Internal consistency and test-retest reliability of an affective task-switching paradigm

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Abstract

Affective flexibility refers to the flexible adaptation of behavior or thought given emotionally relevant stimuli, tasks, or contexts, and has been associated with the efficiency of emotion regulation and dealing with stress and adversity. Experimentally, individual differences in affective flexibility have been measured as behavioral costs (response times, errors rates) of switching between affective and neutral tasks. However, behavioral task measures can only be treated as trait-like characteristics if they have sufficient psychometric quality. We report an analysis of the test-retest reliability (interval two weeks) as well as internal consistencies of behavioral switch costs measured in an affective task switching paradigm. This paradigm elicits strong response time switch costs for both tasks, but higher when switching to the emotion than to the gender task. These ‘asymmetric switch costs’ suggest dominance of the emotional task rule. Reliability analyses indicated excellent internal consistency estimates (Spearman-Brown corrected $r = .92$ for both switch directions) and good test-retest reliabilities (ICC(2,1) of .78 and .82, respectively) for response time-based switch costs. Effect sizes and reliability estimates were substantially lower for switch costs calculated from error rates, which is consistent with previous literature discussing the psychometric properties of task-based cognitive measures. Reliability measures were lower but still acceptable for valence-specific response time-based switch costs, potentially due to lower trial numbers per cell when increasing granularity of the analysis. In conclusion, our results indicate that response time-based affective switch costs are well-suited as individual differences measure, and thus may be a valuable proxy for assessing affective flexibility.

Introduction

Successful self-regulation requires the flexible engagement and disengagement of attention from affective information. In experimental psychology, the ability to flexibly switch between competing demands is typically tested using paradigms in which participants switch between two different behavioral tasks performed on the same (type of) sequentially presented stimuli. The cognitive effort associated with reconfiguration of the ‘task set’ between the two tasks reduces performance accuracy (i.e., error rates; ER) and prolongs response times (RT), an effect that has become known as ‘switch cost’ (Monsell, 2003). Switching efficiency varies between persons (e.g., Armbruster et al., 2012; Armbruster-Genç et al., 2016), and it is more and more recognized that these differences are also important for the regulation of emotions, e.g., when intentionally counteracting ‘bottom-up’ effects of emotional experiences (e.g., Bonanno & Burton, 2013; Kashdan & Rottenberg, 2010). In this context, ‘affective flexibility’ has most often been investigated as the efficiency of switching between two experimental tasks, of which at least one focuses on the affective component of the stimuli. Typically, this is achieved by using stimuli containing two (or more) possible dimensions or layers of information, like images of faces with different emotional expressions (Piguet et al., 2013; Reeck & Egner, 2015), affective words (Genet & Siemer, 2011), or images of potentially arousing scenes (like the International Affective Picture Set; e.g., Grol & De Raedt, 2018; Malooly et al., 2013). Participants are instructed to switch between evaluating either the affective aspect of the stimulus (e.g., the emotional expression of a face) or its affectively neutral dimension (e.g., the gender of the presented face). Beyond the cognitive processes involved in the reconfiguration of task sets, this affective variant of the task switching paradigm additionally requires the flexible engagement and disengagement from emotional information present in the stimulus. For the purposes of the present study, we follow this approach and operationally define affective flexibility as the switching between a neutral and an emotional task in the presence of emotional

information (see also Grol & De Raedt, 2018; Malooly et al., 2013; Wen & Yoon, 2019). We will thus, in the following, use the terms affective flexibility and affective task switching interchangeably.

It is increasingly recognized that dysfunctional cognitive control over emotions and over the processing of emotionally salient stimuli (e.g., Bishop, 2007; Joormann, J., Yoon, K. L., & Siemer, M., 2010) is characteristic for affective disorders like depression or anxiety. In this context, experimental measures aimed at investigating the cognitive control over emotional processing - like the affective task switching paradigm - can contribute important insights into the development and maintenance of psychological disorders. Indeed, first results suggest that individual differences in the efficiency of switching between emotional and neutral tasks are associated with emotion regulation abilities (Malooly et al., 2013) and stress resilience (Genet & Siemer, 2011). Affective switch costs and switch costs from emotionally neutral paradigms have been shown to correlate but despite their procedural similarity, this correlation is of only small to moderate effect size (Genet, Malooly, & Siemer, 2013; Genet & Siemer, 2011; Kraft et al., 2020; Malooly et al., 2013). Also, the affective nature of the stimuli seems to alter the implicit salience of the task rules that are competing for attentional resources. This is demonstrated by a pattern of ‘asymmetric’ RT switch costs, i.e., higher switch costs when switching to the affective than when switching to the neutral task (Reeck & Egner, 2015; Kraft et al., 2020), which can be interpreted as necessitating greater inhibition efforts on the attentionally dominant affective task. This suggests that affective task switching is more than a mere variant of the cognitive task switching paradigm with different stimuli, and thus deserves to be studied in more depth.

In order to detect correlational relationships between measures derived from cognitive tasks and other psychological constructs, trait-like individual differences have to be quantified

accurately. This, in turn, makes it necessary to establish psychometric quality also for measures derived from experimental paradigms (see Enkavi et al., 2019; Hedge, Powell, & Sumner, 2018; Parsons et al., 2019 for in-depth discussions). For affective task switching costs, this has so far not yet been established. However, even though non-affective task-switching paradigms (with affectively neutral stimuli and tasks) have been studied extensively, the psychometric properties of switch costs have so far only rarely been assessed and seem to vary between different implementations of the paradigm. Classical (i.e., affectively neutral) RT switch cost measures (i.e., RT differences between switch and repeat trials) showed moderate test-retest reliabilities. For example, Paap and Sawi (2016) reported a test-retest correlation of $r = .62$ for a color-shape switching task and Timmer et al. (2018) reported correlations of $r = .57$ for a non-linguistic and $r = .74$ for a linguistic switching task, respectively. To the best of our knowledge, there are no studies reporting test-retest reliability for ER switch costs. Internal consistency (i.e., split-half reliability determined within one session) of RT switch costs have been reported to be moderate ($r = .67$; Pettigrew & Martin, 2016) to good ($\alpha = .86$; Hughes et al., 2014), but may be influenced by accuracy, as in the latter study internal consistency dropped to $\alpha = .48$ in a second sample in which more errors were elicited due to a set-up favoring particularly fast response behavior. Internal consistencies of ER-based switch costs were consistently low in this study ($\alpha < .48$ in both samples; Hughes et al., 2014).

This brief and admittedly selective review of the literature suggests that RT- but not ER-based switch costs are well-suited as an experimental measure of individual differences in cognitive flexibility. However, despite the emergent interest in studying individual differences in affective flexibility, the psychometric properties of experimental measurements of *affective switch costs* have so far not been investigated. To fill this gap, we assessed the test-retest reliability and internal consistency of switch costs in a recently-introduced affective task

switching paradigm (Kraft et al., 2020). To give readers an insight into the effects of trial numbers on the reliability of switch cost measures, all analyses were also repeated with only half of the dataset. Lastly, as specific research questions may explicitly require to investigate performance differences depending on the valence of the stimuli, we also repeated all reported analyses with a higher level of granularity, i.e., by resolving switch costs also by the valence of the affective stimuli.

Methods

Data and analysis code are available at the PsychArchives repository under <http://dx.doi.org/10.23668/psycharchives.3104>

Procedure, data exclusion and sample characteristics

A power analysis using the R package ‘pwr’ (version 1.3-0; Champely et al., 2020) yielded a sample size of at least $N=47$ for detecting a minimum acceptable test-retest correlation of $r = .60$ with a power of $1-\beta = .90$ and a conservative significance level of $p = .001$ (to take into account that twelve outcome variables will be tested). Note that we had determined $r = .6$ as a minimally interesting effect size given the literature on reliabilities of cognitive task switching paradigms reviewed above. 51 students of psychology participated on two appointments and were reimbursed with course credits. We excluded one left-handed participant, one participant with a high error rate ($>30\%$) in one of the baseline conditions, and two participants who did not complete the second appointment of the study. Accordingly, the final study sample consisted of 47 participants (12 males) with a mean age of 23.09 ± 4.41 years (18 to 35 years)¹.

¹ Note that one participant showed substantially slower response times than the rest of the sample (i.e., across conditions and sessions on average 349ms slower than the average of the remaining

Test and retest sessions were separated by 11 to 17 days, mean $13.91 \pm .83$ days (SD). Whenever possible, participants were re-tested at the same time of day (mean time lag = 37.64 ± 56.95 minutes; range 1 to 302 minutes). Participants provided written informed consent according to procedures approved by the Ethics Committee of the Department of Psychology of Goethe University, Frankfurt.

Stimuli and experimental paradigm

In line with previously published studies of affective task switching (Dierolf et al., 2016) and given that affective faces have high ecological relevance and elicit well-established effects on attention (see e.g., Engen et al., 2017; Öhman et al., 2001; O'Toole et al., 2011), images of angry and happy faces were used as stimuli. Angry facial expressions are of particular salience and have been shown to elicit strong attentional prioritization effects, which has been attributed to their evolutionary importance as a signal of direct threat (Öhman et al., 2001, 2012). Happy faces, on the other hand, are easily perceptually distinguished from angry faces and allowed us to investigate the contrastive roles of positive vs. negative valence on task switching. Pictures of 120 different faces (60 female, 60 male) were selected from the FACES database (Ebner et al., 2010) according to the discriminatory power of their angry expression, by selecting those images with highest accuracy rates for the emotion 'angry' (based on the normative sample of $N = 154$ raters, accuracy range 83% to 100%; mean 90,92%; see also Kraft et al., 2020). Images of the selected persons were then used for both emotional expressions (angry and happy), so

sample) and also a slowing of RTs from test to retest. However, this participant was not identified as outlier as given our accuracy-based criterion for outlier rejection. Reliability estimates changed only minimally when excluding this participant: internal consistencies ranging between .92 and .93 for RTs (compared to .92 in the full sample; cf. Table 2); test-retest reliability ranging between .73 and .79 for RTs (compared to .79 to .87 in the full sample) and between .79 and .81 for RT-based switch costs (compared to .78 to .88 in the full sample).

that 240 stimuli in total were used for the experiment. We aimed to keep the images as naturalistic as possible to ensure a particularly fast and automatic processing. Accordingly, we decided against removal of hair information or monochromatic presentation of the stimuli.

In the affective flexibility paradigm (see Kraft et al., 2020, for details and Figure 1 for pictorial representation) participants categorize the 240 different affective facial stimuli (per run) either according to an affectively neutral gender task (female vs. male) or an emotion task (happy vs. angry facial expression). Participants were seated in a dimly lit room, in front of a 22'' computer screen while their head was fixated by a chin rest. The task was presented with Presentation software (Version 20.01 10.19.17 build, Neurobehavioral Systems, Inc., Berkeley, CA, www.Neurobs.com). Responses were recorded via four buttons on a conventional keyboard, with task rules assigned to the two response hands. Target images were presented either above or below the central fixation point, and locations changed every 3-7 trials, thereby indicating the necessity to switch task. The rule-location mapping was counterbalanced across subjects but kept constant across sessions. The task comprised two runs of 8 minutes length (separated by a break of ~1 minute), each with 192 repeat and 48 switch trials comprising the same 240 stimuli in randomized order. Stimuli were presented for 1 second and followed by a 1-second inter-trial-interval. Participants were extensively trained and only admitted to the main task when their performance exceeded 65% correct responses in switch and repeat trials. Upon retest, a short refresher training was applied.

Statistical analysis

All statistical analyses were conducted in RStudio (version 1.3.959) running on R version 3.6.3 (2020-02-29; R Core Team, 2020). Trials with response times below 250ms and greater than three standard deviations above the person's condition-specific mean (i.e., repeat vs. switch, after excluding error trials) were considered outliers and excluded from RT analyses (test: mean

= 6.47 ± 2.88 trials, range 0 - 13; retest: mean = 6.21 ± 2.64 trials, range 0 – 11). Note that the number of RT outliers was not influenced by stimulus properties; this is indicated by a repeated-measures ANOVA with numbers of RT outlier trials as dependent variable, which yielded no main effects of Session, Emotion, or Gender, and no interactions, all $p > .19$. Similarly, these stimulus effects also had no significant influence on the number of errors elicited in the task (all $p > .07$). Switch costs in RTs and ERs were calculated by subtracting the mean for all repeat trials from the mean of all switch trials, in each participant and separately for switches to the emotion and to the gender task. Repeated measures ANOVAs evaluated the effects of Session (test vs. retest), Task (emotion vs. gender), and Condition (repeat vs. switch) on RTs and ERs. Post-hoc contrasts were calculated using the *emmeans* package for R (version 1.4.8; Lenth et al., 2020). For descriptive reasons, estimated marginal means (EMMs), as well as corresponding standard errors (SE) and 95% confidence intervals (CI) are reported for significant main effects. As measure of effect size, we calculated ‘Hedges g’ for the difference between repeat and switch trials.

Internal consistency of switch costs was determined via permutation-based split-half reliability estimates (5,000 random splits), obtained separately for each session and task, using the *splithalf* package for R (version 0.7.1; Parsons, 2020). Results are reported as Spearman-Brown corrected correlations (r_{SB}). To determine test-retest reliability, we calculated two-way mixed-effects models for absolute agreement intraclass correlation, ICC(2,1), and Pearson correlations (to ensure comparability with the literature). ICCs, their 95% confidence intervals (CIs), and variance components for between-subject, between-session, and error variances were calculated for mean RTs, mean ERs, and the respective difference measures (switch costs) using the *psych* package for R (version 1.8.12; Revelle, 2020). ICC(2,1) was chosen because this form of ICC treats the two ratings as random effects and thus allows for differences in means (Shrout & Fleiss, 1979). However, choice of statistic does not affect our conclusions, as ICC(3,1)

performed very similar to ICC(2,1). Reliability indicators less than 0.5 were interpreted as poor reliability, values between 0.5 and 0.75 as moderate reliability, and values between 0.75 and 0.9 as good reliability (Koo & Li, 2016). To explore whether the task can also be reliably administered in a shorter version, we also estimated reliabilities for the first block separately (50% of trials, i.e., 240 trials).

As specific research contexts may also make it necessary to analyze switch costs depending of the valence of the stimulus on which the switch is implemented or depending on the valence of the previous stimulus, we repeated all reported analyses at a finer grain of resolution, i.e., by including Current valence and Previous valence as additional factors. To avoid unnecessary model complexity (and given that all previous analyses yielded highly robust switch cost effects; see Results section), these analyses were based on switch costs as dependent variables (so that switch vs. repeat condition was not entered as factor into this analysis). Note that in this analysis switch cost measures were based on substantially lower numbers of observations per cell, with 12 switch trials and 48 or 47 (at the beginning of a block, where the trial has no preceeding stimulus) repeat trials. We first calculated eight valence-specific switch costs (switch – repeat) for each Session (test and retest) and outcome measure (RT and ER), for all possible combinations of Task (emotion vs. gender), Previous valence (angry vs. happy), and Current valence (angry vs. happy). As an example, ‘Switch costs emotion happy – angry’ refer to switch costs in the emotion task that emerged while participants switched from the gender judgment of a happy repeat image to the emotion judgement of an angry switch image (which were calculated by subtracting the average performance in repeat trials on angry faces in the emotion task, preceded by a happy face from the average performance in switch trials on angry faces in the emotion task, preceded by a happy face). Separate repeated measures ANOVAs for RT and ER switch costs were then calculated evaluating the effects of Session (test vs. retest),

Task (emotion vs. gender), Previous valence (angry vs. happy) and Current valence (angry vs. happy).

Results

Characterization of Affective Switch Cost Effects

Response times. Descriptive statistics, including effect size estimates for switch costs, are presented in Table 1. Repeated measures ANOVA indicated a main effect of Condition, $F(1,46) = 296.0, p < .001$, with faster responses in repeat trials (estimated marginal mean (EMM) = 657ms, $SE = 15.6$, 95% CI [626, 688]) than in switch trials ($EMM = 901$ ms, $SE = 15.6$, 95% CI [870, 932]). Participants responded faster in the second session ($EMM = 771$ ms, $SE = 14.4$, 95% CI [742, 800]), than in the first session ($EMM = 788$ ms, $SE = 14.4$, 95% CI [759, 817]), $F(1,46) = 4.28, p = .04$. A main effect of Task reflects faster responses to the gender ($EMM = 767$ ms, $SE = 14.4$, 95% CI [738, 796]) compared to the emotion task ($EMM = 792$ ms, $SE = 14.4$, 95% CI [763, 820]), $F(1,46) = 10.41, p = .002$. Inspection of the interaction terms revealed a significant Condition $\times$ Session interaction, $F(1,46) = 21.38, p < .001$. While switch trials were significantly accelerated during retest compared to the first session, $t(64.4) = 3.81, p < .001$, repeat trials were not, $t(64.4) = -.05, p = .96$. A significant Condition $\times$ Task interaction, $F(1,46) = 15.36, p < .001$, indicated differential task effects on the two conditions. While switch trials were significantly faster in the gender task than in the emotion task, $t(73) = 4.74, p < .001$, repeat trials did not differ between tasks, $t(73) = .86, p = .39$. The Task $\times$ Session and 3-way interaction were not significant.

Error rates. Descriptive statistics of condition-specific error rates and switch costs are presented in Table 1. Repeated measures ANOVA indicated a significant main effect of

Condition, $F(1,46) = 29.74, p < .001$, with fewer errors in repeat ($EMM = .06, SE = .009$, 95% CI [.04, .08]) than switch trials ($EMM = .10, SE = .009$, 95% CI [.09, .12]). Performance was more accurate in the second ($EMM = .08, SE = .008$, 95% CI [.06, .09]) than in the first session ($EMM = .09, SE = .008$, 95% CI [.07, .11]), $F(1,46) = 11.12, p = .002$. ERs did not significantly differ between emotion and gender task, $F(1,46) = 2.73, p = .11$. Analogous to RT switch costs, a Condition $\times$ Session interaction, $F(1,46) = 9.71, p = .003$, indicated differential training effects on error rates in the switch vs. the repeat condition. ERs decreased from first to second session in switch trials, $t(91) = 4.56, p < .001$, but not in repeat trials, $t(91) = .40, p = .69$. Lastly, a Condition $\times$ Task interaction, $F(1,46) = 9.64, p = .003$, reflects that while ERs were significantly higher in switch trials of the emotion task than in switch trials of the gender task, $t(86.2) = 3.20, p = .002$, no task-specific differences were revealed for ERs in repeat trials, $t(86.2) = -.58, p = .56$. No significant Task $\times$ Session or 3-way interaction were found.

Association between RT and ER switch costs. RT and ER switch costs were not correlated in any of the tasks or sessions (all $r_s < .23$, all $p \geq .13$).

Reliability Analyses

Internal consistencies. Internal consistencies for response time (RT) switch costs were consistently high (all $r_{SB} = .92$), but much lower for error rate (ER) switch costs (all $r_{SB} \leq .70$). Task- and session-specific reliability estimates are given in Table 2, together with 95% confidence intervals. Estimating reliabilities for the first block separately (50% of trials, i.e., 240 trials) reduced internal consistencies for RT-based switch costs only marginally (all $r_{SB} \geq .85$), while ER-based switch costs were more strongly reduced (all $r_{SB} \leq .54$, see Table 3).

Test-Retest reliability. As shown in Table 2, test-retest reliability estimates for condition-specific mean RTs and mean ERs were satisfying, i.e., all $ICC(2,1) > .70$. Estimated test-retest agreement for RT switch costs was $ICC(2,1) = .82$, 95% CI [.48, .92], in the gender task and $ICC(2,1) = .78$, 95% CI [.60, .88], in the emotion task. ER switch costs showed lower reliability estimates, with an estimated test-retest agreement of .62, 95% CI [.42, .77], in the gender task and .68, 95% CI [.46, .81], in the emotion task. Variance components for between-subject, between-session and error variance underlying ICCs for RT and ER measures are illustrated in Figure 2. For the sake of comparability to previous work, Table 2 also lists Pearson correlations between test and retest, which were consistently at $r_{\text{Pears}} > .8$ for RT measures and $r_{\text{Pears}} > .65$ for ER measures. Repeating these analyses for the first block of the experiment resulted in lower test-retest reliability, i.e., with $ICC(2,1)$ between .66 and .75 for RT switch costs and $ICC(2,1)$ between .45 and .39 for ER switch costs (see Table 3).

Valence Effects on Affective Switch Costs and their Reliabilities

Response time-based switch cost effects. Descriptive statistics for switch costs when resolving conditions additionally by current and previous valence (see Methods section for details) are presented in Table 4. Equivalent to the main analyses, a repeated measures ANOVA of RT-based switch costs revealed significant main effects of Session, $F(1,46) = 21.66$, $p < .001$, and Task, $F(1,46) = 16.73$, $p < .001$. Overall, participants showed lower RT-based switch costs at retest ($EMM = 228\text{ms}$, $SE = 14.6$, 95% CI [198, 257]) than in the first session ($EMM = 262\text{ms}$, $SE = 14.6$, 95% CI [233, 292]) and in the gender task ($EMM = 228\text{ms}$, $SE = 14.8$, 95% CI [198, 257]) than in the emotion task ($EMM = 262\text{ms}$, $SE = 14.8$, 95% CI [233, 292]). Neither the main effect of Previous valence, $F(1,46) = .91$, $p = .35$, nor the main effect of Current valence, $F(1,46) = .03$, $p = .86$, reached significance. A significant interaction of the factors Task and Current valence, $F(1,46) = 12.13$, $p = .001$, indicated that the valence of the target stimulus had

task-specific effects on switching efficiency. When switching to the emotion task, RT switch costs were lower when participants were judging an angry face compared to a happy face, $t(92) = -2.31, p = .02$. However, this pattern reversed when participants switched to the non-affective task, with *higher* RT switch costs when judging angry as compared to happy faces, $t(92) = 2.56, p = .01$. Lastly, a Session x Previous valence x Current valence interaction emerged, $F(1,46) = 4.55, p = .04$, which could however not be resolved further by post hoc analyses. Besides that, no other 2-way, 3-way or 4-way interaction reached significance (all $p > .12$).

Error rate-based switch cost effects. Repeating this analyses for the error rate (ER-) based switch costs revealed main effects of Session, $F(1,46) = 10.14, p = .003$, and Task, $F(1,46) = 9.45, p = .004$, that had also emerged in the main analysis (see above). Participants showed lower ER-based switch costs in the retest ($EMM = .03, SE = .009, 95\% CI [.02, .05]$) than in the test session ($EMM = .05, SE = .009, 95\% CI [.04, .07]$) and in the gender task ($EMM = .02, SE = .01, 95\% CI [.005, .04]$) than in the emotion task ($EMM = .06, SE = .01, 95\% CI [.04, .08]$). None of the valence-related main effects or interactions reached statistical significance.

Reliability analyses. Compared to the switch costs reported above, i.e., when only resolving by task and condition, internal consistencies and test-reliabilities of switch costs dropped substantially when additionally resolving the data by the valence of the previous and the current stimuli (see Table 5). Note that in this analysis, trial numbers per cell were reduced to only 12 switch trials and a maximum of 48 repeat trials for each combination of task, current and previous valence. Still, internal consistencies of RT-based switch costs could be rated as moderate to good (all r_{SB} between .58 and .80), whereas they were poor to moderate for ER-based switch costs (all r_{SB} between .08 and .56). Test-retest reliabilities behaved comparably with moderate to good test-retest reliabilities for RT-based switch costs (all ICC(2,1) between

.61 and .76) and poor to moderate test-retest reliabilities for ER-based switch costs (all ICC(2,1) between .24 and .64; see Table 5).

Discussion

In this study, we assessed the psychometric quality of an affective task-switching paradigm that produces robust task switching effects. Switch costs differed between tasks, with higher switch costs when switching to the emotion task than when switching to the non-affective gender task. Internal consistencies and test-retest reliabilities were high for response time (RT)-based switch costs, suggesting that this measure is a reliable behavioral indicator for the efficiency of affective task switching. Importantly, test-retest reliability of the RT-based difference measure was not inferior to its components (i.e., to the condition-specific RT means). ER-based switch costs demonstrated only moderate reliability, which is consistent with previous literature for non-affective switch costs (Hughes et al., 2014). Reliability estimates were lower when based on smaller trial numbers per subject, i.e., when repeating the analyses on only the first of two experimental blocks, or when resolving the trials also by stimulus valence. While reliabilities for RT switch costs remained in a moderate to good range, these results clearly indicate that psychometric reliability benefits from measurements with larger trial numbers (see also Enkavi et al., 2019).

Good Psychometric Properties of Affective Response Time Based Switch Costs

From a methodological point of view, our results partly contradict previous reports of lower test-retest reliability for RT difference scores as compared to pure (i.e., condition-specific) RT mean scores from which the difference measure is calculated (Enkavi et al., 2019; Hedge, Powell, & Sumner, 2018b; Paap & Sawi, 2016; Strauss et al., 2005). It is a common scientific

practice to isolate specific cognitive component processes from more general processes shared between tasks or task conditions (e.g., perceiving the visual stimulus, motor processing etc.) by using subtraction methods (Donders, 1969). However, it has also been demonstrated that calculating difference scores can increase error variance at the expense of between-subject variance, which can cause lower reliability of difference-based measures from behavioral tasks (Hedge, Powell, & Sumner, 2018b; Miller & Ulrich, 2013). This effect might also be reflected in the moderate reliabilities that have been reported for switch cost measures in (non-affective) task switching studies (e.g., Paap & Sawi, 2016; Pettigrew & Martin, 2016; Timmer et al., 2018). One reason why this did not happen for the RT-based switch cost measures in the present study may relate to the particularly high effect sizes of affective RT switch costs measured with our paradigm, as compared to other reports in the field (see also Szucs & Ioannidis, 2017 for a more general discussion of effect sizes in psychology). Effect sizes were large for RT-based switch costs (all Hedge's $g > 1.7$; see Table 1), and simulation studies have demonstrated that the reliability of difference scores increases with increasing effect size (Miller & Ulrich, 2013). However, effect sizes were only in the medium range for ER-based switch costs (all Hedge's $g < 1$; see Table 1) and, accordingly, reliability estimates were also substantially lower for ER-based compared to RT-based switch costs.

The reliability of difference scores also depends on the relationship between the cognitive processes that are being contrasted: Miller and Ulrich (2013) predict particularly low reliabilities for difference scores based on 'common' mental processes, i.e., in cases in which the experimental and control processes do not differ qualitatively, but only quantitatively with respect to the amount of engagement of the process of interest (like the maintenance of different working memory loads). In task-switching, however, the need to reconfigure the task set implies (one or more) qualitatively different cognitive processes in the switch relative to the repeat condition. Automatic processes during repeat trials and strategic control processes

recruited for task set reconfiguration might even behave antagonistically: While more automatic processing of the stimuli might speed up response times during repeat trials, it would slow down task switches, as more cognitive effort is necessary to actively overcome the automatic processes related to the previous task set when switching to the new task. In our paradigm, these opposing processes might even be intensified as only one of the tasks engages the brain's emotion processing systems (Reeck & Egner, 2015).

Inferior Psychometric Properties of Affective Error Rate-Based Switch Costs

This general framework might equally offer an explanation for the divergent reliabilities between ER-based and RT-based switch costs. In line with previous reports of poor psychometric properties for ER-based switch costs (Hughes et al., 2014), internal consistency estimates and test-retest reliabilities were relatively low in our study when switch costs were calculated on the basis of ERs. As a probably related phenomenon, effect sizes of ER-based switch costs were much lower than those of RT-based switch costs (see previous paragraphs). This may reflect that ERs potentially aggregate fundamentally different types of errors – task-specific errors reflecting the cognitive ability under investigation, but also errors due to speed-accuracy trade-offs or extraneous factors (e.g., attention or motivation). Following the previous line of argument, the probability of errors might be determined to a greater extent by common factors affecting both conditions (like attention or motivation), and only to a lesser extent to specific processes that differ between conditions. This global ‘pollution’ of task- and condition-specific ERs by error sources that are not intrinsically tied to the construct of interest, might have detrimental consequences for reliability estimates of difference-based performance measures calculated from ERs and thus also complicate their interpretation as a proxy of affective task-switching abilities (see Schmidt et al., 2003, for a general discussion of error sources and their consequences for reliability measures).

In the classical task-switching literature (e.g., Monsell, 2003), it has been assumed that RT and ER switch costs are to be interpreted interchangeably – as two sides of the same medal, both reflecting task-switching ability and general executive control. However, this assumption has recently been questioned by a meta-analysis documenting inconsistent relationships between RT- and ER-based difference scores in a broad range of executive tasks (Hedge, Powell, Bompas, et al., 2018a). The authors of this meta-analysis further concluded that two general factors that influence the nature of a decision – response selection (i.e., the efficiency with which information is accumulated that can differentiate between two response options) and response caution (i.e., the subjective boundary or threshold that defines how much evidence is required before a decision is made) differentially affect these two allegedly congruent measures. Accordingly, these authors argue that RT costs and ER costs are rarely interchangeable as performance measures that reflect processing efficiency, when variance in response caution is not explicitly controlled for (Hedge, Powell, Bompas, et al., 2018a). In line with this notion, RT-based and ER-based switch costs showed no correlation in our study. Taken together, the commonly held view that RT- and ER-based switch costs are highly related task-specific performance measures of the same cognitive construct has to be questioned to some extent. In the case of our affective task-switching paradigm, the consistently better psychometric properties for RT-based switch costs suggest that this measure is the more specific and reliable proxy for individual differences in affective flexibility.

Implications for Clinical and Individual Differences Research

We were able to replicate the phenomenon of ‘asymmetric switch costs’ that has previously been reported for affective task-switching (Kraft et al., 2020; Reeck & Egner, 2015), with higher switch costs while switching to the affective (i.e., emotion) compared to the non-affective (i.e., gender) judgement. In cognitive task-switching, differing switch costs indicate asymmetrical dominance relations between competing tasks sets, with higher switch costs while

switching to the dominant task set, since stronger cognitive effort is necessary to release it from its backward inhibition (Monsell et al., 2000; Wylie & Allport, 2000). Emotional information is of high salience and tends to capture attentional resources via bottom-up processes (Yiend, 2010). Thus, more cognitive control resources may be needed to inhibit emotional responses and a greater amount of inhibition has to be released to reactivate them. Accordingly, when facing bivalent affective stimuli (potentially permitting both emotional and non-emotional responses), the former response appears to be more dominant. This might be of particular interest in the clinical context, as the balance between cognitive control and emotional processes is considered crucial for successful emotion regulation (Joormann et al., 2010) and is disturbed in many clinical conditions, as e.g., anxiety (e.g., Bishop, 2007).

Studies explicitly investigating the connection between performance in affective task-switching paradigms and clinically relevant constructs report positive associations between (partly valence dependent; see below) affective task-switching efficiency and indicators of psychological adjustment – including reappraisal efficiency (Malooly et al., 2013), trait resilience (Genet & Siemer, 2011; Rademacher et al., in prep.) and a better regulation of physiological arousal during stress exposure (Hildebrandt et al., 2016). Negative associations have been reported with indicators of psychological maladjustment – such as the habitual use of rumination (Genet et al., 2013) or higher levels of depression symptoms in a one-month follow-up (Wen et al., 2019). Interestingly, the association between psychological variables and task-switching performance was consistently stronger in affective vs. purely cognitive task-switching paradigms (Malooly et al., 2013; Genet et al., 2013; Rademacher et al., in prep.), indicating that affective task-switching ability might be a better predictor for psychological functioning than its cognitive counterpart. A highly reliable affective task-switching paradigm, such as presented here, is an important precondition for further expanding this research.

The dual-competition model (Pessoa, 2009) states that emotional and cognitive processes compete for limited attentional capacities. In line with this assumption, both detrimental and beneficial effects of affective material on executive functions have been reported, depending on whether emotional information was task-relevant or not (see Zinchenko et al., 2020 for a review). Valence-based analyses of our data supported these findings and indicated an interaction between task-relevance and threat-related information on affective task-switching: While presentation of an angry face accelerated switching towards the emotion judgement (when affective information was task-relevant), it slowed down switching towards the gender judgement (when affective information was task-irrelevant and had thus to be ignored). This pattern replicates previous results measured with the same paradigm in an independent dataset (Rademacher et al., in prep.) and can be aligned with attentional mechanisms, like attentional capture for threat-related stimuli (e.g., Engen et al., 2017; Öhman et al., 2001, 2012).

There is evidence that the ability to maintain cognitive control in face of competing negative affective information is associated with a favorable psychological outcome. Some of the associations between affective task-switching ability and psychological adjustment (as mentioned above) were most pronounced while switching to non-affective features of a negative image (Genet et al., 2013; Malooly et al., 2013). However, studies directly investigating the relationship between cognitive control, affective processes and psychological outcome are still rare. In the present study, reliability estimates decreased for valence-specific switch costs (most likely due to the low number of observations per cell), but were still in an moderate to good range. This indicates that the affective task switching paradigm can also be optimized further for tackling such more specific research questions.

Limitations

One limitation of the present work is that we can at present not generalize our reliability results beyond the specific stimulus materials used. Thus, it remains an empirical question whether different stimulus materials (e.g., images of affective scenes or affective words) or stimuli with other emotional dimensions than anger and happiness would produce task switching effects with comparably good reliabilities. However, comparison with the literature allows the cautious assumption that our results might be transferable to other threat-related stimuli, since asymmetric switch costs (see above) have been reported for fearful faces as well (Reeck & Egner, 2012). On the other hand, in an affective switching task using sad faces (Piguet, 2013) switch costs were not significantly different between the affective and the affectively neutral tasks. Threat-relevant (angry and anxious) faces have similar effects on attentional capture (e.g., Engen, 2017), whereas the effects of sad faces might be weaker (O'Toole, 2011). Still, future studies comparing effects of different stimulus materials will be needed to examine the generalizability of our results.

Second, we cannot rule out the possibility that specific stimulus characteristics (i.e., hair and color information) may have affected the difficulty of our tasks. When selecting the stimulus material, we aimed to select stimuli that are as naturalistic as possible. Therefore, we deliberately decided against removing hair information from the emotional faces and kept the stimuli as color images. However, this may have affected the difficulty of gender assessment, as this task may be relatively simple when taking into account the hair information. However, a closer look at the interaction between Condition (switch vs. repeat) and Task (emotion vs. gender) revealed that response time differences between the gender and the emotion task were only evident in switch trials, but not repeat trials. This contradicts the assumption that general differences in task difficulty may have influenced our response time results, since the assumed differences should then also exist in repeat trials.

Conclusions

In conclusion, we demonstrate good test-retest reliability for a newly developed experimental paradigm measuring the efficiency of affective task switching. The high between-subject variability combined with large effect sizes make affective switch costs a particularly well-suited measure for individual differences analyses. This is of great interest, as previous studies in clinical samples showed that executive control difficulties are particularly evident on tasks that require processing of emotionally relevant stimuli (Murphy et al., 2012). Accordingly, our paradigm might be well-suited for investigating executive control over affective bottom-up processes as well as potential dysfunctions of this important cognitive process in clinical populations.

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Table 1. Descriptive statistics of the affective task-switching paradigm.

Task Measure	T/C	<u>Response times (RT)</u>						<u>Error rates (ER)</u>					
		<i>Test</i>			<i>Retest</i>			<i>Test</i>			<i>Retest</i>		
		Mean	SD	ES	Mean	SD	ES	Mean	SD	ES	Mean	SD	ES
Repeat Gender	192	649.91	67.91		657.01	89.69		.07	.03		.06	.04	
Switch to Gender	48	897.28	123.17		863.87	139.85		.10	.09		.08	.08	
Switch costs Gender	192/48	247.37	107.81	2.47	206.86	106.20	1.75	.03	.08	.45	.02	.06	.27
Repeat Emotion	192	664.10	81.25		657.92	99.57		.06	.04		.06	.05	
Switch to Emotion	48	939.70	142.60		904.34	150.83		.13	.11		.11	.11	
Switch costs Emotion	192/48	275.61	109.00	2.36	246.42	100.44	1.91	.07	.08	.91	.05	.08	.58

Note. T/C = Maximum number of trials per condition (i.e., before exclusion of outliers or error trials), SD = standard deviation, ES = effect size (Hedge's g).

Table 2. Test-retest reliability of behavioral measures from the affective flexibility task.

	T/C	<u>Response times (RT)</u>				<u>Error rates (ER)</u>			
		<i>Internal consistency</i>		<i>Test-retest reliability</i>		<i>Internal consistency</i>		<i>Test-retest reliability</i>	
		r _{SB} (test)	r _{SB} (retest)	ICC(2,1)	r _{Pears}	r _{SB} (test)	r _{SB} (retest)	ICC(2,1)	r _{Pears}
Repeat Gender	192			.79	.82			.80	.82
				[.66, .88]	[.70, .90]			[.67, .88]	[.70, .90]
Switch to Gender	48			.84	.87			.73	.76
				[.68, .92]	[.78, .93]			[.57, .84]	[.60, .86]
Switch costs Gender	192/48	.92	.92	.82	.88	.69	.51	.62	.66
		[.87, .95]	[.88, .96]	[.48, .92]	[.79, .93]	[.54, .81]	[.25, .71]	[.42, .77]	[.46, .80]
Repeat Emotion	192			.82	.83			.80	.83
				[.70, .89]	[.72, .90]			[.68, .89]	[.71, .90]
Switch to Emotion	48			.81	.83			.83	.85
				[.66, .90]	[.72, .90]			[.69, .91]	[.75, .92]
Switch costs Emotion	192/48	.92	.92	.78	.81	.63	.65	.68	.70
		[.88, .96]	[.88, .95]	[.60, .88]	[.68, .89]	[.43, .78]	[.45, .80]	[.46, .81]	[.52, .82]

Note. T/C = Maximum number of trials per condition (i.e., before exclusion of outliers or error trials), ICC(2,1) = intraclass correlation of absolute agreement, CI = confidence interval, r_{Pears} = Pearson correlation; r_{SB} = Spearman-Brown corrected correlations; 95% confidence intervals are specified in square brackets

Table 3. Test-retest reliability of behavioral measures from the affective flexibility task (first run only)

	T/C	<u>Response times (RT)</u>				<u>Error rates (ER)</u>			
		<i>Internal consistency</i>		<i>Test-retest reliability</i>		<i>Internal consistency</i>		<i>Test-retest reliability</i>	
		r _{SB} (test)	r _{SB} (retest)	ICC(2,1)	r _{Pears}	r _{SB} (test)	r _{SB} (retest)	ICC(2,1)	r _{Pears}
Repeat Gender	96			.69	.75			.52	.53
				[.51, .82]	[.59, .86]			[.28, .70]	[.28, .71]
Switch to Gender	24			.78	.81			.59	.63
				[.59, .88]	[.69, .89]			[.36, .75]	[.41, .77]
Switch costs Gender	96/24	.87	.85	.66	.74	.54	.31	.45	.50
		[.80, .92]	[.77, .92]	[.30, .83]	[.58, .85]	[.29, .72]	[-.06, .58]	[.19, .65]	[.24, .67]
Repeat Emotion	96			.82	.83			.65	.67
				[.69, .89]	[.71, .90]			[.45, .79]	[.48, .81]
Switch to Emotion	24			.75	.78			.62	.63
				[.57, .86]	[.64, .87]			[.41, .77]	[.41, .77]
Switch costs Emotion	96/24	.89	.85	.69	.74	.41	.37	.39	.39
		[.83, .94]	[.75, .92]	[.46, .82]	[.57, .85]	[.11, .65]	[.00, .64]	[.12, .60]	[.11, .61]

Note. T/C = Maximum number of trials per condition (i.e., before exclusion of outliers or error trials), ICC(2,1) = intraclass correlation of absolute agreement, CI = confidence interval, r_{Pears} = Pearson correlation; r_{SB} = Spearman-Brown corrected correlations; 95% confidence intervals are specified in square brackets

Table 4. Descriptive statistics of switch costs taking into account the valence of the current and the previously presented information.

	<u>Response times (RT)</u>				<u>Error rates (ER)</u>			
	<i>Test</i>		<i>Retest</i>		<i>Test</i>		<i>Retest</i>	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Switch costs Emotion angry - angry	269.05	122.51	250.66	122.09	.06	.10	.04	.10
Switch costs Emotion angry - happy	285.12	121.31	254.50	98.32	.09	.13	.08	.14
Switch costs Emotion happy – angry	262.79	120.80	231.70	101.84	.07	.13	.03	.10
Switch costs Emotion happy - happy	288.07	128.10	255.77	129.16	.08	.14	.06	.15
Switch costs Gender angry – angry	251.62	118.19	227.71	131.67	.03	.11	.01	.08
Switch costs Gender angry – happy	248.42	104.10	194.33	117.93	.04	.10	.03	.10
Switch costs Gender happy – angry	259.20	129.28	210.48	125.15	.03	.14	-.002	.09
Switch costs Gender happy – happy	234.02	123.45	195.24	93.35	.02	.10	.03	.13

Note: SD = standard deviation. In the variable labels, the first emotion denotes the valence depicted by the stimulus directly preceding the task switch (i.e., Previous valence), whereas the second emotion denotes the valence depicted in the image to which participants had to switch (i.e., Current valence); ‘Switch costs emotion happy – angry’ thus refer to switch costs elicited in the emotion task, when participants switch from a happy image in the gender task to an angry image in the emotion task.

Table 5. Internal consistencies and test-retest reliability of switch costs taking into account the valence of the current and the previously presented information.

			<u>Response times (RT)</u>				<u>Error rates (ER)</u>			
			<i>Test-retest reliability</i>		<i>Internal consistency</i>		<i>Test-retest reliability</i>		<i>Internal consistency</i>	
			ICC(2,1)	R _{Pears}	R _{SB} (test)	R _{SB} (retest)	ICC(2,1)	R _{Pears}	R _{SB} (test)	R _{SB} (retest)
Switch costs	Gender		.76	.78	.72	.78	.33	.34	.33	.13
angry – angry			[.61, .86]	[.63, .87]	[.57, .83]	[.65, .87]	[.05, .56]	[.06, .57]	[-.04, .61]	[-.28, .47]
Switch costs	Gender		.63	.71	.68	.79	.38	.37	.35	.31
angry – happy			[.30, .81]	[.53, .83]	[.52, .81]	[.67, .88]	[.10, .59]	[.09, .60]	[-.13, .56]	[-.05, .57]
Switch costs	Gender		.70	.75	.77	.78	.26	.29	.55	.13
happy – angry			[.59, .85]	[.59, .85]	[.65, .86]	[.65, .87]	[-.02, .50]	[.004, .53]	[.32, .72]	[-.25, .50]
Switch costs	Gender		.61	.67	.75	.58	.55	.57	.28	.58
happy – happy			[.38, .77]	[.50, .81]	[.61, .85]	[.33, .77]	[.32, .72]	[.34, .74]	[-.12, .57]	[.33, .76]
Switch costs	Emotion		.65	.66	.77	.79	.41	.42	.08	.23
angry – angry			[.46, .79]	[.46, .79]	[.63, .87]	[.67, .88]	[.15, .62]	[.15, .63]	[-.28, .44]	[-.16, .53]
Switch costs	Emotion		.70	.74	.78	.65	.64	.64	.43	.61
angry – happy			[.50, .82]	[.57, .85]	[.66, .86]	[.47, .79]	[.44, .78]	[.43, .78]	[.13, .67]	[.37, .79]
Switch costs	Emotion		.68	.71	.72	.68	.24	.27	.52	.37
happy – angry			[.48, .81]	[.53, .83]	[.58, .83]	[.49, .82]	[-.03, .48]	[-.02, .51]	[.29, .71]	[-.02, .65]
Switch costs	Emotion		.74	.76	.77	.80	.45	.45	.49	.56
happy – happy			[.56, .85]	[.60, .86]	[.66, .86]	[.69, .89]	[.19, .65]	[.19, .65]	[.22, .69]	[.31, .74]

Note. ICC(2,1) = intraclass correlation of absolute agreement, CI = confidence interval, r_{Pears} = Pearson correlation; r_{SB} = Spearman-Brown corrected correlations; 95% confidence intervals are specified in square brackets; In the variable labels, the first emotion denotes the valence depicted by the stimulus directly preceding the task switch (i.e., Previous valence), whereas the second emotion denotes the valence depicted in the image to which participants had to switch (i.e., Current valence); ‘Switch costs emotion happy – angry’ thus refer to switch costs elicited in the emotion task, when participants switch from a happy image in the gender task to an angry image in the emotion task.

Figure 1. Graphical depiction of the affective flexibility paradigm. Participants categorize affective facial stimuli either according to an affectively neutral gender task (female vs. male) or an emotion task (happy vs. angry facial expression), with task rules assigned to the two response hands. Target images were presented either above or below the central fixation point, and locations changed every 3-7 trials indicating the task switches. (Figure originally published in Kraft et al. (2020) under a CC-BY 4.0 license.)

Figure 2. Relative size of variance components for A) response time (RT) based measures and B) error rate (ER) based measures, for the gender task and the emotion task respectively. Total variance (as it is decomposed for calculation of test-retest reliability) is subdivided into variance accounted for by differences between participants (mid gray), differences between sessions, as e.g., practice effects (dark gray), and error variance (light gray).