require participants to select a task during a trial when they simultaneously had to deal with the two potential sources presumably biasing task-set activation. We correspondingly used fewer trials per block (i.e., 60) to give participants the possibility for breaks. Second, task locations were constant within a block and did not randomly alternate on trial-by-trial basis. This change was implemented to prevent participants from selecting tasks based on the location (e.g., always perform the task for the stimulus presented at the top). Note that this location-based task selection strategy had been found to partially influence switching
behavior in our previous study (Mittelstädt et al., 2018) as well as in VTS studies with randomness instructions (e.g., Arrington \& Weaver, 2015). Third, we refrained from using any training blocks with instructed task order (e.g., alternating-run blocks as in Mittelstädt et al., 2018) to keep participants from developing any task selection biases/strategies based on their experiences during these blocks. Fourth, we required participants to perform each task 30 times in each block (e.g., after selecting the letter task 30 times participants were only given the number stimulus and thus had to perform the number task in the remaining trials) to avoid strong preferences for one task and to require participants to keep both task sets active throughout the experiment.

## Method

Participants. Based on effect size estimates from Mittelstädt et al. (2018), ${ }^{2} 32$ native German speakers ( 24 female, age 18 to 31 years with $M=23.34$, all right-handed) were individually tested at the University of Freiburg, Germany. In this and in the following experiments, all participants had normal or corrected-to normal vision and gave informed consent before testing. Furthermore, all experiments adhered to the standards set by the local ethics committee. Each participant was tested in a single experimental session lasting approximately 50 min and received either course credit or money for participation.

Apparatus and stimuli. Stimulus presentation and recording of responses were controlled by E-Prime software running on a Fujitsu Eprimo P920 computer with 24-in monitor. All visual stimuli were presented on a black background, which was viewed from a distance of approximately 60 cm . Stimuli were the numbers 2-9 for the number task (i.e., even/odd) and the uppercase letters A, E, G, I, K, M, R, and U for the letter task (i.e., consonant/ vowel). In each trial, the specific identities of the two stimuli were selected randomly with the constraints that no stimulus was pre-

[^3]sented twice consecutively. All stimuli were presented in white 25-pt Courier New font and they were approximately 7 mm in height and 5 mm in width. The stimuli of the two tasks appeared one above the other at the center of the screen and they were surrounded by a white fixation rectangle ( $11 \mathrm{~mm} \times 19 \mathrm{~mm}$ ). The stimulus (task) positions were constant within a block but alternated between blocks. Half of the participants started with a block where the number stimulus was presented at the top and the letter stimulus was at the bottom. For the other half of participants, the stimulus-location mapping in the first block was reversed. Responses for a task were made with the index and middle finger of the same hand on a QWERTZ keyboard with the " $y$ ", " $x$ ", "," and "." keys, and the specific mappings were counterbalanced across participants.

Procedure. Each participant was tested in 22 blocks and in each block participants had to perform 30 trials in the letter task and 30 trials in the number task ( 1320 trials in total).

Figure 1 displays the typical trial sequence of all experiments. Stimuli of the two tasks were only presented simultaneously in the first trial of a block, whereas in the remaining trials only the stimulus needed for a task switch was presented immediately. The other stimulus was presented with an SOA that depended on the length of the current run of responses to this task. The SOA was first 50 ms and increased linearly by 50 ms each time that task was selected again (i.e., SOA increment of 50 ms ). The stimuli remained on the screen until a response was made (i.e., no response deadline). Following correct responses, the stimulus needed for a task switch was presented immediately (i.e., RSI $=0 \mathrm{~ms}$ ). In case of an error, an error screen was presented for $3,500 \mathrm{~ms}$ indicating the stimulus-response mappings for the two tasks, and this was followed by a blank screen for 500 ms . After participants had performed 30 trials of the same task a placeholder (i.e., "\#"-sign) was presented at the corresponding position and key presses for this task were not recognized anymore.

Participants were instructed that they had to perform the letter task in 30 trials and the number task in the other 30 trials in one block and that they could decide in which order they wanted to perform these tasks but with the goal of minimizing the response time. Specifically, participants received a German version of the following instructions:

You have to perform 30 number tasks and 30 letter tasks in one block. You can decide which task to perform in a trial, as long as both tasks are available. Select the tasks to be as fast as possible without committing errors. Reaction time measurement in each trial starts with the presentation of the rectangle and you will receive feedback about your mean reaction time and your error rate at the end of a block.

Breaks between blocks were self-paced and participants received performance feedback (i.e., mean trial time and number of errors) after each block.

## Results

We first categorized the task performed on each trial based on the hand used to respond. Then, trials were classified as repetition or switch trials on the basis of the task performed on trials $n$ and $n-1$. Reported RTs (RTs) always indicate the time from the onset of the stimulus related to the task that the participant performed until the key press. Thus, in switch trials the total trial time was
equal to reaction time (RT), whereas in repetition trials the total trial time was the sum of RT and the trial-specific SOA.

We followed the same data preparation procedures in each experiment, and we excluded the first two blocks of trials as practice. Note that switch rates were higher for the second compared to first block in all experiments and tended to increase across a few following blocks in all experiments. ${ }^{3}$ In addition, we excluded the first trial of each block from any analyses. For all analyses, we then excluded any trials ( $30.6 \%$ ) without the possibility to choose between the two tasks (i.e., any trials when a placeholder was presented for one task), trials in which participants responded prior to stimulus onset ( $0.1 \%$ ) and trials following an error ( $3.7 \%$ ). For task selection and RT analyses, error trials (3.7\%) and trials with RTs less than $200 \mathrm{~ms}(0.1 \%)$ and greater than $3,000 \mathrm{~ms}(0.5 \%)$ were also excluded. ${ }^{4}$

Exclusion of participants for main analyses. After our data trimming procedure, we examined the number of trials separately for each participant in each condition (i.e., switch vs. repetition trials). Almost half of the participants showed basically no switching behavior: We excluded the data of 15 of the 32 participants with fewer than 10 valid switch trials (i.e., 13 participants with no valid switch trials and two participants with eight and two valid switch trials, respectively). Although this cut-off was somewhat arbitrarily set, we reasoned that a minimum of 10 trials is needed not only to obtain a reasonable estimate of individual switch costs but also to ensure that we excluded participants who followed a consistent repeat-strategy and only occasionally switched tasks by accidentally pressing keys associated with a switch task. Note that this cut-off was also applied for the following four experiments.

Task selection. We first checked whether there was any general preference for selecting either the letter or the number task when both tasks were available. Participants performed the two tasks equally often with a mean proportion of $.50(S E=.01)$ for performing the letter task and this rate did not differ from chance (.50), $p=.790$. The mean switch rate was .16 (see Table 1).

Following Mittelstädt et al. (2018), we then calculated the relative frequency distribution of switch SOAs separately for each participant. Assume, for example, a participant had 100 switch trials in total with 10 switches at the first and 20 switches at the second SOA level. This participant would obtain switch proportions of .10 at $\mathrm{SOA}=50 \mathrm{~ms}$ and .20 at $\mathrm{SOA}=100$, respectively. Following this, we computed the corresponding individual cumulative distribution function (CDF) for each participant (i.e., this would be .30 at $\mathrm{SOA}=100 \mathrm{~ms}$ for the participant of our example). To be clear, these CDFs describe the distribution of switches out of the trials in which switches did occur (i.e., number of repetition

[^4]Table 1
Mean Switch Rates, Mean Median Switch Stimulus-OnsetAsynchrony (SOA), and Mean Median Reaction Time (RT) as a Function of Trial Transition (i.e., Task Switch vs. Task Repetition) as Well as Mean Median Switch Costs (i.e., Median Task Switch RT-Median Task Repetition RT) for Experiments 1a and $1 b$

|  | Experiment |  |
| :--- | :---: | :---: |
| Measure | 1 a | 1 b |
| Switch rate | $.16(.02)$ | $.19(.02)$ |
| Switch SOA | $251(32)$ | $214(20)$ |
| Task switch RT | $865(45)$ | $742(20)$ |
| Task repetition RT | $564(21)$ | $518(7)$ |
| Switch cost RT | $301(36)$ | $224(17)$ |

Note. Standard errors of the means in parentheses.
trials play no role). Consider for example another participant with only 10 switch trials in total, with one switch at the first and two switches at the second SOA level. As for our other exemplary participant, this participant would also obtain a cumulative probability of .30 at $\mathrm{SOA}=100 \mathrm{~ms}$. Figure 2A displays the cumulative distribution function averaged over all participants. As can be seen in this figure, the switch proportions were rather low for the smallest SOA and the cumulative probabilities exceeded the $50 \%$ level at an SOA of 250 ms .

Similar to Mittelstädt et al. (2018), we computed each participant's individual median switch SOA as a summary measure of task selection behavior as a function of SOA. However, in contrast to Mittelstädt et al. (2018), we applied linear interpolation to compute those medians. This was done to obtain more fine-grained median estimates because otherwise median switch SOA would have varied in discrete steps according to the corresponding SOA step size used in this experiment (i.e., $50 \mathrm{~ms}, 100 \mathrm{~ms}, 150 \mathrm{~ms}$. . .). This means, for example, a participant with cumulative probabilities of .40 at $\mathrm{SOA}=50 \mathrm{~ms}$ and .80 at $\mathrm{SOA}=100 \mathrm{~ms}$ would obtain a median switch SOA of 63 ms in the present study, whereas this participant would obtain a median switch SOA of 100 ms when calculating the median with the procedure of Mittelstädt et al. (2018). ${ }^{5}$ The resulting averaged median switch SOA in this experiment was 251 ms (see Table 1).

Task performance. To make the measure of switch costs in RT more comparable to the median switch SOAs, we calculated median switch costs for each participant. Table 1 shows the averaged median switch RT, median repetition RT, and the corresponding switch costs of 301 ms (i.e., switch RT-repetition RT). A paired $t$ test revealed that these switch costs were significant, $t(16)=8.39, p<.001, \eta_{p}^{2}=.82$. Overall, percentage of errors (PE) was low ( $4.7 \%$ ) and PEs did not differ between switch ( $4.9 \%$ ) and repetition ( $4.6 \%$ ) trials, $p=.719, \eta_{p}^{2}=.01$.

Relation between task selection and task performance. As can be seen in Table 1, median switch SOAs ( 251 ms ) were only slightly lower than median switch costs ( 301 ms ) and a paired $t$ test indicated no reliable difference, $p=.229, \eta_{p}^{2}=.09$.

To explore individual differences, we then plotted individual median switch costs against individual switch rates (see Figure 3A). The correlation between these two measures was significant, $r(17)=-.56, p=.019 .{ }^{6}$

## Discussion

The results of Experiment 1a revealed that almost half of the participants showed virtually no switching behavior--in contrast to the results observed by Mittelstädt et al. (2018). This contradicts the idea that the early availability of switch stimuli will automatically induce a task switch. Instead, it seems that some participants have a strong reluctance to switch tasks and they guide their task selection behavior just on the task set associated with a repetition. In particular, one of the most striking procedural changes in the current Experiment 1a compared to the ones reported by Mittelstädt et al. (2018)-no interval between trials (i.e., RSI $=0 \mathrm{~ms}$ )-might have encouraged this task selection strategy for some participants. However, before elaborating on this account we investigated in Experiment 1 b whether there is a much more parsimonious explanation for why some participants did not switch-that is, at least some participants might have been not aware of the possibility of switching tasks and/or erroneously assumed that they are not allowed to switch tasks.

Importantly, for those participants who engaged in switching (17 out of 32), we replicated all the other findings observed by Mittelstädt et al. (2018) in the present modified task environment. Switch costs were found and they were correlated with switch rates. Moreover, the comparison of switch-SOAs with switch costs again suggests that the cross-over point to switch rather than repeat tasks was approximately the point at which these measures matched.

## Experiment 1b

Experiment 1b was designed with some minor modifications implemented to increase switching and consequently to reduce the number of participants who never or rarely switch. The major difference from Experiment 1a was that we included training blocks with instructed task order prior to the voluntary task selection blocks to allow for the possibility that participants following a consistent repetition strategy in Experiment 1a were unaware of the possibility of task switching during a block. In addition, we increased the number of participants to compensate for potential loss of participants who did not engage in switching, in case our modifications were not successful.

## Method

Participants. A fresh sample of 48 participants ( 33 female, age 19-36 years with $M=23.73$, 47 right-handed) from the same pool were tested.

[^5]

Figure 2. Cumulative distribution functions (CDFs) of switch stimulus onset asynchronies (SOAs) in Experiments 1a and 1b.

Apparatus, stimuli, and procedure. The apparatus, stimuli, and procedure were the same as in Experiment 1a except for the following modifications. First, we included two training blocks with the same SOA manipulation as in the voluntary task switching blocks but without any block feedback. In these blocks, an arrow indicated which task to perform on a given trial and this task selection was randomly selected in each trial. Second, we slightly changed the instructions and told participants that RT measurement on each trial would immediately start after a correct response was given on the previous trial and with the onset of the rectangle after an erroneous response was made. This change was implemented to make sure that participants were aware that a new trial started immediately after the last trial. Third, we included the currently fastest block mean RT of each participant in the voluntary task switching blocks in the performance feedback after each block.

## Results

The training blocks and the first two voluntary task switching blocks were excluded as practice. In addition, we excluded the first trial of each block. We then excluded any trials (30.0\%) without the possibility of choosing between the two tasks. Further, trials in which a response was given prior to stimulus onset $(0.3 \%)$ and posterror trials $(4.1 \%)$ were removed for all analyses. For RT and task selection analyses, $4.1 \%$ error trials were additionally excluded and we also excluded trials with RTs less than 200 ms $(0.4 \%)$ and greater than $3000 \mathrm{~ms}(0.4 \%)$.

Exclusion of participants for main analyses. Despite our modifications, over one third of the participants showed basically no switching behavior: We excluded the data of 18 participants from the following analyses because our data trimming procedure left less than 10 valid switch trials for these participants (i.e., 15 participants with no valid switch trials and 3 participants with 5 or fewer valid switch trials). Based on an inspection of scatter plots of individual results, the data of one additional participant were excluded due to unusually high switch costs (i.e., switch costs of $1,332 \mathrm{~ms}$ and switch rate of .02 ).

Task selection. Participants selected the letter task on a higher proportion of trials than the number task when both tasks were available (i.e., $.53 ; S E=.01$ ) and this mean probability differed from chance $(.50), t(28)=2.60, p=.015$. The mean switch rate was .19 and the median switch SOA was 214 ms (see Table 1).

Figure 2B shows the corresponding mean CDF to illustrate task selection as a function of SOA in more detail.

Task performance. As can be seen in Table 1, RTs were again larger on switch than on repetition trials and these switch costs of 224 ms were reliable, $t(28)=12.95, p<.001, \eta_{p}^{2}=.86$. PE was again low (3.5\%), and error rates were slightly higher in repetition $(3.8 \%)$ compared to switch trials $(3.1 \%)$, but this difference was not significant, $p=.069, \eta_{p}^{2}=.11$.

Relation between task selection and task performance. Median switch costs were slightly smaller than median switch SOA (see Table 1), but a paired $t$ test yielded no significant differences between these measures, $p=.564, \eta_{p}^{2}=.01$.

Figure 3B show individual median switch costs plotted against individual switch rates. This correlation was significant, $r(28)=-.52, p=.004$.

## Discussion

The results of Experiment 1 b replicated all major findings of Experiment 1a. For participants who engaged in switching, switch costs were found and individual switch costs correlated with individual switch rates. Probably most interesting was again the match of switch SOA and switch costs supporting the idea that once participants make the global decision to adapt to the task environment, switch costs were equally traded off against switch SOA.

Again, a substantial number of participants avoided task switching despite our modifications. This is a major difference in results from the two experiments reported in Mittelstädt et al. (2018) in which all participants showed switching behavior. This suggests that some global characteristics of the task environment play a substantial role in overcoming participants' reluctance to switch. We speculated that the fundamental difference between the present Experiments 1a and 1 b in comparison to the global task environment used by Mittelstädt et al. (2018) is the time between trials.

Specifically, the total interval between a response on trial $n-1$ and presentation of the first stimulus was 750 ms in the experiments of Mittelstädt et al. (2018), whereas there was no interval between trials in Experiments 1 a and 1 b (i.e., $\mathrm{RSI}=0 \mathrm{~ms}$ ). Thus, there was no time for control processes to enable task switches in advance of trials by means of, for example, the inhibition of task sets (e.g., Mayr \& Keele, 2000). This might encourage some participants to decide in advance of a block to always repeat


Figure 3. Scatterplots of individual median switch costs against individual switch rates in Experiments 1a and 1 b . Solid lines represent the corresponding regression lines.
tasks-despite our attempts in instructing participants to optimize their performance in each trial. Similarly, some participants might also have selected a consistent repetition strategy, to avoid the time-consuming online task selection processes that must take place during the trial when the RSI is zero. Furthermore, the maximal SOA delay when following a repetition strategy might have been too low (i.e., $1,450 \mathrm{~ms}$ occurring after 29 repetitions compared to maximal SOA delays of $4,950 \mathrm{~ms}$ and $3,300 \mathrm{~ms}$ in the experiments reported by Mittelstädt et al., 2018) to overcome participants' reluctance to switch tasks and engage in online task selection processes during block.

In any case, Experiments 1a and 1b clearly demonstrate that switch stimuli do not just passively induce task switches which in turn implies that other characteristics of the task environment are involved in participant's global decision to adapt their task selection behavior-that is, to engage in switching at all. ${ }^{7}$ In Experiment 2, we implemented some modifications (e.g., using an RSI) to further investigate the factors influencing switching behavior in more participants.

## Experiment 2

The previous results point to a strong influence of the global characteristics of the task environment in inducing switching behavior. We conjecture that some participants are very reluctant to adapt to small external processing constraints associated with waiting for a repetition stimulus and they instead guide their behavior just on internal processing constraints associated with switching tasks. As a result, these participants may select repetition task sequences in advance of each block to avoid task selection processes during a block. In this experiment, we further modified the set-up of Experiments 1a and 1 b by inserting an RSI of 400 ms between trials and increasing the number of tasks in one block to make the setting more comparable to the one used for the experiments described in Mittelstädt et al. (2018) in which all participants switched.

Most important, however, we also manipulated the SOA step size between blocks to see whether participants were sensitive at all to the temporal dynamics of the stimulus availability manipulation. In our previous study, we observed differences in participants' average switch rates but stable switch costs between experiments with different SOA step sizes (i.e., 50 ms vs. 33 ms ) suggesting that participants are indeed able to adapt their switching behavior to different dynamic environments. To replicate these results in a within-subject design, the SOA increased by 50 ms per task repetition in half of the blocks whereas in the other half of the blocks it increased by 100 ms per repetition. Clearly, we also expected to replicate all other results-that is, switch SOAs should match with switch costs in both conditions, and switch costs and switch rates should correlate.

## Method

Participants. Forty new participants ( 31 female, age 18 to 35 years with $M=21.93$, 35 right-handed) from the same pool participated in the experiment. ${ }^{8}$ Data from one participant with exceptionally high RTs (i.e., mean RT over $2,500 \mathrm{~ms}$ ) were excluded.

Apparatus, stimuli, and procedure. The apparatus, stimuli, and procedure were the same as in Experiment 1b except as
otherwise described. Two major changes were implemented in this experiment. First, an RSI of 400 ms was implemented between trials and during this time the fixation rectangle was colored in gray (see Figure 1). Second, the SOA step size alternated between blocks (i.e., 50 ms vs. 100 ms ). The step size used for the first block was counterbalanced across participants.

In addition, there were five minor procedural changes: First, stimulus position was constant within the experiment instead of alternating between blocks as in the previous two experiments. The assignment of the letter and digit tasks to the upper and lower stimulus positions was counterbalanced across participants. Second, error feedback was reduced from $3,500 \mathrm{~ms}$ to $2,500 \mathrm{~ms}$ and following this feedback the fixation rectangle was immediately presented for the RSI of 400 ms . Third, we increased the number of trials per block from 60 to 90 (i.e., 45 number and 45 letter task), and we correspondingly decreased the number of voluntary task switching blocks (i.e., 14 blocks). Fourth, in the two training blocks before the voluntary task switching blocks, the two stimuli were always presented simultaneously after the RSI of 400 ms (i.e., no SOA manipulation). Fifth, we also slightly changed the instructions by explicitly telling participants that RT measurement started with the presentation of the first stimulus. Specifically, participants received the following instructions:

> You have to perform 45 number tasks and 45 letter tasks in one block. You can decide which task to perform in a trial, as long as both tasks are available. Select the sequence of tasks in a block to be as fast as possible without committing errors. Reaction time measurement in a trial starts when the first task (or a "\#"-sign) is presented and the rectangle turns white.

## Results

First, the training blocks, the first two voluntary task switching blocks, and the first trial of each block were excluded. We then excluded trials when only one task was available ( $8.5 \%$ ), trials with responses prior to stimulus onset $(0.2 \%)$ and posterror trials ( $5.7 \%$ ) from any analyses. For RT and task selection analyses, error trials (5.7\%) and trials with outliers RTs $(0.5 \%$ and $0.3 \%$ trials with RTs less than 200 ms and greater than 3000 ms , respectively) were also excluded.

Exclusion of participants for main analyses. Our modifications were quite successful in inducing switching behavior: None of the participants had to be excluded for having too few switch trials. Data of 7 participants had to be excluded due to 10 or fewer valid repetition trials in at least one of the critical SOA step size conditions (i.e., four participants had four or fewer valid repetition trials in blocks with SOA step size $=100 \mathrm{~ms}$, one participant had

[^6]only four repetition trials in blocks with SOA step size $=50 \mathrm{~ms}$ and two participants had five or fewer valid repetition trials in both SOA step size blocks).

Task selection. The mean overall proportion of trials on which the letter task was performed did not differ substantially from chance (i.e., $M=.52, S E<.01$ ), $p=.056$, and a paired-test between the letter trial proportions in blocks with SOA $=50(M=$ $.53)$ and $\mathrm{SOA}=100(M=.52)$ revealed no significant difference, $p=.152$. The overall mean switch rate was $49(S E=.05)$. As can be seen in Table 2, the mean switch rate was $5 \%$ higher in $\mathrm{SOA}=$ 100 blocks than in SOA $=50$ blocks and this difference was significant, $t(31)=4.99, p<.001, \eta_{p}^{2}=.47$. The overall median switch SOA was $175 \mathrm{~ms}(S E=27 \mathrm{~ms})$. Median switch SOA was significantly higher in the $\mathrm{SOA}=100(203 \mathrm{~ms})$ than in the $\mathrm{SOA}=$ $50(115 \mathrm{~ms})$ step size condition, $t(31)=5.61, p<.001, \eta_{p}^{2}=.50$.

Figure 4A shows the CDF of switch SOAs separately for SOA $=50$ and SOA $=100$ blocks. In contrast to Experiments 1 a and 1b, the switch proportion was already very high (i.e., $>$.40) for the first SOA level in both SOA $=50$ and SOA $=100$ blocks. As is also indirectly reflected in the corresponding median switch SOAs, over $50 \%$ of switches occurred within the first two SOA levels in the two blocks (i.e., within SOAs of 100 ms and 200 ms respectively). Although the cumulative switch probabilities were consistently higher for the first three SOA levels in the $\mathrm{SOA}=100$ compared to SOA $=50$ blocks, the small differences in switch probabilities at the first three SOAs suggest that participants rather globally adapted their task selection behavior to the different SOA step size conditions instead of being influenced by the trialspecific stimulus availabilities. In other words, participants seem to have been influenced more by the number of repetitions than by the absolute delays in repetition stimulus availability.

Task performance. As can be seen in Table 2, median switch costs were quite similar in $\mathrm{SOA}=50(89 \mathrm{~ms})$ and $\mathrm{SOA}=100$ blocks ( 91 ms ). An analysis of variance (ANOVA) on RT with the within-subject factors of transition (repetition vs. switch) and SOA step size ( 50 vs. 100) revealed only a significant main effect of transition, $F(1,31)=17.19, p<.001, \eta_{p}^{2}=.36$, all other $p \mathrm{~s}>$ .450 and all other $\eta_{p}^{2} s<.02$.

Overall, PE was low (5.4\%) but PEs were higher for repetition compared to switch trials in both $\mathrm{SOA}=50$ (i.e., $5.4-5.1 \%$ ) and SOA $=100$ (i.e., $6.4-4.8 \%$ ) blocks. An ANOVA parallel to the one conducted on median RTs revealed no significant effects, however (i.e., $p=.176 ; \eta_{p}^{2}=.06$ and $p=.530 ; \eta_{p}^{2}=.01$ for the
main effects of transition and SOA step size, respectively, and $p=$ $.071 ; \eta_{p}^{2}=.10$ for the interaction between these two factors).

Relation between task selection and task performance. Switch costs were not significantly smaller than the median switch SOA in SOA $=50$ blocks, $p=.195, \eta_{p}^{2}=.05$ but they were significantly smaller in SOA $=100$ blocks, $t(31)=4.15, p<.001$, $\eta_{p}^{2}=.36$ (see Table 2).

Figure 5A shows the scatter plot of individual median switch costs and switch rates separately for the two SOA conditions. The correlations were significant in both SOA $=50, r(31)=-.45$, $p=.005$, and SOA $=100$ blocks, $r(31)=-.63, p<.001$.

## Discussion

The results of Experiment 2 indicate that our modifications successfully induced switching for all participants-in fact, some participants had to be excluded due to adopting a consistent switch strategy. More important, participants were sensitive to the different SOA step size conditions. Specifically, participants' mean switch rates were higher in blocks with SOA step size $=100 \mathrm{~ms}$ compared to switch rates in blocks with SOA step size $=50 \mathrm{~ms}$ whereas switch costs remained rather stable-replicating the findings reported by Mittelstädt et al. (2018). This is also reflected in the number of switches as a function of SOA, because there were more cumulative switches at the same switch SOA levels. Thus, these findings indicate that participants engaging in task selection processes adapt to the different dynamic task environments created by our blockwise SOA manipulation. Because SOA was varied blockwise, of course, participants may have selected tasks in advance of trials (i.e., before stimulus onset) or planned their task selections in advance of several trials. However, even if participants partially guided their behavior based on task sequences-as they presumably also do in the VTS paradigm with randomness instructions (e.g., Vandierendonck, Demanet, Liefooghe, \& Verbruggen, 2012)—participants appear to select task sequences in a manner that is sensitive to the different predictive external processing benefits provided by the SOA manipulation.

Indeed, the additional measure of switching behavior in terms of time provides some direct evidence for a preparatory task selection process in advance of trials (or blocks) when adapting to the predictable external constraints. Specifically, median switch SOAs differed strongly between the two conditions, suggesting that task selection was influenced by more than just the specific temporal

Table 2
Mean Switch Rates, Mean Median Switch Stimulus-Onset-Asynchrony (SOA), Mean Median Reaction Time (RT) as a Function of Trial Transition (i.e., Task Switch vs. Task Repetition) as Well as Mean Median Switch Costs (i.e., Task Switch RT-Task Repetition RT) Separately for the Specific Conditions Used in Experiment 2 (i.e., SOA Step Size of $50 \mathrm{~ms} v \mathrm{v} .100 \mathrm{~ms}$ ), Experiment 3 (i.e., Response-Stimulus Interval [RSI] of $100 \mathrm{~ms} v s .700 \mathrm{~ms}$ ), and Experiment 4 (i.e., RSI of 100 ms vs. 700 ms )

| Measure | Experiment 2 |  | Experiment 3 |  | Experiment 4 |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\mathrm{SOA}=50$ | $\mathrm{SOA}=100$ | RSI $=100$ | RSI $=700$ | RSI $=100$ | $\mathrm{RSI}=700$ |
| Switch rate | . 46 (.05) | . 51 (.05) | . 34 (.04) | . 42 (.04) | . 39 (.04) | . 48 (.04) |
| Switch SOA | 115 (20) | 203 (34) | 180 (31) | 114 (17) | 125 (20) | 121 (20) |
| Task switch RT | 647 (23) | 652 (22) | 731 (24) | 615 (15) | 708 (22) | 614 (18) |
| Task repetition RT | 559 (11) | 561 (15) | 554 (7) | 547 (7) | 563 (8) | 550 (11) |
| Switch costs RT | 89 (22) | 91 (22) | 177 (21) | 68 (12) | 145 (19) | 64 (15) |

Note. Standard errors of the means in parentheses.


Figure 4. Cumulative distribution functions (CDF) of switch stimulus onset asynchronies (SOAs) separately for the specific conditions used in Experiment 2 (i.e., SOA step size of 50 ms vs. 100 ms , see panel A), Experiment 3 (i.e., response-stimulus interval [RSI] of 100 ms vs. 700 ms , see panel B), and Experiment 4 (i.e., RSI of 100 ms vs. 700 ms , see panel C).
stimulus availabilities during a trial, as is also evident when comparing the CDF functions of switch SOA in the two conditions. In other words, task selection may have been completed before stimulus onset in the majority of trials-blurring a systematic influence of stimulus availability on task selection processes during a trial. Thus, participants often used the time in advance of trials (i.e., RSI) to start (or complete) task selection processes and these processes were then less systematically traded off against stimulus availabilities during a trial. This could also explain why we were not able to replicate the switch cost-SOA match observed in Experiment 1a and 1 b for those participants engaging in switching. Specifically, if the RSI is short (or zero, as in the previous experiments), any task selection processes during a block must take place during a trial. As a result, the costs of switching tasks and the benefits of increased switch stimulus availability mutually influence ongoing task selection processes in such a way that participants switch tasks rather than repeating at the SOA step at which these costs and benefits match.

## Experiment 3

The previous experiments indicate that advance preparation of task selection plays a crucial role in participants' adaptation to the task environment. In this experiment, we directly investigated this issue by manipulating the length of the RSI between blocks ( 100 ms vs. 700 ms ). Note that we used only an SOA step size
of 50 ms but adopted the basic modifications implemented in Experiment 2 because these modifications increased switching behavior (e.g., constant stimulus position, shortened error feedback, more trials per block, modified instructions about RT measurement).

The manipulation of RSI is particularly interesting when considering two findings from previous VTS studies with randomness instruction. First, many studies found that both repetition bias and switch costs decrease when the RSI increases (e.g., Arrington \& Logan, 2005; Liefooghe, Demanet, \& Vandierendonck, 2009). At first glance, this suggests that switching limitations are also reflected in task selection behavior by showing that changes in these measures depend on the same manipulation. Note that decreasing switch costs are typically also found with increasing RSI in externally controlled task switching (e.g., Rogers \& Monsell, 1995). However, it is difficult to unravel whether these effects provide an additional hint of participants "accidentally" adapting their switching behavior to a manipulation that also influences the internal processing constraints associated with a switch or whether they were just more successful in fulfilling the randomness instruction. Thus, observing this pattern of RSI on switch rates and switch costs without instructing participants to select tasks randomly would provide more direct evidence for the idea that switch costs are related to task selection when participants are instructed to optimize their performance.


Figure 5. Scatter plots of individual median switch costs against individual switch rates separately for the specific conditions used in Experiment 2 (i.e., stimulus onset asynchrony [SOA] step size of 50 ms vs. 100 ms , see panel A), Experiment 3 (i.e., response-stimulus interval [RSI] of 100 ms vs. 700 ms , see panel B), and Experiment 4 (i.e., RSI of 100 ms vs. 700 ms , see panel C).

Second, the effects of external influences on task selection (e.g., the stimulus availability effect observed by Arrington, 2008) decrease as the RSI between trials increases. This suggests that task selection processes will probably be increasingly completed before stimulus onset when RSI increases, giving stimulus characteristics less (or no) opportunity to further externally bias these processes (e.g., Arrington, 2008). As was already mentioned in the Discussion of Experiment 2, preparatory task selection processes in advance of the trials seem to reduce systematic influences of our dynamic switch stimulus availability manipulation (i.e., SOA). In general, we expected that both switch costs and switch SOA should decrease with increasing RSI, but we were particularly interested in how these measures would relate to each other. Based on the previous findings (i.e., switch cost-switch SOA matches in Experiments 1a and 1b with RSI $=0 \mathrm{~ms}$, but not in Experiment 2 with RSI $=400 \mathrm{~ms}$ ), it seems that if participants decide to switch in blocks with short RSIs ongoing task selection processes during a trial are more systematically influenced by both external and internal constraints which should promote a match of switch cost and switch SOA. However, in blocks with long RSIs task selection is presumably already completed before stimulus onset. Thus, participants can prepare to process the switch stimulus before it appears and as a result switch-related processes are less systematically traded off against the specific SOA in these blocks.

## Method

Participants. A fresh sample of 39 participants ( 26 female, age 18 to 35 years with $M=22.90$, 28 right-handed) was tested in this experiment. One additional participant was also tested but this participant quit the experiment after the training blocks and was not replaced.

Apparatus, stimuli, and procedure. The apparatus, stimuli, procedure, and instructions were the same as in Experiment 2 except that only an SOA increment of 50 ms was used and the RSI alternated blockwise between the 14 voluntary task switching blocks (i.e., RSI was always 400 ms in the cued-training blocks). In half of these blocks, the RSI was 100 ms and in the other half of these blocks the RSI was 700 ms .

## Results

We again excluded training blocks, the first two voluntary tasks switching blocks, and the first trial of each block from any analyses. Following that, trials when only one task was available ( $8.7 \%$ ), trials with responses prior to stimulus onset ( $<0.1 \%$ ) and posterror trials ( $3.9 \%$ ) were excluded. For RT and selection analyses, we also excluded error trials ( $3.9 \%$ ) and trials with outlier RTs ( $<0.1 \%$ trials with RTs less than 200 ms and $0.1 \%$ trials with greater than 3000 ms , respectively).

Exclusion of participants for main analyses. The data of four participants were excluded due to fewer than 10 switch or repetition trials in at least one RSI condition (i.e., two participants had no valid switch trials in both RSI block conditions, two participants had no valid repetition trials in RSI $=100$ blocks). After inspecting the scatter plots of individual results, we also excluded the data of two additional participants with unusual high switch costs (i.e., switch costs of $>768 \mathrm{~ms}$ and switch rates of $<.17$ in all conditions).

Task selection. The mean overall proportion of trials on which the letter task was performed (i.e., $M=.50, S E=.01$ ) did not differ from chance, $p=.957$, and a paired $t$ test between the letter trial proportions in blocks with RSI $=100(M=.50)$ and RSI $=700(M=.50)$ revealed no significant difference, $p=.980$. The overall switch rate was $.38(S E=.04)$. The mean switch rate was $8 \%$ smaller for RSI $=100$ than for RSI $=700$ (see Table 2), and a paired $t$ test between the RSI specific switch rates yielded significance, $t(32)=4.54, p<.001, \eta_{p}^{2}=.39$. The overall median switch SOA was $127 \mathrm{~ms}(S E=19)$. The $66-\mathrm{ms}$ difference between the average median switch SOAs of the two RSI conditions displayed in Table 2 was significant, $t(32)=3.20$, $p=.003, \eta_{p}^{2}=.24$.

The RSI-specific CDFs of switch SOAs are displayed in Figure 4B. As can be seen in this figure, the cumulative switch probability with RSI $=700$ was consistently higher than the one observed with RSI $=100$, indicating that switches tend to occur at shorter SOAs with the longer RSI.

Task performance. On average, median switch costs were strongly reduced in RSI $=700(68 \mathrm{~ms})$ compared to $\mathrm{RSI}=100$ $(177 \mathrm{~ms})$. An ANOVA with the within-subject factors of transition and RSI condition revealed significant main effects of transition, $F(1,32)=60.70, p<.001, \eta_{p}^{2}=.66$, and RSI, $F(1,32)=64.67$, $p<.001, \eta_{p}^{2}=.67$, as well as a significant interaction between these factors, $F(1,32)=57.03, p<.001, \eta_{p}^{2}=.64$.

Mean PE was $4.0 \%$ and there were descriptively higher PEs for repetition compared to switch trials in both RSI $=100$ (i.e., $3.7-3.2 \%$ ) and RSI $=700$ (i.e., $5.1-4.0 \%$ ). An ANOVA with the factors transition and RSI yielded only a significant main effect of RSI, $F(1,32)=11.89, p=.002, \eta_{p}^{2}=.27$, reflecting higher average PEs in RSI $=700$ (4.6\%) compared to RSI $=100$ blocks (3.4\%). The main effect of transition was nearly significant ( $p=$ $.054, \eta_{p}^{2}=.11$ ), whereas the interaction was not significant ( $p=$ $.385, \eta_{p}^{2}=.02$ ).

Relation between task selection and task performance. Switch costs were significantly smaller than switch SOAs in RSI $=$ 700 blocks, $t(32)=2.28, p=.029, \eta_{p}^{2}=.14$, whereas in RSI $=100$ blocks the difference between switch costs and switch SOAs was not significant, $p=.922, \eta_{p}^{2}<.001$ (see Table 2).

Figure 5B shows a scatter plot of individual median switch costs and switch rates separately for each RSI condition. The correlation between median switch costs and switch rates was substantial for both RSI $=100, r(32)=-.36, p=.041$, and RSI $=700$, $r(32)=-.46, p=.007$.

## Discussion

Experiment 3 revealed two important findings. First, switch costs and switch rates were related to each other: Participants' mean switch rates were lower and mean switch costs higher in blocks with RSI $=100$ than in blocks with RSI $=700$-in line with previous VTS studies with randomness instructions (e.g., Arrington \& Logan, 2005). Here, we extend these previous findings by showing that this pattern can be also observed in our task environment in which participants are instructed to optimize their performance. Moreover, there were again correlations between switch costs and switch rates which further point to a link between task selection and task performance. Second, the preparation time available in advance of trials modulates the observed switch cost-
switch SOA trade-offs: Switch costs and switch SOA were virtually identical in the short RSI condition-as they were in Experiments 1 a and 1 b with RSI $=0$-whereas these measures differed in the long RSI condition. This suggests that switch costs are equally traded off against switch SOA when preparatory task selection processes in advance of trials have only limited time to operate-presumably because in that case the ongoing task selection processes during a trial are simultaneously and systematically influenced by previous task selection and stimulus availabilities.

## Experiment 4

Experiment 3 established that participants select more task switches when the environment reliably predicts that they have more time in advance of the trial, but in this case they do not equally trade off switch costs against switch SOA. The main purpose of Experiment 4 was to see whether the effects of RSI on switch rate, switch costs, and the switch cost-SOA trade-off are all due to differential preparatory task selection processes based on known RSIs. Thus, in Experiment 4 RSI varied unpredictably instead of alternating blockwise as in Experiment 3. If part of the switch rate difference between RSIs is due to participants flexibly adjusting their switching behavior on a trial-by-trial basis, then this difference should be also seen even when RSI varies randomly. Moreover, given that participants could not anticipate whether the RSI in a given trial would be short or long, participants should refrain from selecting tasks prior stimulus onset. Thus, task selection processes should be more likely to take place during a trial not only for the short RSI condition as in Experiments 1a, 1b, and 3, but also for the long RSI condition in Experiment 4. If so, the switch cost-switch SOA match should be observed in both the short and the long RSI conditions.

## Method

Participants. A fresh sample of 40 participants ( 29 female, age 19 to 33 years with $M=24.70$, 37 right-handed) from the same pool participated in the experiment.

Apparatus, stimuli, and procedure. The apparatus, stimuli, procedure, and instructions were the same as in Experiment 3 except that the RSI (i.e., 100 ms or 700 ms ) varied within blocks. In each block the RSI varied randomly from trial to trial with the constraint that the two RSIs were used equally often within a block (i.e., 45 trials with RSI $=100 \mathrm{~ms}$ and 45 trials with $\mathrm{RSI}=700 \mathrm{~ms}$ within each block).

## Results

We again excluded training blocks, the first two voluntary task switching blocks, and the first trial of each block. Then, trials in which only one task was available ( $9.1 \%$ ), trials with responses prior to stimulus onset ( $<0.1 \%$ ), and posterror trials ( $4.1 \%$ ) were excluded. For RT and selection analyses, we additionally excluded error trials $(4.1 \%)$ and trials with outlier RTs $(<0.1 \%$ trials with RTs less than 200 ms and $0.1 \%$ trials with RTs greater than 3,000 ms , respectively).

Exclusion of participants for main analyses. The data of three participants were excluded due to fewer than 10 switch or repetition trials in at least one RSI condition (i.e., one participant
had only five valid switch trials in the RSI $=100$ condition, two participants had six or fewer repetition trials in both RSI conditions).

Task selection. The overall letter task selection proportion (i.e., $M=.51, S E=.01$ ) did not differ from chance, $p=.205$, and a paired $t$ test between the letter task selections with RSI $=100$ ( $M=.52$ ) and RSI $=700(M=.50)$ revealed no significant difference, $p=.228$. The overall switch proportion was .43 ( $S E=$ .04). As can be seen in Table 2, the switch rate was $9 \%$ higher in the RSI $=700$ compared to the RSI $=100$ condition, and this difference was significant, $t(36)=4.97, p<.001, \eta_{p}^{2}=.41$. The overall median switch SOA was $125 \mathrm{~ms}(S E=20)$. Interestingly, however, switch SOAs were virtually identical in the two RSI conditions (see Table 2, $p=.426, \eta_{p}^{2}=.02$ ). The CDFs of switch SOAs displayed in Figure 4C further depict this result: The CDFs of the two RSI conditions overlapped across the depicted range of switch SOAs. Note, as described in more detail in the results section of Experiment 1a, the CDFs depict the distribution of switches at different SOAs out of trials in which switches occurred. Thus, this finding only indicates that switches were distributed similarly across SOAs in the two RSI conditions and thus is not incompatible with the finding of differences in switch rates between the two RSI conditions.

Task performance. As expected, switch costs were larger in the RSI $=100$ condition ( 145 ms ) compared to the RSI $=700$ condition ( 64 ms ) and the corresponding average median RTs are depicted in Table 2. An ANOVA with the within-subject factors of transition and RSI again revealed that all effects were significant: the main effect of transition, $F(1,36)=42.07, p<.001, \eta_{p}^{2}=.54$, the main effect of RSI, $F(1,36)=69.78, p<.001, \eta_{p}^{2}=.66$, and the interaction between these factors, $F(1,36)=38.58, p<$ $.001, \eta_{p}^{2}=.52$.

Overall, PE was $4.3 \%$ and PEs were again higher for repetition compared to switch trials in both RSI $=100$ (i.e., $3.9 \%-3.8 \%$ ) and $\mathrm{RSI}=700$ (i.e., $5.5 \%-3.7 \%$ ). A parallel ANOVA on the corresponding PEs yielded a significant main effect of transition, $F(1,36)=5.57, p=.024, \eta_{p}^{2}=.13$, a significant main effect of RSI, $F(1,36)=4.13, p=.050, \eta_{p}^{2}=.10$, and a significant interaction between transition and RSI, $F(1,36)=4.62, p=.038$, $\eta_{p}^{2}=.11$.

Relation between task selection and task performance. For the RSI $=100$ condition, switch SOA and switch costs did not differ significantly, $p=.315, \eta_{p}^{2}=.03$. For the RSI $=700$ condition, switch SOAs were significantly larger than switch costs, $t(36)=2.56, p=.015, \eta_{p}^{2}=.15$.

Figure 5C shows scatter plots of individual median switch costs and switch rates separately for each RSI condition. There was a significant correlation between these measures both for the RSI $=$ 100 condition, $r(36)=-.64, p<.001$, and for the RSI $=700$ condition, $r(36)=-.57, p<.001$.

## Discussion

The results of Experiment 4 replicate Experiment 3's most important findings and generalize these findings to a setting with unpredictable RSIs. In particular, the pattern of switch costs and switch rates in the two RSI conditions, as well as the correlations between switch costs and switch rates, clearly indicates that task selection was sensitive to task performance, with switching avoided to
a greater extent when it was more detrimental to performance. Furthermore, this study also indicates that participants can flexibly select tasks on a trial-by-trial basis even if they partially guide their behavior on task sequences.

As in Experiment 3, average switch SOA was similar to switch costs in the short RSI condition. This indicates that-when time in advance of trials is limited and participants perform a task switch-ongoing task selection processes during a trial are influenced systematically both by cognitive constraints on task switching and by external constraints on waiting to perform the repetition task. In the long RSI condition, however, switch SOA again exceeded switch costs. This indicates that even when participants could not anticipate at the beginning of the RSI whether it would be short or long, they would (at least on some trials) prepare a task switch after the short RSI time had passed (and thus before the stimulus of trial $n$ appears). Thus, much of the processing required to select a switch is done before stimulus onset with an $\mathrm{RSI}=700$, even if that long RSI is unpredictable. We will return to this issue in our General Discussion, when we discuss this finding against the background of current task-switching accounts.

It was somewhat surprising that the distribution of switch SOAs (and the corresponding CDFs) differed between the RSI conditions in Experiment 3 but not in Experiment 4-in particular because of the strong differences in switch rates between the two RSI conditions in both experiments. Note, however, that the comparison of switch SOAs between these experiments is difficult because with a blockwise RSI manipulation (Experiment 3) individual runs of trials (i.e., sequence of task repetitions ending with a task switch) occur within the same RSI condition whereas with a trialwise RSI manipulation (Experiment 4) runs can start, for example, in the condition RSI $=700$ but end with a switch in the condition $\mathrm{RSI}=$ 100. In other words, the discrepancy in average median switch SOAs (and CDFs) between experiments nicely demonstrates that our summary measure for switching behavior as a function of SOA (i.e., switch SOA) only reflects when the switches occurred without considering how many switch and repetition trials there were in total. To see whether a difference between RSIs would appear in SOAs when considering the total number of trials at each SOA, we developed a somewhat different measure of SOA-based CDFs and used it to compute a "new" (interpolated) median switch ${ }_{\text {total }}$ SOAs. In essence, as is described in more detail in the Appendix, we computed the proportion of switches at each SOA separately for each participant (and condition) and accumulated the probabilities across SOAs. Indeed, this procedure revealed a significant difference in average median switch ${ }_{\text {total }}$ SOAs between the RSI $=$ 100 (i.e., switch $_{\text {total }} \mathrm{SOA}=148 \mathrm{~ms}$ ) compared to the $\mathrm{RSI}=700$ (i.e., switch $_{\text {total }} \mathrm{SOA}=116 \mathrm{~ms}$; see the Appendix), whereas the comparisons in median switch ${ }_{\text {total }}$ SOAs between the corresponding condition in Experiment 2 (i.e., difference between SOA step size $=50$ vs. SOA step size $=100$ ) and Experiment 3 (i.e., difference between RSI $=100$ vs. RSI $=700$ with RSI manipulated blockwise) remained unaffected. We then also compared the median switch $_{\text {total }}$ SOAs with the corresponding median switch costs in each condition of Experiments 1a-4 and the corresponding results mirrored the ones reported in the main text (i.e., only switch cost-SOA matches in Experiment 1a, 1b with no RSI and with short RSI in Experiment 3 and 4). Finally, we also checked whether this computation of CDFs would produce different result patterns in our previous experiments (including the ones in Mit-
telstädt et al., 2018) in which no factor was randomly manipulated within blocks. In all these earlier experiments these new switch ${ }_{\text {total }}$ SOAs measures were quite similar to the original switch SOA measures. Thus, the choice of switch measures did not influence the conclusions (see the Appendix).

## General Discussion

In the present study, we investigated how people adapt their task selection behavior to cognitive and environmental constraints to obtain more direct insight into the mechanisms of task selection in the context of multitask performance. To this end, we used a self-organized task switching paradigm in which the stimulus needed for a task repetition was delayed by an SOA that increased with each consecutive repetition, whereas the stimulus needed for a task switch was always presented immediately. Across five experiments, we investigated how internal processing constraints in switching tasks (i.e., as measured by switch costs) were traded off with the temporal dynamics of the stimulus availability manipulation.

## Overview of Findings

The most obvious finding to emerge from these experiments is that task selection (as measured by switching behavior) and task performance (as measured by switch costs) were related to each other: Although numerous participants seemed to have a strong general reluctance to switch tasks (Experiments 1a and 1b)presumably because of the effortful and time-consuming cognitive constraints involved in these transitions-participants who did engage in switching were able to adapt their switching behavior to different task environments. Specifically, they switched more often when the predictable external costs in waiting for a repetition task were higher, even under conditions where switch costs remained stable (i.e., different SOA step sizes in Experiment 2). In addition, switch rates increased and switch costs decreased with an increasing interval in advance of the trial (Experiments 3 and 4)—a manipulation which is known to facilitate task switching (e.g., Koch, 2001; Rogers \& Monsell, 1995). Furthermore, switch costs were correlated with switch rates across participants (Experiments 1a-4), which further supports a link between switch costs and switch rates.

Importantly, our procedure allowed us to get some additional insights into the mechanisms by which participants adapted their behavior to these different dynamic task environments by measuring the size of the SOA in switch trials (i.e., switch SOA). Overall, these analyses revealed that participants (at least partially) start to prepare for task selection in advance of trials. Interestingly, whenever the times in advance of trials were limited (i.e., with no RSI in Experiments 1a and 1 b and with an RSI of 100 ms in Experiments 3 and 4), switch SOAs were approximately equal to switch costs when participant decide to switch tasks. This suggests that switch SOA was just another measure of switch costs when preparatory task selection processes could only operate minimally in advance of trials —presumably because both task selection and task performance were systematically influenced by previous task selections and stimulus availabilities.

Overall, our conclusion that task selection is linked to task performance seems in contrast to previous suggestions that differ-
ent cognitive processes influence task selection and task performance in the context of VTS studies with randomness instructions (e.g., Arrington \& Yates, 2009; Chen \& Hsieh, 2013). After we have discussed our findings in the context of previous VTS findings, we discuss the implications of our study concerning the idea that switch costs can be linked to switching behavior via a simple framework of competing multiple task-set activations driven by both internal and predictable external contexts (e.g., previous task selections and stimulus availabilities, respectively).

## Relation to Previous VTS Findings

In general, effects of both previous task selections and the environment on task selection behavior have also been observed in VTS studies with randomness instructions (for an overview of findings, see Arrington, Reiman, \& Weaver, 2014). As reviewed in the introduction, task selection behavior in VTS experiments is mainly interpreted as a competition between randomness and availability heuristics (e.g., Arrington \& Logan, 2005; Chen \& Hsieh, 2013). Thus, factors impacting on task selection are typically interpreted as influencing the availability of task sets, making it more likely that the availability heuristic wins the competition against the instructed goal of selecting tasks randomly. In line with this interpretation, we also suggest that both factors (i.e., previous task selections and predictable stimulus availability) influence the availability of tasks in our experiments-that is, they influence task-set activations. However, given that we did not instruct participants to select tasks randomly, competition should just take place between the two available task sets. Thus, task-set activation could also be a causal factor influencing task selection behavior in our paradigm, as indirectly suggested by availability heuristic accounts of behavior in paradigms with randomness instructions (e.g., Arrington, 2008). However, we also suggest that the participants' sensitivity to external and internal cognitive influences on switching behavior observed in the present study is not necessarily an indication of weak control-as is assumed when such influences dominate randomness instructions-but reflects adaptive task selection behavior-that is, reflects attempts to incorporate both internal and external constraints to improve overall performance.

Thus, we do not think that the mechanisms underlying task performance and task selection necessarily differ, as has sometimes been suggested in previous VTS studies (e.g., Arrington \& Yates, 2009; Chen \& Hsieh, 2013). Critically, the evidence for different mechanisms came at least partially from weak or absent correlations between switch costs and switch rates across participants (e.g., Arrington \& Yates, 2009; Mayr \& Bell, 2006; Yeung, 2010). Intuitively, if task performance and task selection were somehow related to each other, one would expect that participants with higher switch costs would also have a stronger tendency to avoid switching tasks (or vice versa). Furthermore, observing a relation between these measures in previous VTS studies also seems plausible when considering that previous cued taskswitching studies have found that switch costs increase as taskswitch frequency decreases (e.g., Mayr, 2006; Monsell \& Mizon, 2006; Schneider \& Logan, 2006). However, we speculate that the requirement to follow randomness instructions might induce additional processes whose impact on task selection and task performance may differ and might thus also obscure the relation between these measures. In contrast, we found that switch rates and switch
costs did correlate in each experiment, which suggests that these correlations can likely only be observed when instructing participants to optimize their task performance without the global requirement to fulfill the randomness instruction. This provides further evidence for the idea that task selection serves to improve task performance.

## Toward a Task-Set Activation-Competition Framework for Voluntary Task Switching

The idea that task selection and task performance are related raises the possibility of common underlying mechanisms accomplishing both task selection and task performance in our multitasking environments. As was already indicated above-and in line with previous VTS studies-it seems likely that task-set activation plays a crucial role in influencing task selection behavior. Using this construct in the context of task performance provides an interesting view on the vulnerability of our cognitive system to external influences because stimulus-based interference effects are usually observed in externally controlled task switching studies (for more details, see Goschke, 2000). First, stimulus-based priming effects indicate that task-irrelevant stimuli can activate task sets in a current trial, thereby contributing to the observed switch costs (e.g., Koch \& Allport, 2006; Waszak, Hommel, \& Allport, 2003). Second, between-task interference effects indicate that taskrelevant stimulus processing is influenced by the specific response indicated by the task-irrelevant stimulus: Responses are faster when the responses indicated by the two stimuli are spatially congruent compared to incongruent (e.g., Kiesel, Wendt, \& Peters, 2007; Meiran \& Kessler, 2008; Schneider, 2018; Yeung, 2010). These two findings support the idea that not only the relevant but also the irrelevant task set is active in each trial making both task sets vulnerable to external influences. However, these influences do not necessarily reflect a failure of our cognitive system to impose effective task readiness but can also be seen as the signature of an adaptive design (Goschke, 2000). It would be maladaptive to suppress one of the task sets completely because our (multitasking) environment is rapidly changing and sometimes strongly favors a voluntary task switch-as in the present task environments.

Thus, we suggest that in both externally controlled and voluntary task switching settings, two or more task sets are always activated to some degree. The total amount of activation available at one time is limited (for similar suggestions, see, e.g., Dreisbach \& Fröber, 2019; Koch, 2001; Sohn \& Carlson, 2000), so there is competition between task sets. Many theoretical accounts of cognitive control are now based on the idea that the degree of task-set activation modulates the efficiency of translating stimulus information into motor responses (e.g., Egner \& Hirsch, 2005; Hübner, Steinhauser, \& Lehle, 2010; Miller \& Cohen, 2001). Not surprisingly, this basic idea has also been incorporated within sophisticated models to explain task performance in externally controlled task switching (e.g., Gilbert \& Shallice, 2002; Meiran, 2000). In essence, a task can be executed only after the relevant task set in a trial gets sufficiently activated and the competition between two task sets is resolved. In many experimental settings, this competition is primarily biased by internal contexts-that is previous task switches (i.e., higher repetition compared to switch task-set activation; e.g., Altmann \& Gray, 2008; Gilbert \& Shallice, 2002; Schuch \& Koch, 2003). Consequently, the task-set competition
requires more time to get resolved in switch than in repetition trials resulting in switch costs. Furthermore, this competition can be further influenced by the external context during a trial-that is by the precise stimuli conditions (e.g., Rubin \& Koch, 2006; Steinhauser \& Hübner, 2007).

Interestingly, there is also evidence that the competition between task sets can be biased by the predicted forthcoming task demands in order to optimize task processing (e.g., Aufschnaiter, Kiesel, Dreisbach, Wenke, \& Thomaschke, 2018; Dreisbach \& Haider, 2006; Dreisbach, Haider, \& Kluwe, 2002; Jiang, Wagner, \& Egner, 2018; Mayr, 2006). Specifically, people are apparently able to reconfigure task-set activations based on trial-by-trial probability cues (lower switch costs when cue predicts a switch, e.g., Mayr, 2006), and they are also able to incorporate internally generated predictions based on global task processing requirements (lower switch costs when task environments require many switches, e.g., Dreisbach \& Haider, 2006). Probably the most specific evidence that these two types of predictions jointly influence task performance comes from a recent study by Jiang et al. (2018). Specifically, they provided evidence for an integrative neural representation (i.e., in the left dorsolateral prefrontal cortex) for this joint type of proactive task set updating. Based on their findings, they suggested that the weighting of competing task sets is adjusted based on these (externally and internally generated) task predictions to jointly guide task processing to optimize task performance based on the relevant task set (Jiang et al., 2018).

Critically, in the current study-where stimulus availability varied predictably-there are initially two potentially relevant task sets in each trial, which means that it is under the participant's control to choose the desired task set. We propose that task selection can be linked to task performance via a similar framework of competing task-set activations as in externally controlled task-switching (e.g., Jiang et al., 2018). Specifically, when we are required to select tasks voluntarily, we guide task selection on the activity of task sets (i.e., the most-active task set) which in turn is biased by the joint influences of internal and external processing requirements. Thus, in the present study participants seem to adjust task-set activations when they select tasks to improve task performance by jointly incorporating (i.e., trading off) both the predictable external processing constraints imposed by having to wait for the stimulus associated with the repetition task as well as the internal forthcoming cognitive processing constraints associated with processing the potential switch stimulus.

From this line of reasoning, the effects on switch rate of the manipulations used in the current experiments indicate that taskset activations are biased to impact on task performance and task selection. Specifically, participants adapt their behavior to external processing constraints such as different SOA increments as in Experiment 2 or different RSIs in Experiments 3 and 4. Note that the finding in the latter two experiments in which both switching behavior (i.e., increased switch rates with increased RSI) and switch costs (i.e., decreased switch costs with increased RSI) were sensitive to the RSI manipulation can be interpreted from twonot mutually exclusive-perspectives: First, participants may decide to switch tasks more often when more time is available before stimulus onset, because this extra time gives time-consuming control processes involved in implementing a switch more time to operate (e.g., Rogers \& Monsell, 1995). Second, activation of the task set applied in the previous trial has more time to decay when
the time between trials is longer (e.g., Altmann \& Gray, 2008; Gilbert \& Shallice, 2002). Consequently, the relative activation difference between the two task sets is smaller for longer delays, and this increases the likelihood that participants select a task switch. It seems likely that decaying task-set activation plays at least a partial role in influencing task selection behavior because of the results in Experiment 4 in which RSI varied unpredictably (e.g., Altmann, 2002).

In addition, the task-set competition idea is especially attractive when considering the switch cost—switch SOA matches observed with no (i.e., Experiments 1a and 1 b ) or with short RSI (i.e., RSI = 100 ms in Experiments 3 and 4). Specifically, these findings might indicate that repetition task-set activation was equally counteracted by switch task-set activations. In other words, the crossover point of switching tasks seems to correspond to equal task-set activations meaning that the observed switch SOA was just another estimate of switch costs-which would be in line with the idea that task selection is merely determined by the degree of task-set activations, which can be mutually and simultaneously influenced by both internal and external contexts.

Notably, the mismatch of switch costs and switch SOA with longer RSIs (i.e., RSI $=400 \mathrm{~ms}$ in Experiment 2 and RSI $=700$ ms in Experiments 3 and 4) does not necessarily speak against the idea that the specific predictable waiting time is traded off against the specific costs associated with switching tasks when selecting tasks at this RSI level. However, as was already mentioned in the discussion of Experiment 4, the switch cost-switch SOA mismatch suggests that preparation that happens in advance of selecting a task switch has probably started before the stimulus appearsthereby blurring a systematic influence on task performance (as measured in switch costs) and task selection (as measured in switch SOA). Thus, there is also an effect of predictable stimulus availabilities at long RSI, meaning that people incorporate these upcoming external processing constraints into their switching behavior. However, the time during the RSI is presumably used at least on some trials for selecting and preparing the potential switch task set. As a result, there are reduced switch costs due to this preparation, but the task selection time would not contribute to the RT measure after stimulus onset because task selection happened during the RSI (i.e., before RT measurement started). Given that the mismatch between switch costs and switch SOA was also observed when RSI varied randomly on a trial-by-trial basis (Experiment 4), one might speculate that participants attempted to abandon the potentially aversive "free decision context" as soon as possible. Thus, participants also selected a task in advance of stimulus onset at long RSI when this interval varied randomly while task-set activations are continuously updated. According to this idea, then, tasks are not selected as soon as an absolute threshold of activation is reached but rather the difference between activations is crucial—meaning that participants might even just select the currently most active task set as soon as possible.

From this line of reasoning, however, it is somewhat surprising that switch cost-switch SOA matches were observed in the two experiments reported by Mittelstädt et al. (2018) in which the total RSI was 750 ms . A possible post hoc explanation for the discrepancy with the current findings (i.e., no switch cost-SOA matches when RSI was long) is that preparatory processes only operated to a small degree in the earlier study because stimulus position varied unpredictably. This made it impossible to bias spatial attention
toward one location in order to prepare for the corresponding switch tasks after participants decided on switching. As a result, participants might have postponed task selection until stimulus onset when task position became clear-thereby moving task selection into the RT interval and producing a switch cost-switch SOA match.

## Relation to Other Factors Modulating the Link Between Task Selection and Task Performance

Although we have interpreted the current findings against the background of the specific manipulations applied in this study, it seems very likely that other aspects impact on the proposed link between task selection and task performance in multitasking. For example, it is not clear whether participants have metacognitive awareness of their task performance and, if so, how their introspective abilities come into play when adapting to the task environment. On the one hand, recent evidence suggests that people are quite good at noticing even small variations in their task performance (e.g., Questienne, Atas, Burle, \& Gevers, 2018; Questienne, van Dijck, \& Gevers, 2018), and their metacognitive abilities allow them to report the costs associated with switching tasks (Bratzke \& Bryce, 2019). On the other hand, people underestimate the beneficial effects of longer RSIs on switch costs (Bratzke \& Bryce, 2019), which shows that there are limits to this introspective ability. Thus, it might be worthwhile to investigate, for example, whether the observed mismatch between switch costs and switch SOA at long RSI might be at least partially also a byproduct of participants' erroneous subjective estimation of the effect of RSI on their switch costs.

Clearly, the finding that the number of participants engaging in switching was strongly influenced by the exact characteristics of our task environment first and foremost indicates that the overall context-and not just our dynamic SOA manipulation-plays a crucial role in overcoming participants' global switch avoidance (see also Fröber \& Dreisbach, 2017). For example, it seems likely that the instruction for participants to minimize RTs (and that RT measurements start in each trial when the first stimulus is presented) contributes at least partially to induce switching behavior in participants experiencing the SOA manipulation. Furthermore, one might speculate that accuracy as another aspect of task performance may also play a role in participants' task selection behavior. Specifically, participants might avoid the rather long error feedback used in the current experiments (i.e., $>2.5 \mathrm{~s}$ ) and thus only switch tasks when the first available switch stimulus is processed to a degree that reduces the likelihood of an error. The overall low error rates in all experiments (i.e., $<6.4 \%$ ) with (descriptively) higher error rates in repetition than switch trials (except for Experiment 1a) would fit to this idea which in turn suggests that some preprocessing of switch stimuli takes place.

However, the finding that many participants also engaged in switching behavior in Experiments 1a and 1b suggests that individual differences must be considered when investigating voluntary task switching strategies, especially when participants are not instructed to select tasks randomly. For example, whereas some participants might have avoided the mental effort needed to implement task switches (e.g., Dunn, Lutes, \& Risko, 2016; Kool, McGuire, Rosen, \& Botvinick, 2010)—such as the reconfiguration of new task sets (e.g., Rogers \& Monsell, 1995) or inhibition of old ones (e.g., Mayr \& Keele, 2000)—for other participants engaging
in effortful mental processes is intrinsically rewarding (for a review, see, e.g., Inzlicht, Shenhav, \& Olivola, 2018) and as a result there is not even a reluctance to switch in the first place. Similarly, individual differences in the preference for different types of task organization might also play a role in influencing switching (e.g., Brüning \& Manzey, 2018; Reissland \& Manzey, 2016). For example, Reissland and Manzey (2016) found that some participants mainly repeated tasks, whereas other participants mainly switched tasks in a task-switching paradigm with full preview of potential switch task stimuli.

Thus, even though the current study demonstrates that participants' behavior was mutually influenced by predictable external constraints in performing a task repetition and cognitive constraints in performing a task switch, it is clear that future research is needed to clarify how other internal factors (e.g., metacognitive awareness, effort avoidance, motivation) trade off with different aspects of the environment (e.g., adaptive SOA manipulation, speed instruction, error feedback) to modulate peoples' behavior to flexibly select tasks. Jointly studying task selection and task performance seems to provide a fruitful approach for developing more sophisticated accounts of the links between task selection and performance in multitasking within a task-set competition framework. Given that a complete absence of (internal or external) context in making "voluntary decisions" is scientifically implausible (e.g., Bode et al., 2014; Haggard, 2008; Schüür \& Haggard, 2011), such accounts could start from the premise that our cognitive system is using the same basic mechanisms for voluntarily selecting a task as for performing a task: A threshold applied to the outputs of an evidence accumulator biased by both internal and external contexts (e.g., Bode et al., 2014; Mattler \& Palmer, 2012; Schurger, Sitt, \& Dehaene, 2012).

## Conclusion

In the present study, we elaborated whether and how people adapted their task selection behavior to cognitive constraints (i.e., switch costs) and environmental constraints (i.e., stimulus availabilities). For this purpose, we conducted a series of experiments using a self-organized task switching paradigm (Mittelstädt et al., 2018), in which the availabilities of stimuli for two tasks in a trial were dynamically adjusted in such a way that the stimulus needed for a task repetition appeared with an SOA that increased linearly with the number of consecutive task repetitions. Overall, our results suggest that participants adapted their behavior to the mutual effects of external and internal influences on task performance, indicating a link between task selection and task performance. Examining switching behavior in terms of time (i.e., switch costs vs. switch SOA) revealed that this adaptive behavior was partially realized by preparatory task selection processes in advance of a trial. Interestingly, switch SOAs were equally traded against switch costs when time in advance of trials was limited, pointing to systematic mutual influences of previous task selections and stimulus availabilities on the corresponding task-set activations. We propose that both task selection and task performance can be integrated within a framework of competing multiple task-set activations biased by internal and external contexts.

## References

Abrahamse, E., Braem, S., Notebaert, W., \& Verguts, T. (2016). Grounding cognitive control in associative learning. Psychological Bulletin, 142, 693-728. http://dx.doi.org/10.1037/bul00000047
Allport, D. A., Styles, E. A., \& Hsieh, S. (1994). Shifting intentional set: Exploring the dynamic control of tasks. In C. Umilta \& M. Moscovitch (Eds.), Attention and performance XV (pp. 421-452). Cambridge, MA: MIT Press.
Altmann, E. M. (2002). Functional decay of memory for tasks. Psychological Research, 66, 287-297. http://dx.doi.org/10.1007/s00426-002-0102-9
Altmann, E. M., \& Gray, W. D. (2008). An integrated model of cognitive control in task switching. Psychological Review, 115, 602-639. http:// dx.doi.org/10.1037/0033-295X.115.3.602

Anderson, J. R. (1990). The adaptive character of thought. Hillsdale, NJ: Erlbaum.
Arrington, C. M. (2008). The effect of stimulus availability on task choice in voluntary task switching. Memory \& Cognition, 36, 991-997. http:// dx.doi.org/10.3758/MC.36.5.991

Arrington, C. M., \& Logan, G. D. (2004). The cost of a voluntary task switch. Psychological Science, 15, 610-615. http://dx.doi.org/10.1111/ j.0956-7976.2004.00728.x

Arrington, C. M., \& Logan, G. D. (2005). Voluntary task switching: Chasing the elusive homunculus. Journal of Experimental Psychology: Learning, Memory, and Cognition, 31, 683-702. http://dx.doi.org/10 .1037/0278-7393.31.4.683
Arrington, C. M., \& Reiman, K. M. (2015). Task frequency influences stimulus-driven effects on task selection during voluntary task switching. Psychonomic Bulletin \& Review, 22, 1089-1095. http://dx.doi.org/ 10.3758/s13423-014-0777-0

Arrington, C. M., Reiman, K. M., \& Weaver, S. M. (2014). Voluntary task switching. In J. Grange \& G. Houghton (Eds.), Task switching (pp. 117-136). Oxford, UK: Oxford University Press. http://dx.doi.org/10 .1093/acprof:osobl/9780199921959.003.0006
Arrington, C. M., \& Weaver, S. M. (2015). Rethinking volitional control over task choice in multitask environments: Use of a stimulus set selection strategy in voluntary task switching. The Quarterly Journal of Experimental Psychology, 68, 664-679. http://dx.doi.org/10.1080/ 17470218.2014.961935

Arrington, C. M., Weaver, S. M., \& Pauker, R. L. (2010). Stimulus-based priming of task choice during voluntary task switching. Journal of Experimental Psychology: Learning, Memory, and Cognition, 36, 10601067. http://dx.doi.org/10.1037/a0019646

Arrington, C. M., \& Yates, M. M. (2009). The role of attentional networks in voluntary task switching. Psychonomic Bulletin \& Review, 16, 660665. http://dx.doi.org/10.3758/PBR.16.4.660

Aufschnaiter, S., Kiesel, A., Dreisbach, G., Wenke, D., \& Thomaschke, R. (2018). Time-based expectancy in temporally structured task switching. Journal of Experimental Psychology: Human Perception and Performance, 44, 856-870. http://dx.doi.org/10.1037/xhp0000494
Bode, S., Murawski, C., Soon, C. S., Bode, P., Stahl, J., \& Smith, P. L. (2014). Demystifying "free will": The role of contextual information and evidence accumulation for predictive brain activity. Neuroscience and Biobehavioral Reviews, 47, 636-645. http://dx.doi.org/10.1016/j.neubiorev.2014.10.017
Bratzke, D., \& Bryce, D. (2019). Introspection is not always blind to the costs of multitasking: The case of task switching. Journal of Experimental Psychology: Learning, Memory, and Cognition, 45, 980-992. http://dx.doi.org/10.1037/xlm0000635
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. http://dx.doi.org/10.1007/s00426-017-0924-0
Chen, P., \& Hsieh, S. (2013). When the voluntary mind meets the irresistible event: Stimulus-response correspondence effects on task selection
during voluntary task switching. Psychonomic Bulletin \& Review, 20, 1195-1205. http://dx.doi.org/10.3758/s13423-013-0437-9
Demanet, J., Verbruggen, F., Liefooghe, B., \& Vandierendonck, A. (2010). Voluntary task switching under load: Contribution of top-down and bottom-up factors in goal-directed behavior. Psychonomic Bulletin \& Review, 17, 387-393. http://dx.doi.org/10.3758/PBR.17.3.387
Dignath, D., Kiesel, A., \& Eder, A. B. (2015). Flexible conflict management: Conflict avoidance and conflict adjustment in reactive cognitive control. Journal of Experimental Psychology: Learning, Memory, and Cognition, 41, 975-988. http://dx.doi.org/10.1037/xlm0000089
Dreisbach, G., \& Fröber, K. (2019). On how to be flexible (or not): Modulation of the stability-flexibility balance. Current Directions in Psychological Science, 28, 3-9. http://dx.doi.org/10.1177/0963721418 800030
Dreisbach, G., \& Haider, H. (2006). Preparatory adjustment of cognitive control in the task switching paradigm. Psychonomic Bulletin \& Review, 13, 334-338. http://dx.doi.org/10.3758/BF03193853
Dreisbach, G., Haider, H., \& Kluwe, R. H. (2002). Preparatory processes in the task-switching paradigm: Evidence from the use of probability cues. Journal of Experimental Psychology: Learning, Memory, and Cognition, 28, 468-483. http://dx.doi.org/10.1037/0278-7393.28.3.468
Dunn, T. L., Lutes, D. J., \& Risko, E. F. (2016). Metacognitive evaluation in the avoidance of demand. Journal of Experimental Psychology: Human Perception and Performance, 42, 1372-1387. http://dx.doi.org/ 10.1037/xhp0000236

Egner, T., \& Hirsch, J. (2005). Cognitive control mechanisms resolve conflict through cortical amplification of task-relevant information. Na ture Neuroscience, 8, 1784-1790. http://dx.doi.org/10.1038/nn1594
Fröber, K., \& Dreisbach, G. (2017). Keep flexible - Keep switching! The influence of forced task switching on voluntary task switching. Cognition, 162, 48-53. http://dx.doi.org/10.1016/j.cognition.2017.01.024
Gilbert, S. J., \& Shallice, T. (2002). Task switching: A PDP model. Cognitive Psychology, 44, 297-337. http://dx.doi.org/10.1006/cogp . 2001.0770
Goschke, T. (2000). Intentional reconfiguration and involuntary persistence in task set switching. In S. Monsell \& J. S. Driver (Eds.), Control of cognitive processes: Attention and performance XVIII (pp. 331-355). Cambridge, MA: MIT Press.
Gray, W. D., Sims, C. R., Fu, W. T., \& Schoelles, M. J. (2006). The soft constraints hypothesis: A rational analysis approach to resource allocation for interactive behavior. Psychological Review, 113, 461-482. http://dx.doi.org/10.1037/0033-295X.113.3.461
Haggard, P. (2008). Human volition: Towards a neuroscience of will. Nature Reviews Neuroscience, 9, 934-946. http://dx.doi.org/10.1038/ nrn2497
Hübner, R., Steinhauser, M., \& Lehle, C. (2010). A dual-stage two-phase model of selective attention. Psychological Review, 117, 759-784. http://dx.doi.org/10.1037/a0019471
Inzlicht, M., Shenhav, A., \& Olivola, C. Y. (2018). The effort paradox: Effort is both costly and valued. Trends in Cognitive Sciences, 22, 337-349. http://dx.doi.org/10.1016/j.tics.2018.01.007
Jersild, A. T. (1927). Mental set and shift. Archives of Psychology, 14, 89. Jiang, J., Wagner, A. D., \& Egner, T. (2018). Integrated externally and internally generated task predictions jointly guide cognitive control in prefrontal cortex.eLife, 7, e39497. http://dx.doi.org/10.7554/eLife . 39497
Kessler, Y., Shencar, Y., \& Meiran, N. (2009). Choosing to switch: Spontaneous task switching despite associated behavioral costs. Acta Psychologica, 131, 120-128. http://dx.doi.org/10.1016/j.actpsy.2009.03 . 005
Kiesel, A., Steinhauser, M., Wendt, M., Falkenstein, M., Jost, K., Philipp, A. M., \& Koch, I. (2010). Control and interference in task switching-a review. Psychological Bulletin, 136, 849-874. http://dx.doi.org/10.1037/ a0019842

Kiesel, A., Wendt, M., \& Peters, A. (2007). Task switching: On the origin of response congruency effects. Psychological Research, 71, 117-125. http://dx.doi.org/10.1007/s00426-005-0004-8
Koch, I. (2001). Automatic and intentional activation of task sets. Journal of Experimental Psychology: Learning, Memory, and Cognition, 27, 1474-1486. http://dx.doi.org/10.1037/0278-7393.27.6.1474
Koch, I., \& Allport, A. (2006). Cue-based preparation and stimulus-based priming of tasks in task switching. Memory \& Cognition, 34, 433-444. http://dx.doi.org/10.3758/BF03193420
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, 557583. http://dx.doi.org/10.1037/bul0000144

Kool, W., McGuire, J. T., Rosen, Z. B., \& Botvinick, M. M. (2010). Decision making and the avoidance of cognitive demand. Journal of Experimental Psychology: General, 139, 665-682. http://dx.doi.org/10 .1037/a0020198
Kushleyeva, Y., Salvucci, D. D., \& Lee, F. J. (2005). Deciding when to switch tasks in time-critical multitasking. Cognitive Systems Research, 6, 41-49. http://dx.doi.org/10.1016/j.cogsys.2004.09.005
Liefooghe, B., Demanet, J., \& Vandierendonck, A. (2009). Is advance reconfiguration in voluntary task switching affected by the design employed? Quarterly Journal of Experimental Psychology, 62, 850-857. http://dx.doi.org/10.1080/17470210802570994
Liefooghe, B., Demanet, J., \& Vandierendonck, A. (2010). Persisting activation in voluntary task switching: It all depends on the instructions. Psychonomic Bulletin \& Review, 17, 381-386. http://dx.doi.org/10.3758/PBR.17.3 .381
Lien, M. C., \& Ruthruff, E. (2008). Inhibition of task set: Converging evidence from task choice in the voluntary task-switching paradigm. Psychonomic Bulletin \& Review, 15, 1111-1116. http://dx.doi.org/10 .3758/PBR.15.6.1111
Masson, M. E., \& Carruthers, S. (2014). Control processes in voluntary and explicitly cued task switching. The Quarterly Journal of Experimental Psychology, 67, 1944-1958. http://dx.doi.org/10.1080/ 17470218.2013.879390

Mattler, U., \& Palmer, S. (2012). Time course of free-choice priming effects explained by a simple accumulator model. Cognition, 123, 347360. http://dx.doi.org/10.1016/j.cognition.2012.03.002

Mayr, U. (2006). What matters in the cued task-switching paradigm: Tasks or cues? Psychonomic Bulletin \& Review, 13, 794-799. http://dx.doi .org/10.3758/BF03193999
Mayr, U., \& Bell, T. (2006). On how to be unpredictable: Evidence from the voluntary task-switching paradigm. Psychological Science, 17, 774780. http://dx.doi.org/10.1111/j.1467-9280.2006.01781.x

Mayr, U., \& Keele, S. W. (2000). Changing internal constraints on action: The role of backward inhibition. Journal of Experimental Psychology: General, 129, 4-26. http://dx.doi.org/10.1037/0096-3445.129.1.4
Meiran, N. (2000). Modeling cognitive control in task-switching. Psychological Research, 63(3-4), 234-249. http://dx.doi.org/10.1007/s0042 69900004
Meiran, N. (2010). Task switching: Mechanisms underlying rigid vs. flexible self control. In R. R. Hassin, K. Ochsner, \& Y. Trope (Eds.), Self control in society, mind and brain (pp. 202-220). New York, NY: Oxford University Press. http://dx.doi.org/10.1093/acprof:oso/978 0195391381.003.0011

Meiran, N., \& Kessler, Y. (2008). The task rule congruency effect in task switching reflects activated long-term memory. Journal of Experimental Psychology: Human Perception and Performance, 34, 137-157. http:// dx.doi.org/10.1037/0096-1523.34.1.137

Miller, E. K., \& Cohen, J. D. (2001). An integrative theory of prefrontal cortex function. Annual Review of Neuroscience, 24, 167-202. http://dx .doi.org/10.1146/annurev.neuro.24.1.167

Mittelstädt, V., Dignath, D., Schmidt-Ott, M., \& Kiesel, A. (2018). Exploring the repetition bias in voluntary task switching. Psychological Research, 82, 78-91. http://dx.doi.org/10.1007/s00426-017-0911-5
Mittelstädt, V., Miller, J., \& Kiesel, A. (2018). Trading off switch costs and stimulus availability benefits: An investigation of voluntary taskswitching behavior in a predictable dynamic multitasking environment. Memory \& Cognition, 46, 699-715. http://dx.doi.org/10.3758/s13421-018-0802-z
Monsell, S., \& Mizon, G. A. (2006). Can the task-cuing paradigm measure an endogenous task-set reconfiguration process? Journal of Experimental Psychology: Human Perception and Performance, 32, 493-516. http://dx.doi.org/10.1037/0096-1523.32.3.493
Navon, D., \& Gopher, D. (1979). On the economy of the human-processing system. Psychological Review, 86, 214-255. http://dx.doi.org/10.1037/ 0033-295X.86.3.214
Pashler, H. (1984). Processing stages in overlapping tasks: Evidence for a central bottleneck. Journal of Experimental Psychology: Human Perception and Performance, 10, 358-377. http://dx.doi.org/10.1037/00961523.10.3.358

Pashler, H. (2000). Task switching and multitask performance. In S. Monsell \& J. Driver (Eds.), Control of cognitive processes: Attention and performance XVIII (pp. 277-309). Cambridge, MA: MIT Press.
Payne, S. J., Duggan, G. B., \& Neth, H. (2007). Discretionary task interleaving: Heuristics for time allocation in cognitive foraging. Journal of Experimental Psychology: General, 136, 370-388. http://dx.doi.org/ 10.1037/0096-3445.136.3.370

Questienne, L., Atas, A., Burle, B., \& Gevers, W. (2018). Objectifying the subjective: Building blocks of metacognitive experiences in conflict tasks. Journal of Experimental Psychology: General, 147, 125-131. http://dx.doi.org/10.1037/xge0000370
Questienne, L., van Dijck, J.-P., \& Gevers, W. (2018). Introspection of subjective feelings is sensitive and specific. Journal of Experimental Psychology: Human Perception and Performance, 44, 215-225. http:// dx.doi.org/10.1037/xhp0000437

Reissland, J., \& Manzey, D. (2016). Serial or overlapping processing in multitasking as individual preference: Effects of stimulus preview on task switching and concurrent dual-task performance. Acta Psychologica, 168, 27-40. http://dx.doi.org/10.1016/j.actpsy.2016.04.010
Rogers, R. D., \& Monsell, S. (1995). Costs of a predictible switch between simple cognitive tasks. Journal of Experimental Psychology: General, 124, 207-231. http://dx.doi.org/10.1037/0096-3445.124.2.207
Rubin, O., \& Koch, I. (2006). Exogenous influences on task set activation in task switching. The Quarterly Journal of Experimental Psychology, 59, 1033-1046. http://dx.doi.org/10.1080/02724980543000105
Rubinstein, J. S., Meyer, D. E., \& Evans, J. E. (2001). Executive control of cognitive processes in task switching. Journal of Experimental Psychology: Human Perception and Performance, 27, 763-797. http://dx.doi .org/10.1037/0096-1523.27.4.763
Salvucci, D. D., \& Taatgen, N. A. (2010). The multitasking mind. New York, NY: Oxford University Press.
Schneider, D. W. (2018). Categorization difficulty modulates the mediated route for response selection in task switching. Psychonomic Bulletin \& Review, 25, 1958-1967. http://dx.doi.org/10.3758/s13423-017-1416-3
Schneider, D. W., \& Logan, G. D. (2006). Priming cue encoding by manipulating transition frequency in explicitly cued task switching. Psychonomic Bulletin \& Review, 13, 145-151. http://dx.doi.org/10.3758/BF03193826
Schuch, S., \& Koch, I. (2003). The role of response selection for inhibition of task sets in task shifting. Journal of Experimental Psychology: Human Perception and Performance, 29, 92-105. http://dx.doi.org/10.1037/ 0096-1523.29.1.92
Schurger, A., Sitt, J. D., \& Dehaene, S. (2012). An accumulator model for spontaneous neural activity prior to self-initiated movement. Proceedings of the National Academy of Sciences of the United States of America, 109, E2904-E2913. http://dx.doi.org/10.1073/pnas. 1210467109

Schüür, F., \& Haggard, P. (2011). What are self-generated actions? Consciousness and Cognition: An International Journal, 20, 1697-1704. http://dx.doi.org/10.1016/j.concog.2011.09.006
Sohn, M. H., \& Carlson, R. A. (2000). Effects of repetition and foreknowledge in task-set reconfiguration. Journal of Experimental Psychology: Learning, Memory, and Cognition, 26, 1445-1460. http://dx.doi.org/10 .1037/0278-7393.26.6.1445
Steinhauser, M., \& Hübner, R. (2007). Automatic activation of task-related representations in task shifting. Memory \& Cognition, 35, 138-155. http://dx.doi.org/10.3758/BF03195950
Vandamme, K., Szmalec, A., Liefooghe, B., \& Vandierendonck, A. (2010). Are voluntary switches corrected repetitions? Psychophysiology, 47, 1176-1181.
Vandierendonck, A., Demanet, J., Liefooghe, B., \& Verbruggen, F. (2012). A chain-retrieval model for voluntary task switching. Cognitive Psychology, 65, 241-283. http://dx.doi.org/10.1016/j.cogpsych.2012.04.003
Vandierendonck, A., Liefooghe, B., \& Verbruggen, F. (2010). Task switching: Interplay of reconfiguration and interference control. Psychological Bulletin, 136, 601-626. http://dx.doi.org/10.1037/a0019791
Verbruggen, F., McLaren, I. P., \& Chambers, C. D. (2014). Banishing the
control homunculi in studies of action control and behavior change. Perspectives on Psychological Science, 9, 497-524. http://dx.doi.org/10 .1177/1745691614526414
Waszak, F., Hommel, B., \& Allport, A. (2003). Task-switching and longterm priming: Role of episodic stimulus-task bindings in task-shift costs. Cognitive Psychology, 46, 361-413. http://dx.doi.org/10.1016/S0010-0285(02)00520-0
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, 2-19. http://dx.doi.org/10.1111/j.2044-8295 .1952.tb00322.x
Yeung, N. (2010). Bottom-up influences on voluntary task switching: The elusive homunculus escapes. Journal of Experimental Psychology: Learning, Memory, and Cognition, 36, 348-362. http://dx.doi.org/10.1037/ a0017894
Yeung, N., \& Monsell, S. (2003). Switching between tasks of unequal familiarity: The role of stimulus-attribute and response-set selection. Journal of Experimental Psychology: Human Perception and Performance, 29, 455-469. http://dx.doi.org/10.1037/0096-1523.29 .2.455

## Appendix

## Additional Analyses of Experiments 1a, 1b, 2, 3, and 4

In this Appendix, we present the corresponding results when computing the individual interpolated median switch SOAs based on the corresponding cumulative distribution functions $\left(\mathrm{CDF}_{\text {total }}\right)$ for which we considered both repetition and switch trials ${ }^{9}$ (see Table A1 for a numeric example of the following descriptions). More precisely, we first created the probability density function $\left(\mathrm{PDF}_{\text {total }}\right)$ separately for each participant (and separately for each condition if applicable) by computing the relative proportion of switches at each SOA (i.e., $\mathrm{f}_{\text {switch }}$; number of switch trials at the specific SOA divided by the total number of trials at that SOA),

$$
\begin{equation*}
f_{\text {switch }}(t)=N_{\text {switch }}(t) /\left[N_{\text {switch }}(t)+N_{\text {rep }}(t)\right] \text { for } t=1 \ldots i, \tag{1}
\end{equation*}
$$

where $\mathrm{N}_{\text {switch }}(t)$ and $\mathrm{N}_{\text {rep }}(t)$ represent the numbers of switches and repetitions at the specific SOA level $t$ (e.g., 50, 100, 150 in Experiment 1a) and $i$ represents the maximum SOA level.

Then, we created the $\mathrm{CDFs}_{\text {total }}$ for each participant (and separately for each condition) by computing the cumulative probability at each SOA (i.e., $F_{\text {switch }}$ ) as the cumulative probability at the previous SOA plus the product of the proportion of the not-yet switched ones,
$F_{\text {switch }}(t)=F_{\text {switch }}(t-1)+\left[1-F_{\text {switch }}(t-1)\right] \times f_{\text {switch }}(t)$

$$
\begin{equation*}
\text { for } t=2 \ldots i \tag{2}
\end{equation*}
$$

Note that the cumulative switch probability at the first SOA level $F_{\text {switch }}(1)$ just equals the switch proportion at the first SOA
level $f_{\text {switch }}(l)$ because no earlier switches are possible. Finally, as in the current study, we applied linear interpolation to compute the corresponding medians.

We reanalyzed the results of the two experiments reported by Mittelstädt, Miller, et al. (2018) with this procedure. The difference between median switch costs and (interpolated) median switch ${ }_{\text {total }}$ SOA (Experiment 1a: 109 ms ; Experiment 1b: 126 ms ) in each experiment was again not significant (Experiment 1a: $p=.706$; Experiment 1b: $p=.566 \mathrm{~ms}$ ). Next, we applied the same data analyses procedure to the current experiments. Table A2 shows the corresponding "new" interpolated average median switch SOAs in each experiment (separately for each condition if necessary). As is already evident and is elaborated in more detail below, except for an expected significant difference in median switch ${ }_{\text {total }}$ SOA between the RSI conditions in Experiment 4, the results of this analysis were virtually identical to those of the main analysis in all experiments.

## Experiment 1a and 1b

There were no reliable differences between median switch costs and (interpolated) median switch $_{\text {total }} \mathrm{SOA}$ in either Experiment 1a ( $p=.706, \eta_{p}^{2}=.01$ ) or in Experiment 1b $\left(p=.566, \eta_{p}^{2}=.01\right)$.

[^7]Table A1
Numeric Example of the Cumulative Distribution Function ( $C D F_{\text {Total }}$ ) of Stimulus Onset Asynchronys (SOA) for One Participant Computed Based on the Probability Density Function (PDFtotal), Which in Turn Was Computed Based on Both Number of Switch $\left(N_{\text {switch }}\right)$ and Repetition Trials $\left(N_{\text {rep }}\right)$

| Variable | SOA |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 50 ms | 100 ms | 150 ms | 200 ms | 250 ms | 300 ms | 350 ms | 400 ms |
| $\mathrm{N}_{\text {switch }}$ | 30 | 42 | 56 | 60 | 35 | 18 | 7 | 5 |
| $\mathrm{N}_{\text {rep }}$ | 252 | 201 | 136 | 75 | 38 | 17 | 10 | 3 |
| $\mathrm{PDF}_{\text {total }}$ | . 11 | . 17 | . 29 | . 44 | . 48 | . 51 | . 41 | . 63 |
| $\mathrm{CDF}_{\text {total }}$ | . 11 | . 26 | . 48 | . 71 | . 85 | . 93 | . 96 | . 99 |

Note. See text for more details.

Table A2
Mean Median Switch ${ }_{\text {Total }}$ Stimulus-Onset-Asynchrony (SOA in Ms) Separately for Experiment 1a, Experiment $1 b$, and for the Specific Conditions Used in Experiment 2 (i.e., SOA Step Size of $50 \mathrm{~ms} v \mathrm{~s} .100 \mathrm{~ms}$ ), Experiment 3 (i.e., Response-Stimulus Interval [RSI] of 100 ms vs. 700 ms ) and Experiment 4 (i.e., RSI of 100 ms vs. 700 ms )

| Measure | Experiment 1a and 1b |  | Experiment 2 |  | Experiment 3 |  | Experiment 4 |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1a | 1 b | $\mathrm{SOA}=50$ | $\mathrm{SOA}=100$ | $\mathrm{RSI}=100$ | $\mathrm{RSI}=700$ | RSI $=100$ | RSI $=700$ |
| Switch $_{\text {total }} \mathrm{SOA}$ | 312 (47) | 235 (22) | 124 (23) | 215 (40) | 210 (44) | 117 (17) | 148 (23) | 116 (21) |

Note. Standard error of the means in parentheses.

## Experiment 2

Median switch ${ }_{\text {total }}$ SOA was significantly higher in SOA $=100$ blocks than in SOA $=50$ blocks, $p<.001, \eta_{p}^{2}=.47$. Median switch $_{\text {total }}$ SOAs were significantly larger than median switch costs in SOA $=50$ blocks, $p<.001, \eta_{p}^{2}=.35$ and they were also descriptively-but not reliably-higher than switch costs in SOA $=100$ blocks, $p=.092, \eta_{p}^{2}=.09$.

## Experiment 3

The difference between the median switch ${ }_{\text {total }}$ SOAs of the two blockwise manipulated RSI conditions was significant, $p=.007$, $\eta_{p}^{2}=.21$. The difference between median switch costs and median switch $_{\text {total }}$ SOA was significant in RSI $=700$ blocks, $p=.019$, $\eta_{p}^{2}=.16$, whereas there was no significant difference between
median switch costs and switch $_{\text {total }}$ SOA in RSI $=100$ blocks, $p=$ $.470, \eta_{p}^{2}=.02$.

## Experiment 4

Median switch ${ }_{\text {total }}$ SOAs were reliably smaller in the RSI $=700$ compared to the RSI $=100$ condition, $p<.001, \eta_{p}^{2}=.32$. There was also a significant difference between median switch costs and switch $_{\text {total }}$ SOA in the RSI $=700$ condition, $p=.033, \eta_{p}^{2}=.12$. However, median switch costs and switch ${ }_{\text {total }}$ SOA did not differ significantly in the RSI $=100$ condition, $p=.859, \eta_{p}^{2}<.001$.

Received March 6, 2019
Revision received July 8, 2019
Accepted July 8, 2019


[^0]:    This article was published Online First August 22, 2019.
    Victor Mittelstädt, Department of Psychology, University of Freiburg, and Department of Psychology, University of Otago; Jeff Miller, Department of Psychology, University of Otago; Andrea Kiesel, Department of Psychology, University of Freiburg.

    This research was supported by a grant within the Priority Program, SPP 1772 from the German Research Foundation (Deutsche Forschungsgemeinschaft), Grant KI1388/8-1. Jeff Miller and Victor Mittelstädt were

[^1]:    further supported by grants from the Alexander von Humboldt foundation. We thank Pauline Beckmann, Jonathan Bercher, Julia Haimerl, and Jonas Maus for assistance in data collection. Raw data are available via the Open Science Framework at https://osf.io/sve4k/.

    Correspondence concerning this article should be addressed to Victor Mittelstädt, Department of Psychology, University of Freiburg, Engelbergerstraße 41, 79085 Freiburg, Germany. E-mail: victor.mittelstaedt@ psychologie.uni-freiburg.de

[^2]:    ${ }^{1}$ Yeung (2010) observed asymmetrical switch costs and corresponding switching behavior in a VTS setting with randomness instructions. One potential explanation for the discrepancy between the findings of Liefooghe et al. (2010) and Yeung (2010) could be that the tasks in the former study differed less in their relative strength than the tasks in the latter study. Thus, asymmetries can also be observed in VTS studies with randomness instructions as long as the two tasks differ substantially in their difficulty.

[^3]:    ${ }^{2}$ More precisely, we reasoned that it is important to see whether switch costs can be observed in our paradigm to investigate how these costs are traded off against the stimulus availability manipulation. Thus, we first conducted a power analysis based on the effect size of switch costs $\left(\eta_{p}^{2}=\right.$ .65) in the first experiment of Mittelstädt et al. (2018) for detecting a similar effect with a power level of $80 \%$ and a significance level of $5 \%$ (one-sided). This power analysis yielded a minimum number of seven participants. Note that the sample size in our experiments after exclusion of participants for our main analyses in the individual experiments were considerably higher. In general, we felt it was important to test a larger sample size than suggested by the power analysis for the following reasons. First, the procedure is in general quite novel and we have considerably modified the paradigm introduced by Mittelstädt et al. (2018). Note that power is a function of test and design (including preciseness of measures), and this reasoning also motivated us to have at least 10 trials in each of our conditions in order to obtain fairly precise measurements of our variables of interest (and consequently we excluded some participants for our main analyses). Second, a sample size similar to the final sample of 31 participants tested by Mittelstädt et al. (2018) seemed appropriate to us. For example, we were also interested in the comparison of switch costs with switch SOA, and a $95 \%$ confidence interval for that difference had a reasonable width in the earlier study (i.e., $[-17-65 \mathrm{~ms}]$ ). Third, we reasoned that larger sample sizes in the individual experiments would also allow us to explore the correlations between switch costs and switch rates to see whether we could find a consistent pattern across experiments. For Experiment 1b, then, we used the same power analysis and arguments but we decided to increase the sample size to allow for the possibility of finding hardly any switching behavior in some participants.

[^4]:    ${ }^{3}$ Qualitatively very similar results were also obtained when comparing the first and second half of blocks in all experiments. Only in Experiment 1b, we observed significantly smaller switch SOA than switch costs in the first half of the experiment. Note that for these analyses, we applied the same outlier criteria as for the main analyses, and thus we had to additionally exclude data of some participants (with only one or less valid trials in at least one condition).
    ${ }^{4}$ Note that the other trials in an individual run sequence were retained in all experiments-that is an individual run could end with a switch trial at a certain SOA but some of the repetition trials preceding this switch trials were excluded. However, qualitatively very similar results were also obtained in analyses in which we only excluded trials without voluntary choice at the end of blocks in order to maintain all trials of a run.

[^5]:    ${ }^{5}$ Note that we also checked whether this type of computation would have substantially changed the results of the two experiments reported in Mittelstädt et al. (2018). This was not the case. Specifically, we obtained a mean (interpolated) switch SOA median of 106 ms compared to the reported (not interpolated) median of 130 ms and a mean (interpolated) median of 95 ms compared to the reported (not interpolated) median of 112 ms .
    ${ }^{6}$ The correlation between individual median switch costs and median switch SOA was not substantial, $r(17)=.31, p=.228$ ). However, as already noted by Mittelstädt et al. (2018), the discreteness of median switch SOA seems to make this variable less suitable to detect potential relations with switch costs across participants despite the application of linear interpolation. This is further supported by a significant correlation between mean switch costs and mean switch SOA, $r(17)=.58, p=.014$.

[^6]:    ${ }^{7}$ Engaging in preparatory task selection processes in advance of blocks (i.e., selection of repetition task-sequences) might then also lead to a consistent bias in spatial attention towards one of the (constant) task location thereby additionally reducing potential influences of switch stimulus availabilities on task-set activations (and thus on task selection) during blocks. Note that task location changed randomly on a trial-by-trial basis in the study by Mittelstädt et al. (2018).
    ${ }^{8}$ Because we modified the paradigm after Experiment 1a and 1 b to make it more comparable to the one used in Mittelstädt et al. (2018), we expected that the modifications would reduce the number of participants showing no switching behavior, and we correspondingly also reduced the sample size to 40 participants for Experiment 2, 3, and 4.

[^7]:    ${ }^{9}$ Note that we used the same outlier criteria as for our main analyses.

