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# **Modulating Cognitive Flexibility Through Associative Learning and Personality: The Influence of Context and Need for Cognition on Task Switching**

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Universiteit Leiden

**Psychologie**  
Faculteit der Sociale Wetenschappen



# **Modulating Cognitive Flexibility Through Associative Learning and Personality**

The Influence of Context and Need for  
Cognition on Task Switching

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## **Abstract**

Previous research has emphasized the trade-off between cognitive stability and flexibility. Our main research aim within the present study was to assess whether demand on cognitive flexibility can become associated with specific stimulus contexts (i.e., locations), whether these learned associations are being transferred to a subsequent phase, and whether such associations correlate with need for cognition. In 107 participants we assessed switch costs both in terms of reaction times and error rates in a learning phase where task switch frequencies were manipulated across two contexts (25%/75%) and a subsequent diagnostic phase where task switch frequencies were balanced. We further included individual differences in need for cognition in the analyses, which we measured using the NCS-6 questionnaire. As expected, we found a reduction in switch costs in the high task switch frequency context in the learning phase. We did not observe the expected transfer of effects to the diagnostic phase, but instead an unexpected increase in switch costs in the previous high task switch frequency context. Moreover, there were no modulations of effects by need for cognition. However, there were increases in switch costs during the diagnostic phase for participants who showed a response to the manipulation during the learning phase. Altogether, our results suggests that context indeed plays a role in our ability to adjust to demand on cognitive flexibility. Facilitating associations between these two can modulate task switching performance in terms of speed and accuracy.

*Keywords:* cognitive flexibility, task switching, associative learning, need for cognition

## **Introduction**

The term cognitive control refers to higher-order cognitive processes that guide behavior in line with internal goals and the current context (Diamond, 2013). We rely on cognitive control in situations where our well-learned automatic responses are unasked for (Diamond, 2013), such as when we are reading an article and we hear the sound of an incoming email. Here, we rely on cognitive control to stay focused on reading the article by overriding our learned response of checking our inbox. In the present example, we have to maintain our focus and shield our current goals from distractions, which is referred to as cognitive stability (Fröber & Dreisbach, 2017). By contrast, cognitive flexibility refers to the ability to update and shift our goals in light of significant changes in the environment (Fröber & Dreisbach, 2017), such as when switching from writing an email to attending a Teams call. Accordingly, cognitive control is commonly described as a dynamic balance

between cognitive stability and cognitive flexibility (Hommel, 2015; Fröber & Dreisbach, 2017; Fröber et al., 2020).

The significance of this trade-off has become apparent in the past year, where people had to adjust to a lockdown situation in which their homes did not only turn into their offices, but also into the schools and daycare centers of their children, their gym as well as the place for other leisure activities. Instead of having distinct locations for all kinds of daily life activities, suddenly, they all occur in the same place—that is, people’s homes. Considering these recent changes, people’s ability to multitask and be cognitively flexible has become increasingly relevant when trying to adapt to this new daily routine revolving around switching between tasks. However, in working from home, one also needs to be able to ignore the distractions that accompany the new office and focus on the task at hand, which emphasizes the great importance of cognitive stability. Considering these circumstances, the necessity of better understanding the manifestation of the stability-flexibility trade-off is highly evident.

One way to investigate this trade-off is by tapping into the task switching paradigm, in which participants are required to switch between two or more tasks (e.g., dissociating between colors and shapes; Druey, 2014). One typical observation is that reaction times (RTs) on trials in which the task rule remains the same (i.e., task repetitions) are generally lower and error rates (ERs) are generally smaller than on trials in which the task rule changes (i.e., task switches)—a behavioral cost which is referred to as the switch cost (e.g., Sohn & Anderson, 2001; Fröber & Dreisbach, 2017; Braem & Egner, 2018). Interestingly enough, studies have repeatedly found that switch costs increase with an increase in task repetition probability (Monsell & Mizon, 2006; Leboe et al., 2008; Liu & Yeung, 2020). This finding has been interpreted as the result of committing to a task in light of frequently experiencing task repetitions (Liu & Yeung, 2020), and adjusting cognitive control accordingly. Recently, Liu and Yeung (2020) did not only observe an increase in switch costs when participants were presented with more task repetitions than task switches, they also reported increased switch costs whenever participants merely expected switches to be rare, while such trials were in fact balanced with task repetitions—an effect which was primarily pronounced in increased error making on task switch trials when instructions indicated frequent task repetitions. Put differently, participants adjusted their cognitive control based on the expectation they would have to frequently repeat tasks, which led them to make more errors when they actually had to switch. Overall, these results indicate that cognitive control is not only adjusted in light of the experience of increased task switches, but similarly that

adjustments can be made due to the mere expectation of task switch probability (Liu & Yeung, 2020).

Recently, Musslick and colleagues (2019) aimed to obtain a better understanding of this allocation of recruited control, and thereby the balancing of the stability-flexibility trade-off, by constructing a computational model. First of all, in line with previous work, they observed smaller switch costs in situations that required more frequent task switches, reflecting higher cognitive flexibility. Furthermore, the results of their computational model suggested that this increase in cognitive flexibility can be explained by higher constraints on control. Specifically, participants became better at switching tasks whenever they allocated less control to a single task (Musslick et al., 2019). Accordingly, for situations with little task switching demand, higher allocation of control to single tasks can be considered best practice. Therefore, in addition to the general greater recruitment of cognitive control in light of higher demand (e.g., see Liu and Yeung, 2020), the amount of control that is allocated to the specific task at hand appears to be a crucial indicator of performance.

Interestingly enough, extending the work by Musslick and colleagues (2019) showing that control can be adjusted based on specific demands, a review article by Braem and colleagues (2019) has recently been published indicating that particular situations can become associated with demand on cognitive control. Specifically, Braem and colleagues (2019) describe that within a different, yet related paradigm that when facing higher demand on cognitive flexibility in a specific context, people are able to recruit more cognitive control and perform relatively better when compared to a lower-demand context.

Taken together, switch costs might be modulated by higher demands on cognitive flexibility, the expectation of such (Liu & Yeung, 2020), the amount of control that is being allocated to specific tasks (Musslick et al., 2018, 2019), as well as contextual features (Braem et al., 2019). Within the present study, we elaborate on these previous findings by investigating whether demand on cognitive flexibility can become associated with specific stimulus contexts (i.e., locations). We aim to extend the knowledge on these effects by tapping into the question whether people can learn to associate particular contexts with a specific task switch frequency. Accordingly, we manipulated the task switch frequency in the first phase of our study, which we refer to as the learning phase, by associating two different contexts (i.e., location above and location below middle of the screen) with a 25% and 75% task switch-to-repetition ratio, respectively. The two contexts are subsequently referred to as high task switch frequency (HTSF) and low task switch frequency (LTSF) context. By means of this design, we aimed to conceptually replicate the finding that contextual features, such as stimulus locations, can become associated with differences in

task switch frequency and related demand on cognitive flexibility. Specifically, combining the effects observed by Braem and colleagues (2019) with the finding that switch costs decrease with an increase in task switch probability (see above, Monsell & Mizon, 2006; Leboe et al., 2008; Liu & Yeung, 2020), gives rise to the expectation that people can also learn to adjust cognitive control based on the demand on cognitive flexibility cued by a specific context.

Additionally, we aimed to investigate whether these associations between demand on cognitive flexibility and context are being transferred to a subsequent situation in which such established associations are no longer valid. Therefore, within the second half of our experiment, which we refer to as the diagnostic phase, we lifted our task-switch frequency manipulation, resulting in identical task switch frequencies in both contexts. Inspired by Liu and Yeung's (2020) findings, where effects were based on explicit expectations, we wanted to test whether similar effects would show for implicit expectations. Accordingly, we did not include any instructions containing information about switch frequencies in our study. In other words, we expect that participants learn the association between context and demand on cognitive flexibility to a certain extent during the learning phase and that this learned association persists as explicitly learned rules (e.g., expected task switch frequency in Liu & Yeung, 2020) in the diagnostic phase.

Furthermore, Liu and Yeung (2020) observed the effects of an instruction-induced global control influence in task switching only when participants were motivated to follow instructions. Along similar lines, people who are more willing to engage in difficult cognitive activities might be more likely to be able to learn an association between context and demand on cognitive flexibility. Therefore, we aimed to tap into such individual differences by measuring participants' need for cognition (NFC), which is defined as their tendency to engage in and enjoy thinking (Lins de Holanda Coelho et al., 2020): "Individuals high in need for cognition are more likely to seek out, attend to, and think about the data that make up their world than individuals low in need for cognition" (Cacioppo et al., 1996). Moreover, NFC has been found to be highly correlated with typical intellectual engagement (TIE) (Woo et al., 2007), which is characterized by intellectual curiosity (von Stumm & Furnham, 2012). TIE in turn, is positively correlated with deep learning approaches characterized by exploring topics as much as possible and trying to gain a better understanding of the background and the wider context of the topic (von Stumm & Furnham, 2012). Consequently, willingness to engage in cognitive ability, measured by NFC, might modulate learning, and thereby associated switch costs. In reference to Liu and Yeung's (2020) findings regarding motivation, we expect that participants who are high in NFC are

inherently motivated to perform well on the task and figure out the differences in task switch frequency between contexts and therefore show the effects as if they had been informed about the manipulation explicitly.

The above-described theoretical background of the present study translates to the following hypotheses. First, we expected that, in the learning phase, participants would show smaller switch costs in the HTSF context compared to the LTSF context. The reasoning is that an increase in task switch frequency would result in decreased switch costs (e.g., Fröber & Dreisbach, 2017), while increased task repetitions would lead to higher control allocation to the task itself leaving one unprepared to switch (Musslick et al., 2019). Second, for the diagnostic phase, we hypothesized that participants show smaller switch costs in the context they previously learned to associate with a HTSF compared to the context they previously learned to associate with a LTSF, even though the actual task switch frequencies are equal across both contexts (50%/50%). This hypothesis refers to the transfer of previously learned associations between context and task switch frequency. Finally, we hypothesized that participants would show both learning effects and transfer effects relative to their level of NFC. Specifically, participants high in NFC will show the expected effects more pronounced than those lower in NFC.

## **Methods**

### **Participants**

A total of 107 participants (female = 100, mean age = 19.66,  $SD = 2.63$ , range = 17-32 years) performed the experiment. Participants were recruited via the Leiden University research participation system (SONA) and via personal correspondence. Students who participated via SONA received 2 credits for completing the study. All participants reported to have no history of psychiatric disorders or drug use, normal or corrected-to-normal vision and no color-blindness. Prior to the start of the experiment, participants provided online informed consent. The study protocol was approved by the local ethics committee (Leiden University, Institute of Psychology, 2020-10-22-B.J.Jongkees-V2-2667).

### **Procedure**

The study consisted of a single 60-minute session, including a task switching paradigm with a practice phase, a learning phase and a diagnostic phase, a demographics form, and the NCS-6 questionnaire (Lins de Holanda Coelho et al., 2018). Participants performed the experiment at home on their own laptop or PC and were asked to make use of a common size credit card to resize a presented field accordingly, to ensure that stimuli would be the same size for all participants. Prior to the start of the experimental session,

participants were asked to provide informed consent. At the beginning of the experimental session, participants performed three practice blocks; two single-task and one mixed-task block (e.g., block 1: color only; block 2: shape only; block 3: mixed, task-to-block mapping for blocks 1 and 2 counterbalanced between participants), of a color-shape task switching task. If a participant's accuracy rate fell below 85% on any of the practice blocks, the specific practice block was reinitialized. For participants who did not manage to complete any of the three practice blocks with an accuracy of at least 85% on three consecutive tries, the study was concluded.

Participants who successfully completed all three practice blocks continued with the two main phases (i.e., learning and diagnostic phase) of the experiment. In each phase, participants were presented with a color-shape task switching paradigm. The task included a sequence of short blocks (i.e., mini-blocks). Within the first mini-block, for half of the participants, stimuli were presented "above the center of the screen", while the other half started with stimuli being presented "below the center of the screen". On a mini-block to mini-block level, this context was alternated (i.e., ABAB mini-block design, counterbalanced across participants), while, within each of these mini-blocks, the context (i.e., location) where stimuli were presented remained constant. Roughly half of our participants were presented with a HTSF in the context above the center of the screen (55/107 participants), while the context below the center of the screen displayed a LTSF. In the diagnostic phase, stimulus contexts were the same as within the learning phase, with the crucial adjustment that, for all participants, both contexts were now associated with a 50% task switch frequency. Contexts were alternated on a mini-block to mini-block level (i.e., ABAB mini-block design, counterbalanced across participants), while, within each mini-block, the location where stimuli were presented remained constant.

The learning phase consisted of 4 blocks composed of 8 mini-blocks of 17 trials each, while the diagnostic phase consisted of 2 blocks composed of 8 mini-blocks of 17 trials each. At the end of each mini-block participants could choose whether to take a five second break or continue right away with the next mini-block, which was included to keep participants from taking extended breaks.

After having completed these two main phases, participants were presented with the NCS-6, some demographic questions (e.g., age, gender) and questions about their attitude during their performance on the task, importantly, they were asked to indicate whether they noticed any differences between the two contexts. Concluding the study, participants were debriefed and compensated for their participation.



## Materials

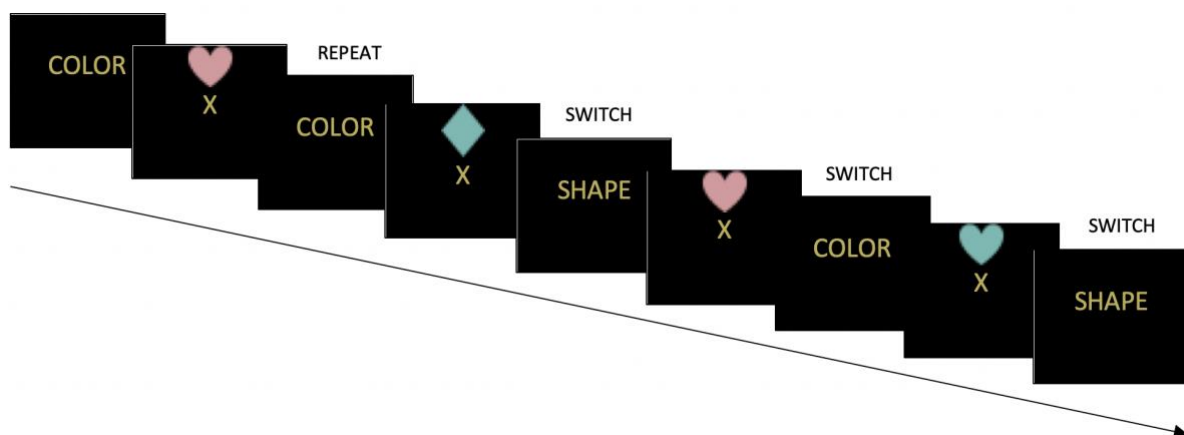
### *Color-shape task switching paradigm*

Participants switched between performing a color and a shape task. Each trial commenced with the presentation of a fixation cross for a duration of 500 ms. Next, prior to stimulus presentation, either the word “COLOR” or “SHAPE” was presented in khaki (RGB: 188, 175, 81) on a black background for 1500 ms, indicating the to-be-performed task. Hereafter, Cyan colored (RGB: 110, 185, 180) and salmon colored (RGB: 217, 152, 158) diamonds (167 x 146 pixels) and hearts (138 x 146 pixels) were presented on a black screen (i.e., either above or below fixation cross, depending on context) until response or for a period of 1500ms. If participants did not respond within 1500 ms, the trial was concluded and an error was recorded (i.e., non-response). On each of the practice trials, participants obtained performance-contingent feedback for 1500 ms.

Response mappings were counterbalanced between participants, with the “A” and the “L” keys being mapped on one of the two to-be-responded to colors (i.e., cyan and salmon) and one of the two to-be-responded to shapes (i.e., diamond and heart). Within the learning phase, the task switch-to-repetition ratio was manipulated. Specifically, participants were presented with 75% task switch trials (i.e., task alternation between trial n-1 and trial n) and 25% task-repetition trials (i.e., task repetition between trial n-1 and trial n) for above- and below screen context presentations, respectively (counterbalanced across participants). Figures 1 and 2 show examples of trials of a mini-block in the two contexts with a HTSF and LTSF respectively. Within the diagnostic phase, task transitions were kept constant (i.e., at 50%) for each stimulus context.

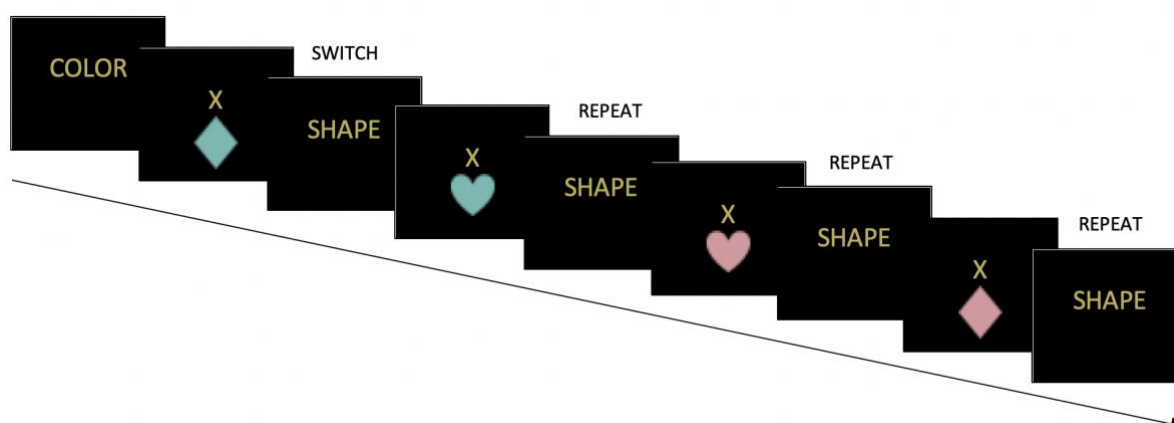
### **Figure 1**

*Example trials of a mini-block with a HTSF in the context above the center of the screen*



**Figure 2**

*Example trials of a mini-block with a LTSF in the context below the center of the screen*



### *Need for Cognition Scale (NCS-6; Lins de Holanda Coelho et al., 2018)*

The six-item version of the Need for Cognition Scale measures people's tendency to engage in and enjoy difficult cognitive activity. It entails the presentation of 6 statements (e.g., "I would prefer complex to simple problems."). Participants are asked to indicate on a scale from 1 to 5 (1= extremely uncharacteristic of me, 5 = extremely characteristic of me) how characteristic each statement is of them (see Appendix A for the items composing the NCS-6).

### **Statistical Analyses**

All statistical analyses were conducted in the analysis software R (R Core Team, 2021; Version 4.0.4). In order to test whether participants were able to learn to associate demand on cognitive flexibility and context, we conducted multiple hierarchical multiple linear regression analyses. These analyses were separately performed for the learning- and diagnostic phase, for switch costs in terms of median RTs and ERs respectively. We compared all hierarchical models reported below using the ANOVA function from the R package *car*. We checked whether more complex models including the higher-order interaction terms outperformed more parsimonious models. If this was not the case, we selected the model with the lowest Bayesian Information Criterion (BIC) score.

### **Preprocessing**

First, we made sure that participants who initially answered "yes" to any of the exclusion criteria, but who then restarted the experiment, or participants who restarted the

experiment after having failed the practice blocks, were excluded from all analyses. We also made sure that, in case participants participated more than once, only data from their first participation was included in the analyses. Furthermore, we excluded participants that were, on a sample level, considered outliers in terms of accuracy, which we identified using the interquartile range method with a factor of 2.2. The practice blocks, the first trial of each mini-block, error trials and post-error trials were removed before performing the analyses. We performed all analyses for the switch costs both in terms of median RTs and ERs. We calculated the switch costs as median RTs and ERs on switch trials minus median RTs and ERs on repetition trials.

### ***Learning phase***

For the analyses of the learning phase, we defined hierarchical multiple linear regression models in which the mean switch costs in terms of RTs and ERs were estimated by the context (i.e., HTSF, LTSF) and the block (i.e., blocks 1, 2, 3 and 4). The first model only contained the main effects, while the second model included both the main and the interaction effects. All models reported below adhered to the assumptions of multicollinearity of residuals, normality of residuals, linearity of residuals and homoscedasticity (Tabachnick & Fidell, 2012), while for each of these models the assumption of independent errors was violated. Note that the violation of this latter assumption is non-surprising, as all collected datapoints were obtained as a function of a meaningful time sequence.

Additionally, in order to test for individual differences with regard to NFC in modulating switch costs, we included the sum score of the NFC scale in subsequent analyses. For these analyses we defined the same linear regression models as described above, with the only difference being the additional inclusion of the NFC sum score and interactions between the NFC sum score and all other factors (i.e., context and block). We again checked whether the more complex model outperformed the more parsimonious model.

### ***Diagnostic phase***

For the analyses of the diagnostic phase, we defined hierarchical multiple linear regression models in which the mean switch costs in terms of RTs and ERs were estimated by context (i.e., previous HTSF, previous LTSF; from now onwards referred to PHTSF and PLTSF) and block (i.e., blocks 1, 2). The first model only contained the main effects, while the second model included both the main and the interaction effects. All models reported below adhered to the assumptions of multicollinearity of residuals, normality of residuals, linearity of residuals and homoscedasticity (Tabachnick & Fidell, 2012), while for some, but

not all of these models the assumption of independent errors was violated.

Additionally, in order to test for individual differences with regard to NFC in modulating switch costs, we included the sum score of the NFC scale in the analyses. For these analyses we defined the same linear regression models as described above, with the only difference being the additional inclusion of the NFC sum score and interactions between the NFC sum score and all other factors (i.e., context and block).

Finally, we tested for individual differences in learning the association between switch frequency and context during the learning phase, and the effect this had on the diagnostic phase. For this analysis, we first defined a linear mixed model in which we set, separately for each participant, a random slope and intercept for the factor context (HTSF vs. LTSF). Subsequently, we extracted the associated beta weights—that is, the per-participant adjustments in fixed slopes. The larger the value of the slope parameter, the larger the difference in switch costs between the HTSF and LTSF context, presumably reflecting the extent to which participants responded to our task switch frequency manipulation. Subsequently, we added this extracted per-participant slope as a continuous predictor to the regression analyses of the diagnostic phase. We defined a hierarchical multiple linear regression analysis both for the switch costs in terms of median RTs and ERs to investigate whether participant's switch costs changed as a function of the context (i.e., PHTSF, PLTSF), the block (i.e., block 1, 2) and the slope. For both the switch costs in terms of RTs and ERs, we defined two models. The first model only contained the main effects, while the second model included both the main and the interaction effects.

## Results

### Learning phase

For each of the analyses reported below, ANOVAs revealed that updating the models with the factors' higher-order interaction terms did not significantly increase the model fits (all  $F$ s < 1.89, all  $p$ s > .13).

### *Switch costs in terms of RTs*

The regression analysis predicting switch costs as a function of context (HTSF, LTSF) and block revealed significant associations ( $F(4, 859) = 7.94, p < .001$  adjusted  $R^2 = .03; \beta = -6.28, 95\% \text{ CI } [-11.78, -0.79], |t|(859) = 2.25, p = .025; \beta = -28.87, 95\% \text{ CI } [-39.86, -17.88] |t|(859) = 5.16, p < .001$ , for context and block, respectively). Specifically, switch costs were generally smaller in the HTSF location ( $M = 44.9 \text{ ms}, SD = 105.2 \text{ ms}$ ) as compared to the LTSF location ( $M = 57.4 \text{ ms}, SD = 101.4 \text{ ms}$ ). Moreover, as displayed in

Figure 3, switch costs decreased as a function of block ( $M_1 = 70.0$ ,  $SD_1 = 78.7$ ;  $M_2 = 59.0$ ,  $SD_2 = 88.7$ ;  $M_3 = 43.3$ ,  $SD_3 = 75.0$ ;  $M_4 = 32.2$ ,  $SD_4 = 89.0$ ).

Post-hoc pairwise comparisons revealed that participants responded faster on task repetition trials in the LTSF ( $M = 504.7$ ,  $SD = 34.5$ ) compared to the HTSF location ( $M = 515.0$ ,  $SD = 36.7$ ),  $t(106) = 2.53$ ,  $p = .013$ ). In contrast, no such difference was present for task switch trials ( $t(106) = 0.77$ ,  $p = .44$ ), indicating that RTs were comparable for both locations ( $M = 562.2$ ,  $SD = 45.1$  and  $M = 566.1$  and  $SD = 34.5$ , for LTSF and HTSF locations respectively).

### ***Switch costs in terms of ERs***

The regression analysis predicting switch costs as a function of location (HTSF, LTSF) and block revealed a significant association between location and switch costs, but no association between block and switch costs ( $F(4, 859) = 2.15$ ,  $p = .07$  adjusted  $R^2 = .01$ ;  $\beta = -0.01$ , 95% CI [-0.01, -0.00],  $|t/(859) = 2.14$ ,  $p = .033$ ;  $\beta = -0.00$ , 95% CI [-0.01, 0.01]  $|t/(859) = 0.38$ ,  $p = .71$ , for location and block, respectively). Specifically, switch costs were generally smaller in the HTSF location ( $M = 0.036$ ,  $SD = 0.10$ ) as compared to the LTSF location ( $M = 0.050$ ,  $SD = 0.12$ ), which can be observed in Figure 3. In contrast, block number did not predict switch costs, indicating that, over the course of the learning phase, participants' switch costs in terms of ERs remained relatively stable ( $M_1 = 0.038$ ,  $SD_1 = 0.07$ ;  $M_2 = 0.053$ ,  $SD_2 = 0.10$ ;  $M_3 = 0.042$ ,  $SD_3 = 0.07$ ;  $M_4 = 0.039$ ,  $SD_4 = 0.10$ ).

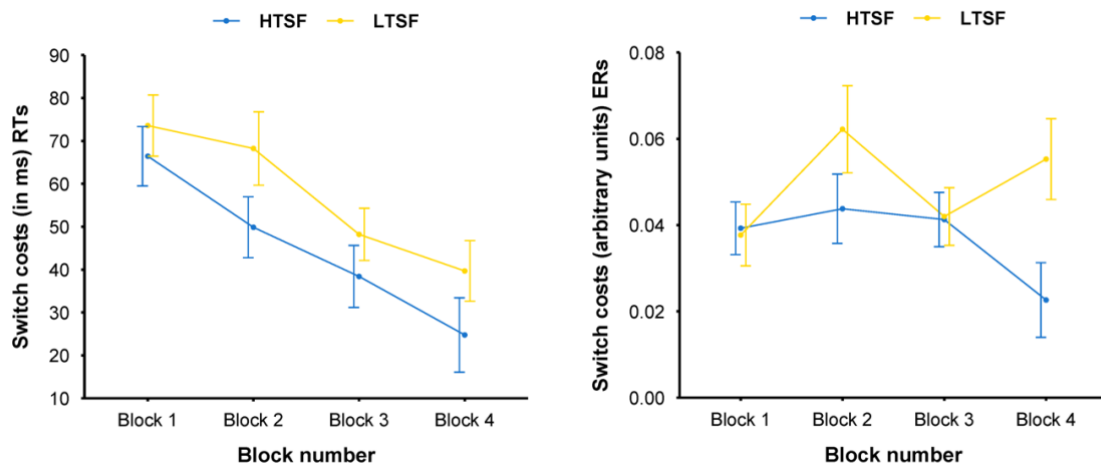
Post-hoc pairwise comparisons revealed that accuracy rates were marginally significantly smaller on repetition trials for the LTSF location ( $M = 0.052$ ,  $SD = 0.03$ ) compared to the HTSF location ( $M = 0.059$ ,  $SD = 0.03$ ),  $t(106) = 1.77$ ,  $p = .080$ . No such trend was present for task switch trials ( $|t/(106) = 1.23$ ,  $p = .22$ ), indicating that ERs were comparable for both locations ( $M = 0.10$ ,  $SD = 0.04$  and  $M = 0.095$  and  $SD = 0.03$ , for LTSF and HTSF locations respectively).

### ***Switch costs as a function of NFC***

In order to test whether, and if so, to what extent the NFC sum scores affected switch costs in terms of RTs and ERs, we added the NFC scores to the abovementioned analyses. The regression analyses revealed no significant associations between switch costs and NFC ( $F(5, 858) = 6.65$ ,  $p < .001$ , adjusted  $R^2 = .03$ ;  $\beta = 0.95$ , 95% CI [-0.59, 2.49]  $|t/(858) = 1.21$ ,  $p = .23$ ;  $F(5, 858) = 2.4$ ,  $p = .036$  adjusted  $R^2 = .01$ ;  $\beta = -0.00$ , 95% CI [-0.00, 0.00]  $|t/(858) = 1.84$ ,  $p = .066$ , for switch costs in terms of RTs and ERs, respectively). These results indicate that there switch costs were not modulated by NFC scores.

**Figure 3**

*Switch Costs in the HTSF and LTSF Contexts as a Function of Block Number*



*Note.* The relationship between switch costs in terms of response times (in ms) and error rates as a function of context (i.e., HTSF, LTSF) and block (i.e., block 1, 2, 3, 4).

## Diagnostic phase

### *Switch costs in terms of RTs*

An ANOVA demonstrated that the more complex model outperformed the more parsimonious one ( $F(1, 428) = 5.29, p = .022$ ). The regression analysis revealed no significant associations between switch costs, context (PHTSF, PLTSF) and block, ( $F(3, 428) = 2.38, p = .07$  adjusted  $R^2 = .01; \beta = 3.55, 95\% \text{ CI} [-2.41, 9.51], |t/(428) = 1.17, p = .24; \beta = 2.99, 95\% \text{ CI} [-5.43, 11.42] |t/(428) = 0.69, p = .49$ , for context and block respectively). However, there was a significant association between switch costs and the interaction of context and block ( $\beta = 9.86, 95\% \text{ CI} [1.43, 18.29], |t/(428) = 2.30, p = .022$ ).

Specifically, post hoc analyses indicated that, while switch costs on the PLTSF ( $M = 31.3, SD = 60.3$ ) and the PHTSF location ( $M = 25.1, SD = 55.9$ ) were comparable for the first block ( $t(106) = 0.70, p = 0.49$ ), switch costs were significantly smaller in the PLTSF ( $M = 22.3, SD = 53.0$ ) compared to the PHTSF location ( $43.2, SD = 53.7$ ),  $|t/(106) = 2.69, p = .008$  (see Figure 4) for the second block. However, further analyses of these effects did not reveal any significant difference between locations for neither task repetition ( $|t/(106) = 1.43, p = .15$ ) nor task switch trials ( $t(106) = 1.68, p = .096$ ).

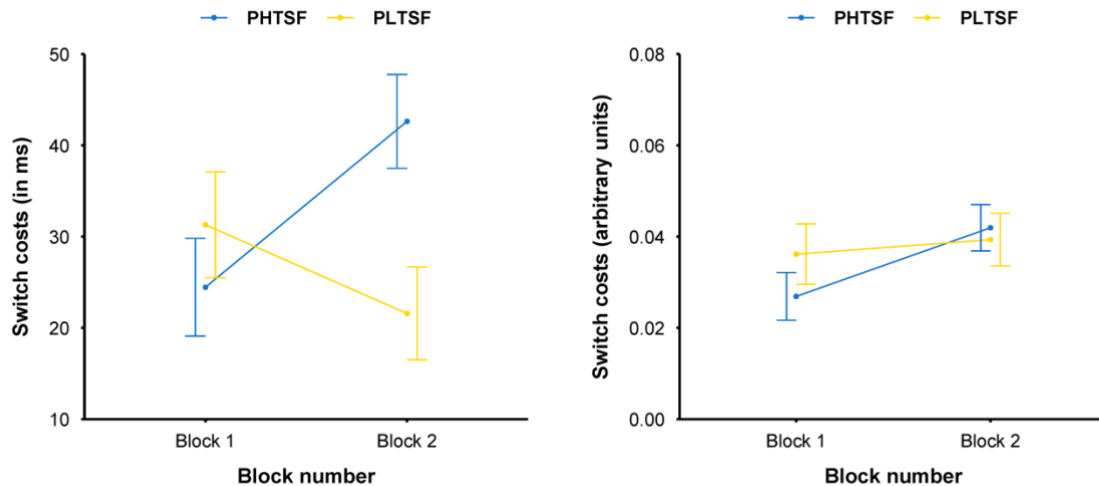
### *Switch costs in terms of ERs*

An ANOVA revealed that updating the model did not significantly increase the model fit ( $F(1, 428) = 0.82, p = .37$ ). The regression analysis on the relationship between

switch costs, context and block revealed no significant associations ( $F(2, 429) = 1.09, p = .34$  adjusted  $R^2 = .00; \beta = -0.00, 95\% \text{ CI } [-0.01, 0.00], |t/(429) = 0.51, p = .61; \beta = 0.01, 95\% \text{ CI } [-0.00, 0.02] |t/(429) = 1.39, p = .17$ , for location and block, respectively), which can also be observed in Figure 4.

**Figure 4**

*Switch Costs in the HTSF and LTSF Contexts as a Function of Block Number*



*Note* The relationship between switch costs in terms of response times (in ms) and error rates) as a function of context (i.e., PHTSF, PLTSF) and block (i.e., block 1, 2).

### *Switch costs as a function of NFC*

In order to test whether, and if so, to what extent the NFC sum scores affected switch costs, we added the NFC scores to the abovementioned analyses. The regression analyses revealed no significant associations between switch costs and NFC ( $F(3, 428) = 0.80, p = .49$ , adjusted  $R^2 = -.00; \beta = 0.64, 95\% \text{ CI } [-1.04, 2.32] |t/(428) = 0.75, p = .452; F(3, 428) = 0.96, p = .41$  adjusted  $R^2 = -.00; \beta = -0.00, 95\% \text{ CI } [-0.00, 0.00] |t/(428) = 0.83, p = .41$ , for switch costs in terms of RTs and ERs, respectively). These results indicate that there are no significant differences in switch costs regarding NFC scores in the diagnostic phase either.

### *Exploratory Analyses*

In order to test whether, and if so, to what extent the slope affected switch costs, we added the slope as a continuous predictor to the abovementioned analyses. Importantly, for each of the analyses reported below, an ANOVA revealed that updating the models did significantly increase the model fits,  $F_s(1, 428) > 7.07, p_s < .0008$ ).

The regression analyses revealed significant associations between switch costs and slope ( $F(3, 428) = 9.04, p < .001$ , adjusted  $R^2 = .05; \beta = -4.81, 95\% \text{ CI } [-6.7, -2.93] |t/(428) =$

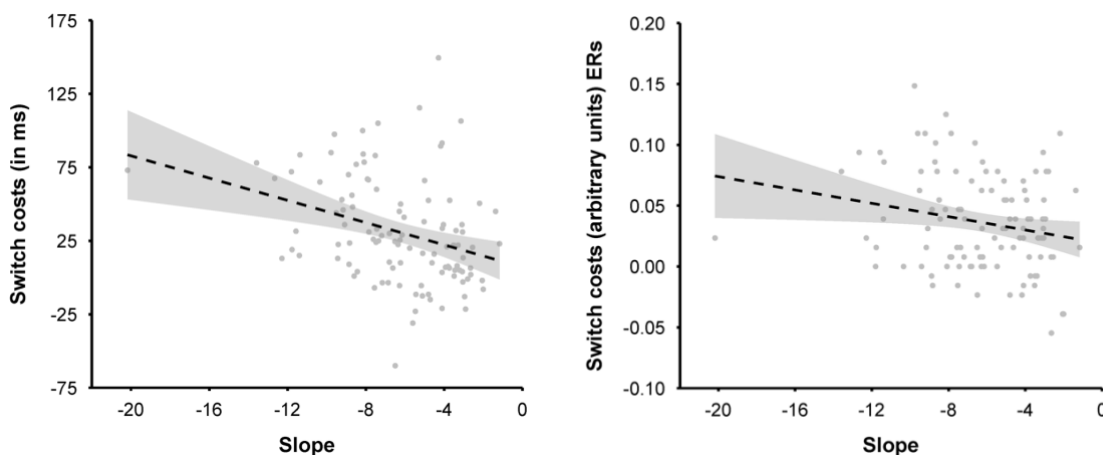
5.02,  $p < .001$ ;  $F(3, 428) = 3.1$ ,  $p = .027$ , adjusted  $R^2 = .01$ ;  $\beta = -0.00$ , 95% CI [-0.00, -0.00]  $|t/(428) = 2.66$ ,  $p = .008$ , for switch costs in terms of RTs and ERs, respectively). Specifically, those participants who showed a large difference in switch costs both in terms of RTs and ERs between the two contexts during the learning phase (i.e., participants with a large slope value), showed larger overall switch costs during the diagnostic phase than did participants with smaller slope values from the learning phase (see Figure 5). However, note that these effects were independent of context, meaning that there was no difference in switch costs regarding the slope between the PHTSF and PLTSF context.

When correlating individuals' slopes with RTs in the diagnostic phase we observed no correlation with task repetition trials ( $r(105) = -0.13$ ,  $p = .183$ ), but did observe a significant correlation with task switch trials ( $r(105) = -0.22$ ,  $p = .021$ ). Specifically, for individuals with a larger, negative slope (i.e., larger difference in switch costs between HTSF and LTSF during learning phase) RTs on switch trials were larger. We did not observe any differences when correlating individuals' slopes with ERs neither for task repetitions ( $r(105) = -0.02$ ,  $p = .85$ ), nor for task switches ( $r(105) = -0.15$ ,  $p = .11$ ).

Moreover, there was no significant correlation between the slope parameter and the sum NFC scores,  $r(106) = -0.06$ ,  $p = .51$ , indicating that there is no linear relationship.

## Figure 5

### *Switch Costs as a Function of Slope*



*Note* The relationship of switch costs (i.e., in terms of response times and error rates) with slope. Each dot represents an individual participant.



## Discussion

Our main research aim within the present study was to assess whether demand on cognitive flexibility can become associated with specific stimulus contexts (i.e., locations), whether these learned associations are being transferred to a subsequent phase, and whether such associations correlate with NFC. Our research was inspired by the current task-switching literature, the work by Musslick and colleagues (2018, 2019), as well as the finding that cognitive control can be triggered by external factors such as context (Braem et al., 2019). Altogether, these observations inspired us to create an experiment in which we manipulated the task switch frequencies across two contexts during the learning phase, which we then lifted in the diagnostic phase, in order to assess whether effects of the learning phase are transferred. Additionally, for both phases, we tested whether individual's NFC affected task-switching performance. Finally, by means of an exploratory analysis, we tested whether switch costs in the diagnostic phase differed based on how individual participants displayed a response to the task switch frequency manipulation in the learning phase (i.e., slope). We will address each of these questions in turn.

First, for the learning phase, both in terms of RTs and ERs, our analyses revealed significantly smaller switch costs in the HTSF compared to the LTSF context. This finding is in line with numerous previous studies (e.g., Fröber & Dreisbach, 2017; Leboe et al., 2008; Liu & Yeung, 2020; Monsell & Mizon, 2006; Musslick et al., 2019) and has been argued to stem from an induced preparation to switch tasks in situations where this is frequently required (e.g., Fröber & Dreisbach, 2017), characterized by decreased allocation of cognitive control to single tasks (Musslick et al., 2019). More specifically, post-hoc analyses indicated that during the learning phase, RTs and ERs (latter only marginally) differ for the HTSF and LTSF contexts on task repetitions but not on task switches. This finding is in line with previous research (e.g., Liu & Yeung, 2020) and shows that smaller switch costs in a HTSF context result from larger RTs (ERs) on task repetitions rather than smaller RTs (ERs) on task switches. Specifically, smaller switch costs in a HTSF context actually do not mean that task switching is faster or more accurate (in terms of RTs and ERs), but rather that task repetitions are slower and less accurate. Nonetheless, a decrease in switch costs with an increase in task switch frequency is generally interpreted as an increase in cognitive flexibility (Fröber & Dreisbach, 2017; Musslick et al., 2018; Musslick et al., 2019), even though there is no actual increase in performance on task switching in terms of RTs and ERs. This interpretation clearly differs from the general notion that there is a gain in task switching performance in HTSF contexts. More specifically, performance on task repetitions in the HTSF context was actually faster and more accurate. At this moment we have no clear

explanation for these findings, which demonstrates the importance for future research to address this discrepancy.

Second, for the diagnostic phase, we expected these effects to persist, in the sense that participants would show smaller switch costs in the context in which they were previously presented with the HTSF compared to the LTSF manipulation. In contrast to our hypothesis, the analyses revealed that, in the second half of the diagnostic phase, switch costs in terms of RTs were significantly larger in the PHTSF context compared to the PLTSF context. Evidently, even though switch frequency was equal across the two contexts in this phase, switch costs became larger with time in the PHTSF context compared the PLTSF context. The finding that there are significant differences in switch costs between the two contexts in the diagnostic phase, despite the balanced switch frequency, suggests an effect of the manipulation during the learning phase that persists even when the manipulation is lifted. However, post-hoc analyses revealed no significant differences between the contexts in terms of RTs for neither task repetitions nor task switches in block 2. Accordingly, the observed difference in switch costs in the second half of the diagnostic phase is not solely driven by either performance on task repetition trials, or task switch trials. An explanation for the higher switch costs in the PHTSF context might be inadequate preparation. More specifically, Dreisbach and Haider (2006) suggest that when provided with information about task switch frequencies, people prepare more strongly for HTSF situations than for LTSF situations. They further argue that preparation for the probable task is associated with inhibition of the improbable task, such as inhibition of the previous task when task switches are probable. Hence, in our study, preparation for the PHTSF context would be accompanied by inhibition of previous tasks, supposedly leading to faster RTs on task switches. However, when facing an equal number of repetitions rather than only 25%, participants might have started getting confused. It might be that this confusion about expected and actual task switch frequency is the reason why switch costs in the PHTSF context increased in block 2. The fact that participants were not similarly confused in the PLTSF context would be in line with Dreisbach and Haider's (2006) finding that people generally prepare less for LTSF situations.

Third, similarly contradicting our hypothesis, we did not find any significant effect for switch costs in terms of ERs in the diagnostic phase suggesting that they were unaffected by effects of the learning phase. This finding is rather unexpected, since Liu and Yeung (2020) predominantly found effects of false expectations in terms of errors. However, note that the main difference between their and our study is that Liu and Yeung (2020) provided explicit instructions about task-switch frequencies allowing for preparation, while we did

not. Hence, this finding indicates that our manipulation in the learning phase, even though some of our participants did report to have correctly noticed the difference between the two contexts, does not cause the same effects as explicitly formed expectations did in the Liu and Yeung (2020) study. A possible cause for this might be that noticing a difference while performing a task is inherently different from being informed of a difference prior to initiating a task, mainly due to the certainty allowing for preparation present in the latter but not in the first condition. This is being referred to as endogenous preparation (Sohn & Anderson, 2001) as well as proactive control and has been shown to benefit cognitive performance by allowing for anticipatory activation of goal relevant information (Braver, 2012). In contrast with Liu and Yeung's (2020) study, it is likely that the behavior of participants in our study is shaped reactively (as compared to proactively), characterized by later activation of goal relevant information (Braver, 2012). Moreover, even when noticing a difference between the two contexts, participants in our study cannot be certain of this difference, which also became apparent in their report after having completed the experiment. Hence, any preparation based on this uncertainty has at least some element of a gamble, which would explain a less pronounced preparation, which is in line with the general absence of significant effects for the diagnostic phase. Specifically, when uncertain of a manipulation, adjusting one's cognitive control accordingly might result in negative effects on performance, which is why cautious control allocation would result in a higher chance for maximized performance in terms of the stability-flexibility trade-off.

Furthermore, and in contrast to our expectations, for both switch costs in terms of RTs and ERs and for both experimental phases, we did not observe a modulation of effects by NFC. Our expectation regarding NFC was based on the strong relation between NFC and typical intellectual engagement (TIE) and learning (Woo et al., 2007; von Stumm & Furnham, 2012), indicating an increase in motivation to understand and explore the tasks and wider context one is dealing with. Along similar lines, Liu and Yeung (2020) have found motivation to follow instructions to be crucial in global control influences in task switching, however, contrary to ours, their study included explicit instructions. In fact, our findings of no modulation of effects by NFC might relate to the lack of explicit instructions in our study.

Finally, for both the switch costs in terms of RTs and ERs, our analyses revealed that those participants who showed a large difference in switch costs between the two contexts during the learning phase (i.e., participants with a large negative slope), showed larger overall switch costs during the diagnostic phase, however, independent of context. Our post-hoc analysis of the correlation of individual's slopes with RTs and ERs, revealed increasingly slower RTs and higher ERs on task switches with increasing slope.

Specifically, those individuals with a larger slope show higher switch costs in the diagnostic phase as a result of larger RTs and ERs on task switches. This finding could be explained by inadequate endogenous preparation related to incorrect foreknowledge. Specifically, foreknowledge facilitates endogenous preparation providing a performance benefit (Sohn & Anderson, 2001) in terms of reduced switch costs only if the foreknowledge is correct. Incorrect foreknowledge, however, would result in inadequate endogenous preparation, likely resulting in decreased performance. By contrast, reactive control relies on external factors that indicate a certain sequence of actions, which, once activated, provides a benefit when repeating tasks (Sohn & Anderson, 2001; Braver, 2012). Our findings suggest that those participants with a large slope during the learning phase acquired foreknowledge in some form (implicitly) and are consequently prepared to perform task switches in one, and task repetitions in the other context during the diagnostic phase. However, they encounter equal switch and repetition frequencies in both contexts, meaning they are inadequately prepared in both contexts, which could further explain why the finding is independent of context. Participants with a smaller slope value and seemingly no foreknowledge, in contrast, benefit from task repetitions and hence show smaller switch costs in comparison. Moreover, and along similar lines as previously discussed, there was also no relation between NFC scores and the slope values. Consequently, the slope value might not show actual effects of learning, which would relate to NFC, but rather implicit associations between context and task switch frequency that subsequently do not result in the same effects as explicit instructions in the Liu and Yeung (2020) study.

Concluding, within the present study we first established that demand on cognitive flexibility can become associated with specific stimulus contexts in our learning phase. Interestingly, even though we found a reduction in switch costs in the HTSF context, performance on task repetitions was still faster and more accurate, which is the reason for our suggestion that future research should investigate this. For the diagnostic phase, we did not observe a transfer of these effects, but instead an unexpected increase in switch costs in terms of RTs in the previous HTSF context with time. Moreover, there were no modulations of effects by NFC, which we suggest might be a consequence of missing explicit instructions. Interestingly, there were increases in switch costs during the diagnostic phase for participants with a large slope, indicating that there were not only differences between participants in the extent to which they were affected by the manipulation in the learning phase, but that these differences affected performance in the diagnostic phase.

The results of our study provide insights into some practical implications, especially since one of the crucial aspects that changed in daily life due to the recent COVID-19

pandemic is in fact context. Pre-COVID our daily life was naturally divided into different contexts for us: we worked at the office, we exercised in the gym, we had drinks in bars, all of which now take place in the same context, that is people's homes. Our study suggests that context indeed plays a role in our ability to adjust to demand on cognitive flexibility and facilitating associations between these two can lead to an increase in performance in terms of speed and accuracy. When working from home we largely rely on cognitive flexibility allowing us to manage the variety of tasks we encounter. Dedicating different contexts (e.g., locations) to task repetitions and task switches might therefore enhance performance at home, though the implications of the current findings in real life still require further investigation. Nonetheless, our study provides a starting point, especially in light of the trend to keep working from home (at least partly) even after the pandemic is under control (see e.g., Vyas & Butakhieo, 2020).

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## Appendix A

### **Items That Compose the Need for Cognition Scale-6 (NCS-6) (Lins de Holanda Coelho et al., 2020).**

01. I would prefer complex to simple problems.
02. I like to have the responsibility of handling a situation that requires a lot of thinking.
03. Thinking is not my idea of fun. (R)
04. I would rather do something that requires little thought than something that is sure to challenge my thinking abilities. (R)
11. I really enjoy a task that involves coming up with new solutions to problems.
15. I would prefer a task that is intellectual, difficult, and important to one that is somewhat important but does not require much thought.