Depressive Symptoms and Cognitive Control: The Role of Affective Interference

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Abstract

Depressive symptoms are characterized by reduced cognitive control. However, whether depressive symptoms are linked to difficulty in exerting cognitive control in general or over emotional content specifically remains unclear. To better differentiate between affective interference or general cognitive control difficulties in people with depressive symptoms, we employed a non emotional (cold) and an emotional (hot) version of a task-switching paradigm in a nonclinical sample of young adults (N = 82) with varying levels of depressive symptoms. Depressive symptoms were linked to greater difficulties in exerting cognitive control in complex situations (mixed-task blocks) compared to simple and semiautomatic situations (single-task blocks) in both task versions. Moreover, greater depressive symptoms were associated with longer latencies in the emotional version of the task across all trial types. Thus, the emotion-specific effect was not modulated by the degree of cognitive control required to perform the task. In sum, depressive symptoms were characterized by a general difficulty to exert cognitive control in both emotional and non emotional contexts and by greater difficulty in even simple attentional processing of emotional material. This study granted novel insights on the extent of cognitive control difficulties in emotional and non emotional contexts for people with depressive symptoms.

Keywords: depressive symptoms, cognitive control, affective interference, behavioural data, task-switching

Introduction

Difficulties in cognitive control have been acknowledged as relevant to the development and maintenance of depressive symptoms (e.g., De Raedt & Koster, 2010; Disner et al., 2011; Keller et al., 2019). Indeed, although the core symptoms of depression are sustained negative affect and anhedonia, the *Diagnostic and Statistical Manual of Mental Disorders* (5th ed.; *DSM-5*; American Psychiatric Association, 2013) has included a "diminished ability to think or concentrate" as a diagnostic criterion for depression. Depression has been linked to difficulties in cognitive control, a set of high-order functions that allow people to flexibly achieve goal-directed behaviour (Kashdan & Rottenberg, 2010; Meiran et al., 2011; Stange et al., 2017).

Moreover, a recently emerging approach, especially in the study of depressive symptoms, is to differentiate cognitive control functions exerted in emotional contexts (*hot* functions) from general non emotional cognitive control functions (*cold* functions; Fossati, 2018; Roiser & Sahakian, 2013; Salehinejad et al., 2021). This distinction conceptualizes cognitive control on a continuum, where each function can be relatively hot or cold depending on the context (Salehinejad et al., 2021).

A wealth of evidence has demonstrated that individuals with depressive symptoms are characterized by broad cognitive control difficulties (Bortolato et al., 2014; Dotson et al., 2020; Rock et al., 2014; Snyder et al., 2013). Cognitive inflexibility has been documented in individuals with different levels of depressive symptoms across different non emotional neuropsychological tests (e.g., Harvey et al., 2004; Lin et al., 2014; Moritz et al., 2002; Parkinson et al., 2020; Rokke et al., 2002; Wilkinson & Goodyer, 2006). Of note, the effect sizes of cognitive control difficulties were larger for older adults or individuals with clinical depression (Dotson et al., 2020). Indeed, other studies have not found depressive symptoms to have a significant effect on cognitive inflexibility in samples of adolescents and young adults

without clinical depression (Goodall et al., 2018; Vilgis et al., 2015). Some researchers who have specifically employed computerized task-switching paradigms in studies on depression have found longer latencies in switch trials compared to repeat trials (i.e., greater switch costs; Hoffmann et al., 2017), whereas others have failed to find switch cost differences in individuals with depression and healthy controls (Meiran et al., 2011; Remijnse et al., 2013; Whitmer & Gotlib, 2012;).

Notably, a separate line of research has focused on the study of cognitive control in hot contexts in relation to depressive symptoms (e.g., Joormann & Vanderlind, 2014; Koster et al., 2011). In particular, the preferential processing of unpleasant stimuli across all domains of information processing is thought to influence cognitive control performance in individuals with depressive symptoms (Gotlib & Joorman, 2010; Joormann & Vanderlind, 2014; LeMoult & Gotlib, 2019). Using various paradigms, several studies have shown that depressive symptoms or the risk of developing depression was related to difficulties in switching away from or inhibiting unpleasant stimuli (i.e., angry and sad faces, threatening and sad scenes and words; Epp et al., 2012; Everaert et al., 2017; Goeleven et al., 2006; Lisiecka et al., 2012; Murphy et al., 2012; Wen & Yoon, 2019) and updating working memory when the content was unpleasant (Joormann, 2010; Levens & Gotlib, 2010), corroborating the view that unpleasant content interferes with cognitive control functions (Gotlib & Joorman, 2010; Joormann, 2010; LeMoult & Gotlib, 2019;). Moreover, greater difficulties in switching away from unpleasant stimuli have also been related to psychological aspects linked strictly to depressive symptoms, such as ruminative thinking (Genet et al., 2013), reduced adaptive emotional regulation strategies (i.e., reappraisal; Grol & De Raedt, 2021; Malooly et al., 2013), and resilience (Grol & De Raedt, 2018). Additionally, a study showed that individuals with depressive symptoms, compared to those in a control group, had poorer switching abilities for unpleasant stimuli but better switching abilities for pleasant stimuli (Deveney & Deldin, 2006). Instead, longer

latencies in switching away from pleasant stimuli than from unpleasant stimuli were documented in individuals with clinical depression (Quigley et al., 2020). Furthermore, affective switching difficulties for both pleasant and unpleasant content were found in individuals with depression (De Lissnyder et al., 2012) and depression in remission (Lange et al., 2012) and were found to prospectively predict increased depressive symptoms in a remitted sample (Demeyer et al., 2012).

Generally, valence-specific effects in hot task-switching paradigms in relation to depressive symptoms are still unclear. For instance, valence-specific effects on pleasant stimuli have not been thoroughly explored. Considering the evidence on the reduced processing of pleasant stimuli in individuals with depressive symptoms (e.g., Mennella et al., 2015; Messerotti Benvenuti et al., 2015, 2019; Nandrino et al., 2004; Shane & Peterson, 2007; for a review, see Winer & Salem, 2016), the investigation of cognitive control over both unpleasant and pleasant stimuli would allow a better understanding of potential valence-specific cognitive control difficulties in individuals with depressive symptoms.

To date, only a limited number of studies have employed both cold and hot versions of the same paradigm to investigate cognitive control in people with depressive symptoms. These few studies have linked depression to a selective difficulty in cognitive control in emotional task versions compared to non emotional task versions (Lo & Allen, 2011; Murphy et al., 2012). However, the employment of paradigms tackling distinct processes (e.g., go/no-go, internal shifting task) and the fact that the investigation was restricted exclusively to clinical samples make reaching a consensus hard regarding the distinct involvement of cold and hot functions in people with depressive symptoms.

Hence, despite the evident involvement of cognitive control processes in modulating depressive symptoms, whether depressive symptoms are linked to a general difficulty to exert cognitive control or to a selective difficulty to exert cognitive control over emotional content

remains unclear (Grahek et al., 2018; Joorman & Tanovic, 2014). On one hand, although cognitive control in cold contexts does not directly involve emotional processing, several researchers have suggested it may facilitate the implementation of emotional regulation strategies and protect performance in hot contexts, counteracting the risk conferred by depression-related emotion-processing biases (Roiser et al., 2012; Roiser & Sahakian, 2013; Whitmer & Gotlib, 2012). Therefore, depressive symptoms may be associated with general cognitive control difficulties that, in turn, affect control over emotional information. On the other hand, a classical view of cognitive processes in individuals with depressive symptoms postulates that negative schemas generate a processing advantage for unpleasant stimuli, leading to the altered encoding and processing of all other information (Beck & Bredemeier, 2016; Clark & Beck, 2010; Siegle et al., 2002). Therefore, individuals with depressive symptoms may display difficulties in switching away from emotional stimuli in hot contexts not because of impaired switching mechanisms, but because of enhanced reactivity to emotional stimuli that impact cognitive control functions (e.g., Lo & Allen, 2011).

To better understand whether depressive symptoms are characterized by selective difficulties in emotional contexts or by general cognitive control difficulties, studies comparing performance in cold and hot versions of the same paradigm are warranted (Quigley et al., 2020). To this end, we employed both a cold and a hot version of a task-switching paradigm in a nonclinical sample of young adults with varying levels of depressive symptoms. This paradigm requires participants to perform tasks either in isolation (single-task blocks) or in an intermixed fashion (mixed-task blocks, composed of switch and repeat trials; Meiran, 2010; Monsell, 2003). This paradigm evaluates different aspects of cognitive control, including the cost of switching from one rule to the other, the cost of keeping multiple task sets active, and the disengagement from a previous task set and stimulus (Kiesel et al., 2010; Meiran, 2010; Monsell, 2003). Specifically, two distinct and dissociable processes can be assessed with this

paradigm: (a) the so-called "switching cost," namely the process of task-set reconfiguration, a phasic and transient activation required to switch between tasks, assessed based on the performance difference between switch and repeat trials; and (b) the so-called "mixing cost," a sustained process reflecting the increase in active demands due to the concurrent maintenance and management of multiple task sets, assessed based on the performance difference between repeat and single trials (Monsell, 2003; Rubin & Meiran, 2005).

Because this was the first study to directly compare the participants' performance on both hot and cold versions of a task-switching paradigm in relation to depressive symptoms, the main hypothesis was twofold. Based on the reviewed literature linking depressive symptoms to a general reduction in cognitive control abilities, we expected more depressive symptoms to be associated with cognitive control difficulties in both task versions. Additionally, based on the few studies that have linked depression to a selective difficulty in affective cognitive control (Lo & Allen, 2011; Murphy et al., 2012), we expected these cognitive control difficulties to be more pronounced (i.e., longer response times) in the emotional compared to the non emotional task version. Moreover, specifically for the emotional version of the task, we expected higher levels of depressive symptoms to be related to a valence-specific bias, with longer RTs in switching away from unpleasant stimuli compared to pleasant stimuli.

Methods

Participants

Ninety-five Caucasian young adults (35 males; M_{age} = 25.4 years, SD_{age} = 2.9) were recruited through local advertisements or by word of mouth and voluntarily took part in the online study. Exclusion criteria included the presence of any mental disorder and the use of psychotropic drugs. Furthermore, only individuals between the ages of 18 and 35 years were recruited because young adults with depressive symptoms already show poor cognitive control, and this

has been suggested to be an early risk factor for depression (Goodall et al., 2018). Of the total sample of 95, seven volunteers were excluded from the study after an anamnestic interview because they reported clinical depression or anxiety in pharmacological treatment (n = 4) and substance abuse (n = 3). Individuals who reported a diagnosis of clinical depression were excluded because the study was conducted online and confirming the diagnosis was not possible through a clinical interview (e.g., structured clinical interview for *DSM-5*). Another reason for not including those on medications or with diagnoses was that most of the participants had only subthreshold levels of depression; therefore, including seven participants with clinical depression, anxiety, or substance abuse would have led to an unbalanced sample. In addition, six participants could not complete the task due to technical issues. The final sample consisted of 82 participants (30 males; M_{age} = 25.5 years; SD_{age} = 3.0), medically healthy and free from psychotropic medications, as assessed with an ad hoc anamnestic interview. Because it was not possible to assess the presence of a depressive disorder through clinical interviews, depressive symptoms were evaluated on a continuum. Moreover, the examination of subclinical depressive symptoms provides an advantage because it allows isolation of the effects of interest without any alterations produced by the use of antidepressant medications or the chronicity of the disorder.

The participants were not compensated for their participation. This study was conducted with adequate understanding and written consent of the participants in accordance with the Declaration of Helsinki and was approved by the Ethics Committee, University of Padua (Protocol No. 3640).

Sensitivity power analysis

Our sample consisted of a convenience sample recruited via online advertisements through social networks or identified via researchers' personal networks. The method introduced by

Westfall et al. (2014) was used to perform a sensitivity power analysis for a fully crossed linear mixed-effects model, assuming participants, stimuli, and residual variance partitioning coefficients of .25, .05, and .7, respectively, as estimated conservatively from some recent unpublished studies with a similar design to ours. The other variance partitioning coefficients were set to 0, because those effects were not included in the models we tested. This analysis revealed that the sample size (82 participants and eight stimuli, see below) was large enough to detect a small effect size (Cohen's $d = 0.15$) with a power of .80. However, this approach is not fully adequate for complex mixed-effects models such as the one used in this work, but it nonetheless provided a useful estimation of the so-called minimal statistically detectable effect for our study (i.e., the lower bound of the range of effect sizes that can be detected). Indeed, to the best of our knowledge, to date, no accepted analytical approaches have been ascertained to compute statistical power accurately for such models. To provide another estimate of our minimal statistically detectable effect, which could also facilitate comparison with future studies using more standard analytical approaches, a sensitivity power analysis in G*Power for a repeated measure analysis of variance (ANOVA) for the domain by condition interaction, assuming a correlation between repeated measures of .85, was performed. This analysis revealed that the sample size was large enough to detect a small effect size ($d = 0.17$, corresponding to $\eta_p^2 = .007$) with a power of .80. Notably, however, G*Power (and to the best of our knowledge, all other software commonly used to compute power) does not support a power calculation for general linear model effects including both multiple within-subjects factors and continuous covariates.

Data were analysed using R (Version 1.2.5001; R Core Team, 2012), the stats package (R Core Team, 2013), lme4 (Bates et al., 2015), and lmerTest (Kuznetsova et al., 2017).

Self-report measure of depressive symptoms

Depressive symptoms were assessed using the Beck Depression Inventory-II (BDI-II; Beck et al., 1996; Italian version by Ghisi et al., 2006). The BDI-II scale is a reliable and valid self-report questionnaire developed to assess the severity of depressive symptoms over the previous 2 weeks. Specifically, the BDI-II is composed of 21 items, each based on a 4-point Likert scale, and scores range from 0 to 63, with higher scores indicating greater depressive symptoms (Ghisi et al., 2006). Internal consistency was high for the 21 items of the BDI-II (Cronbach's $\alpha = .92$).

Task-switching paradigm and behaviour data reduction

Cognitive control in cold and hot contexts was assessed with two versions (emotional and non emotional) of a task-switching paradigm adapted from Rubin and Meiran (2005) and created in the PsychoPy software (Peirce et al., 2019). Figure 1 graphically represents the task design. Each version consisted of a total of four single-task blocks, each comprising 30 trials, and two mixed-task blocks, each comprising 40 trials. A "sandwich-like" design was adopted: Two single-task blocks, each comprising 10 practice trials, were followed by two mixed-task blocks, comprising 10 practice trials, and then again by two single-task blocks. The order of single-task blocks was counterbalanced across participants. Half of the participants started with the hot version, and the other half with the cold one.

The single-task blocks required the participants to perform two types of subtasks, one at a time in different blocks. In the mixed-task blocks, the participants had to categorize the target stimulus based on a categorization rule indicated by a cue, which changed unpredictably trial by trial. The task could be either repeated (repeat trials) or switched (switch trials) based on a pseudorandom order. Within the single-task blocks, a trial started with the presentation of a black fixation cross on a grey background positioned at the centre of the screen for 500 ms,

followed by the presentation of the target stimulus until the participants produced a response. The inter-trial interval included a black fixation cross on a grey background positioned at the centre of the screen, and its duration was either 500 or 700 ms. Within the mixed-task blocks, before stimulus presentation, a visual cue that indicated the task to be performed appeared at the centre of the screen for 1,000 ms.

The stimuli included in the cold version of the paradigm were two geometric shapes (triangle and circle) coloured in red or blue, presented individually at the centre of the screen on a grey background. The participants were asked to respond according to either the shape or the colour of the target stimulus. The single-task blocks required the participants to categorize the target stimulus selectively based on either colour or shape. Instead, the mixed-task blocks included the categorization of the target (either a "colour task" or a "shape task") based on a cue. The participants had to press the left arrow button to indicate either a triangle or a blue shape and the right arrow button to indicate either a circle or a red shape.

The stimuli included in the hot version of the paradigm were four coloured images of faces with no hairline from the A series of the Karolinska Directed Emotional Faces database (Lundqvist et al., 1998) selected from a validation study of the database's picture set (Goeleven et al., 2008),[1] presented individually at the centre of the screen on a grey background. The stimuli included two happy faces (one female, one male) and two sad faces (one female, one male) selected from a validation study of the database's picture set based on intensity ratings (happy, $M = 6.34$, $SD = 1.64$; sad, $M = 6.55$, $SD = 1.70$) and arousal ratings (happy, $M = 3.7$, $SD = 2.85$; sad, $M = 4.0$, $SD = 1.84$; Goeleven et al., 2008). The happy and sad faces did not differ in arousal ratings ($p = .57$). The participants were asked to respond according to the emotion or gender of the face. Particularly, the single-task blocks required the participants to categorize the target stimulus selectively based on either the emotion or gender of the face. The mixed-task blocks included the categorization of the target (as either an "emotion task" or a

"gender task") based on a cue. The participants had to press the left arrow button to indicate either an unpleasant stimulus or a female face and the right arrow button to indicate either a pleasant stimulus or a male face.

The task was self-paced, and RTs and accuracy were measured. The first trial of each block was excluded from the analysis. Incorrect trials (3.49% of all trials) and RTs longer than 3,000 ms or shorter than 100 ms (0.41% of correct trials) were also excluded from the analyses. The RTs were then inversely transformed (−1,000/RTs in ms) to produce the normal distribution required to conduct linear mixed-effects models, because the RT distributions were heavily skewed (skewness = 2.61) as typically observed (e.g., Schmidt & Weissman, 2016). The reliability of the transformed RTs in the single, repeat, and switch trials in the cold and hot tasks was evaluated by computing split-half correlations corrected with the Spearman-Brown formula (2,000 random splits).

General procedure

This study was conducted within an extensive research project on vulnerability to depression, and self-report measures of emotional regulation, anxiety, and heart rate were collected but not analysed in this work. First, each participant completed an online survey administered via Google Modules that included informed consent, a sociodemographic and anamnestic interview, and the BDI-II self-report questionnaire. Subsequently, the participants received a link to complete the task-switching paradigm on their computers through the Pavlovia.org online platform. The participants were instructed to find a quiet and comfortable room free of distractions and to avoid completion of the task during night hours (completion time was checked on the output data) and the consumption of alcohol or caffeine in the hours preceding the experiment.

Statistical analyses

Statistical analyses were performed in R (Version 1.2.5001; R Core Team, 2012). The effects of depressive symptoms on cognitive control in both cold and hot contexts were investigated by performing a linear mixed model with the RTs as the dependent variable using the lmer function from the lmerTest library (Kuznetsova et al., 2017). Specifically, we tested for the effects of BDI-II scores, domain (emotional or hot, non emotional or cold), and condition (trial types: single, repeat, switch) and all their two- and three-way interactions as fixed effects of primary theoretical interest.

Mixed-effects models have several advantages over traditional linear model analysis (i.e., repeated-measures ANOVA). Because this analysis was conducted at the trial level, it accounted for variability at the individual level and avoided potential bias due to data aggregation (i.e., comparing mean values; Singmann & Kellen, 2019). Moreover, unlike general linear models, mixed-effects models are very robust at handling missing data and unbalanced data sets (Baayen et al., 2008; Quène & van den Bergh, 2008).

The simplest, best linear mixed-effects model to fit the dependent variable (RTs) was determined by iteratively comparing simpler models (starting from the null model) with more complex models using the ANOVA function (R stats library), which provided the chi-square statistics and the related *p* value of the likelihood ratio test. The Bayes factors in favour of the simpler models (BF_{12}) using the BayesFactor package (Morey et al., 2015) were also computed.[2] Particularly, the models were as follows: (a) a null model that included only the participant ID and experimental stimuli as random intercepts and the trial order as both a fixed effect and a by-participant random slope to control for possible confounding time-on-task effects, (b) more complex models that also included the main fixed effects of condition, domain, and BDI-II scores, (c) more complex models that also included their two-way interactions, and (d) the full-factorial model that also included their three-way interaction. After

this model-building procedure, the statistical significance of the fixed effects included in the final model was assessed as detailed below.

The final model was refitted after we excluded outliers, which were identified as observations with absolute standardized residuals greater than 3 (Ambrosini et al., 2015). For the fixed effects, the estimated coefficient (*b*), standard error (*SE*), and *t* values for each parameter included in the final model were reported. In addition, the *p* values obtained through the Satterthwaite approximation (implemented in the lmerTest library) were reported. A *p* value of .05 was the cutoff for statistical significance.

Regarding the specific valence-effects within the emotional version of the paradigm, a separate linear mixed-effects model was conducted to explore the potential influences of the valence (pleasant, unpleasant) of the previous trial in simple and complex cognitive control conditions (i.e., trial types) on the RTs as a function of the participants' BDI-II scores. Specifically, we tested BDI-II, condition (trial types: single, repeat, switch), valence of the previous trial (pleasant, unpleasant), and their two- and three-way as fixed factors of primarily theoretical interest. The same model-building procedure detailed above was conducted to identify the simplest, best linear mixed-effects model to fit the dependent variable (RTs), and statistical analysis of the final model was conducted as detailed above. The same analysis was conducted with the valence of this trial.

Accuracy was not analysed because it was very high (> 96%), indicating the participants' performance was at the ceiling level. Indeed, 68 of the 82 participants (corresponding to approximately 83% of the sample) had perfect accuracy in at least one experimental condition. This prevented the reliable estimation of the experimental effects on accuracy. Nonetheless, we checked for the presence of a speed–accuracy trade-off by correlating the participants' mean RTs and accuracy. This analysis revealed a near-zero correlation, $r = .001$, $t(80) = 0.01$, $p = .990$, indicating the absence of a speed–accuracy trade-off in our sample.

Results

Descriptive statistics

The average BDI-II score of the sample was 10.7 (*SD* = 9.2), and the scores ranged from 0 to 43, with a skewness of 1.48 and a kurtosis of 2.04. Regarding the RTs for each trial type (single, repeat, switch), domain (cold, hot), and accuracy, the descriptive statistics are displayed in Table 1. The reliability estimates of the inverse-transformed RTs were very high (median value across the 2,000 random splits > 0.95 in all cases), indicating the adequacy of the online assessment of task-switching ability.

Depressive symptoms and task performance in the cold and hot task versions

The model-building procedure revealed that the inclusion of the three-way interaction (Condition × Domain × BDI-II scores) was not justified, $\chi^2(2) = 0.12$, $p = .94$; $BF_{12} = 685$. Instead, the simplest, best linear mixed-effects model to fit the dependent variable (RTs) was the model that included the main fixed effects (condition, domain, BDI-II), their two-way interactions, the fixed effect for trial and its random by-participant slope, and the participants and stimuli as random intercepts. The R notation for the final model was as follows*:*

*lmer(RTs ~ trial + domain * condition + domain * BDI-II + condition * BDI-II + (trial/participant) + (1/stimulus)).*

The marginal R^2 of the final model, which represents the variance explained by the fixed effects, was .18; the conditional R^2, which is the variance explained by both the fixed and random effects, was .44. The statistics for the fixed effects of the final model are displayed in Table 2. A significant main effect of trial emerged, $F(1, 77) = 21.47$, $p < .001$, reflecting an overall decrease of RTs as the experimental session progressed. Moreover, a significant main effect of domain emerge, $F(1, 22) = 178.70$, $p < .001$, reflecting overall longer RTs for the emotional (i.e., hot) compared to the non emotional (i.e., cold) task version. Additionally, a

significant main effect of condition emerged, $F(2, 31605) = 920.63$, $p < .001$, with longer RTs for the switch trials compared to both the repeat and single trials and longer RTs for the repeat trials compared to the single trials (all ps < .001). A significant interaction between domain and condition (Figure 2) also emerged, $F(2, 31067) = 115.68$, $p < .001$, showing that the domain effect, that is, the increase in RTs for the emotional (i.e., hot) compared to the non emotional (i.e., cold) task version, was smaller for both the repeat and switch trials compared to the single trials ($p < .001$), whereas no significant difference was observed for the domain effect between the repeat and switch trials ($p = .607$).[3]

Moreover, the BDI-II × Domain interaction was significant, $F(1, 1242) = 14.95$, $p < .001$, showing a BDI-II-dependent increase in RTs that was stronger for the emotional (i.e., hot) than the non emotional (i.e., cold) task version (Figure 3, Panel B). The BDI-II × Condition interaction was also significant, $F(2, 31066) = 13.23$, $p < .001$, showing that the BDI-II-dependent increase in RTs was stronger for both the switch and repeat trials compared to the single trials (both ps < .001), whereas it did not significantly differ between the switch and repeat trials ($p = .231$; Figure 3, Panel A).

Due to the nonnormality of the BDI-II distribution, a control analysis was performed to verify the robustness of the described results and control for possible biases due to the influence of participants with high BDI-II values. To this aim, the same linear mixed-effects model was conducted after log transforming the BDI-II scores. The control analysis confirmed all the effects described above.

Depressive symptoms and valence-specific effects

The model-building procedure revealed that the inclusion of the three-way interaction (Condition × Valence × BDI-II) was not justified, $\chi^2(2) = 1.99$, $p = .37$; $BF_{12} > 10^5$. Moreover, the inclusion of the valence effect and its interactions with either BDI-II or condition was not

justified (all *p*s > .3; all BF_{12}s > 41). Instead, the simplest, best linear mixed-effects model to fit the dependent variable (RTs) was the model that included the main fixed effects of condition and BDI-II, their two-way interaction, the fixed effect for trial, and its random by-participant slope, and the participants and stimuli as random intercepts. The R notation for the final model was as follows: *lmer(RTs ~ trial + condition * BDI-II + (trial/participant) + (1/stimulus))*.

The marginal and conditional R^2 of the final model were, respectively, 0.09 and 0.39. The analysis confirmed the significant main effect of condition, $F(2, 14938) = 335.89$, $p < .001$, and Condition × BDI-II interaction, $F(2, 14956) = 9.43$, $p < .001$, which replicated the pattern of results in the previous analysis. Again, a control analysis performed with log-transformed BDI-II scores confirmed the general pattern of the results.

Furthermore, a similar control analysis was performed to verify whether the valence modulated the reported result. Again, however, the analysis revealed that the more complex model including the interaction with the valence predictor was not justified, $\chi^2(6) = 11.26$, $p = .08$; $BF_{12} > 10^4$.

Discussion

This study was the first to employ the same task-switching paradigm in emotional (i.e., hot) and non emotional (i.e., cold) versions to assess whether the presentation of emotional material in individuals with greater depressive symptoms would influence cognitive control. We expected more depressive symptoms to be associated with general cognitive control difficulties in both task versions. Alternatively, based on the few studies that have linked depression to a selective difficulty in affective cognitive control (Lo & Allen, 2011; Murphy et al., 2012), we expected higher levels of depressive symptoms to be associated with selective difficulties in the hot contexts. Moreover, specifically for the emotional version of the task, we expected a

valence-specific bias, with longer RTs in switching away from unpleasant stimuli compared to pleasant stimuli.

For the whole sample, condition had a significant effect, namely, as expected in a task-switching paradigm, a difference among the three task conditions, with longer RTs in the switch trials than in repeat (i.e., switching cost) and single trials and longer RTs in repeat than in single trials (i.e., mixing cost). These differences reflect the distinct processes that can be disentangled in a task-switching paradigm, namely a switching cost, determined by the activation of a task set reconfiguration process that is not required in repetition trials, and a general mixing cost, determined by the need to keep multiple task sets active during the mixed block compared to the single block condition (Monsell, 2003; Rubin & Meiran, 2005). However, depressive symptoms were related to greater difficulties in exerting cognitive control in the complex situations (switch and repeat trials) than in the simple and semiautomatic situations (single trials), in both the emotional and non emotional task versions. Hence, the BDI-II scores were not differentially related to the switch and repeat trials, presenting a similar pattern for both trial types. This indicates that the individuals with greater depressive symptoms did not show the typical facilitation effect for the repeat trials compared to the switch trials. Consequently, mixing cost, namely the difference between the repeat and single trials, increased with the BDI-II scores. Although the switching cost has been widely studied as a measure of cognitive control abilities (e.g., Rubin & Meiran, 2005), the study of mixing cost has been fairly neglected, and this is the first study on depressive symptoms to include single-task blocks. However, several researchers have argued that mixing cost may represent an accurate measure of cognitive control in conditions requiring sustained attention and the management of competition between task sets (Ambrosini et al., 2019; Marì-Beffa et al., 2012; Marì-Beffa & Kirkham, 2014; Meiran, 2005). Therefore, in this study, depressive symptoms were associated with a general difficulty in the maintenance of cognitive control (i.e., mixing

cost) due to a diminished differentiation between the switch and repeat trials, leading, in turn, to reduced switching costs. However, this does not necessarily indicate that individuals with greater depressive symptoms do not show difficulties in phasic task-set reconfiguration, because they might also be likely to employ a task-set reconfiguration process in both switch and repeat trials indiscriminately. In the context of computerized task-switching studies on depression, these results are in contrast with some previous studies that reported specific switching difficulties in depression (e.g., Hoffmann et al., 2017) but are in line with other studies that did not report a significant difference between switch and repeat trials (Meiran et al., 2011; Remijnse et al., 2013; Whitmer & Gotlib, 2012). The mixed findings in the literature could be due to the employment of slightly different paradigms, making the comparison between studies rather difficult. Moreover, this study was the first to apply a more robust statistical approach rather than rely on data aggregation (i.e., comparing mean values).

Furthermore, depressive symptoms were related to a selective difficulty in performing tasks with emotional stimuli compared to non emotional stimuli. Indeed, the participants' BDI-II scores were positively associated with longer RTs in the hot version compared to the cold version. However, this effect was not modulated by the degree of cognitive control required to perform the task, because the three-way interaction between condition, domain, and BDI-II scores was not significant. In other words, depressive symptoms were characterized by an affective interference not only in demanding and complex conditions but also even in simple and semiautomatic conditions (i.e., single-task blocks). These results are partly in line with the affective interference hypothesis (Siegle et al., 2002), which suggests that the automatic orienting and processing of affective stimuli interfere with attentional processing by detaining more cognitive resources in depression. Hence, longer latencies in the emotional task may be due to the distribution of cognitive resources between the completion of the task and the attentional processing of the emotional features of the stimulus, which is slowed in individuals

with greater depressive symptoms. Moreover, the reduced readiness to initiate a task under exposure to emotional stimuli compared to non emotional stimuli may be consistent with studies that described a reduced ability to inhibit affective stimuli in individuals with depressive symptoms (e.g., Joorman & Gotlib, 2010; Joorman & Tanovic, 2014). However, the effect was not valence-specific, because no difference was found between trials that required disengagement from a previous unpleasant or pleasant stimulus. The interference of unpleasant stimuli may extend to sustained difficulty in task completion even in trials requiring disengagement from pleasant stimuli rather than selectively modulating the performance of trials requiring disengagement from unpleasant stimuli. For instance, individuals with greater depressive symptoms may have more difficulties in deactivating the unpleasant features of images, which results in poorer control over preventing irrelevant affective information from interfering with the completion of the whole emotional task (Lo & Allen, 2010). Our results are in line with one of the few studies that adopted an emotional (with pleasant and unpleasant trials) rather than a non emotional version of the same task-switching paradigm and found a selective difficulty in the emotional task-switching paradigm, regardless of the stimulus valence, in individuals with depression (Lo & Allen, 2010). However, the authors of that study did not include the RTs for both task versions within a single statistical model but conducted two separate ANOVAs, making it impossible to compare the two task versions directly. Furthermore, contrary to our study, they did not include single-task blocks. Therefore, the previous study did not make it possible to state whether emotional material influences cognition even in relatively simple conditions or if it selectively influences high-order functions that require greater cognitive resources.

The focus on cognitive aspects of depression aligns with the Cognitive System domain within the Research Domain Criteria framework, an initiative developed to better characterize affective, cognitive, and biological factors underlying psychopathology (Insel, 2010; Kozak &

Cuthbert, 2016). The Research Domain Criteria also includes the Positive and Negative Valence Systems, domains that are related strictly to emotional processing (Keller et al., 2019). Studying how these systems interact in people with depressive symptoms is of increasing interest, and our study provides further evidence of the influence of affective stimuli on cognitive control (mixed-task blocks) and simpler attentional processing (single-task blocks). Overall, this study demonstrates that depressive symptoms are characterized by general cognitive control difficulties and the interference of affective stimuli in both complex and simple tasks.

In addition, although the order of the two tasks was counterbalanced, a control analysis revealed that the participants who first completed the emotional task had greater emotion-specific effects (i.e., greater RTs in the emotional task). In addition, those who first completed the non emotional task had greater emotion-specific effects in the single trials compared to the task-switching trials. In this study, the inclusion of other higher order interactions, including the task order factor, was not justified. Overall, these results should be investigated further and considered in future studies.

The results of this study have not only theoretical implications but also implications for the prevention and treatment of depression. These findings suggest that reduced cognitive control abilities and an overall interference of affective stimuli might be useful in early identification of the risk for developing a full-blown depressive episode. In turn, these findings lay the foundation for the implementation of preventive programs for individuals who show difficulties in cognitive control abilities. Moreover, our findings seem compatible with the emerging evidence documenting the efficacy of cognitive control training in diminishing depressive symptoms (Koster et al., 2017). However, a combination of general and affective cognitive control training might be more effective (e.g., Iacovello et al., 2014). To date, task-

switching training has not been employed in the treatment of depression, and future studies on both cold and hot cognitive training with this paradigm are warranted.

In interpreting our findings, several limitations should be considered. First, although the participants were given precise instructions for completing the experiment, the fact that we conducted the study remotely through a web platform, due to the COVID-19 pandemic, might have influenced the results. However, due to the ease of collecting larger samples, online studies are increasingly being conducted, and the accuracy of web platforms has been tested and validated in a recent study (Anwyl-Irvine et al., 2021). In addition, the reliability analysis conducted in this study showed the adequacy of the online assessment of the task-switching paradigm. Moreover, the fact that data collection was conducted during the second wave of the COVID-19 pandemic might limit these results to this specific context. Second, although task-switching paradigms tap distinct aspects of cognition and are considered promising tools for accurately measuring cognitive control (Meiran, 2010; Monsell, 2003), to explore cognition in people with depressive symptoms fully, future studies should consider the use of multiple tasks and employ a latent variable approach (e.g., Ambrosini et al., 2019). Additionally, although the task was extensively piloted to ensure comparability between the two task versions, they were not fully comparable. Furthermore, to make the two task versions as comparable as possible, the emotional task comprised only four emotional faces (two for gender and two for emotion). This represents a limit, because previous studies that explored emotional task-switching abilities have employed many pictures to avoid habituation (e.g., De Lissnyder et al., 2012; Grol & De Raedt, 2018). Therefore, this habituation to the emotional stimuli could have led to the absence of selective difficulties in the emotional task version as a function of depressive symptoms. Lastly, future studies should consider selecting individuals with more severe depressive symptoms to better typify the extent of cognitive control difficulties in both cold and hot contexts in depression.

In conclusion, this study provides novel evidence on the extent of cognitive control difficulties in emotional and non emotional contexts in relation to depressive symptoms. These findings show the presence of depressive symptoms is associated with a general difficulty to exert cognitive control in both contexts and with a more extended difficulty in even simple attentional processing of affective material. Future laboratory studies are warranted to confirm these findings and better understand the interplay between affect and cognition in individuals with depressive symptoms.

Acknowledgments

The authors are very grateful to the participants who took part in this study.

Funding

This work was supported by the "Department of excellence 2018-2022" initiative of the Italian Ministry of education (MIUR) awarded to the Department of Neuroscience and to the Department of General Psychology, University of Padua and by a grant from MIUR (PRIN n. 2017BC4MST) to Prof. Daniela Palomba. Simone Messerotti Benvenuti's work was supported by the University of Padua under the 2019 STARS Grants program (Acronym and title of the project: A-CAOS-BIRD - Asymmetries and Connectivity in Alpha OScillations: toward Biomarkers of Intergenerational Risk for Depression).

Author contributions

C.D.A., E.A., S.M.B., A.V. and D.P. conceived and designed the study; C.D.A. conducted the study; E.A. contributed to methodological and analytic tools; C.D.A., E.A. and S.M.B. analysed the data; C.D.A. and E.A. wrote the paper, and all authors reviewed the manuscript.

Data availability

The data and code that support the findings of this study are available from the corresponding author, C.D.A., upon reasonable request.

Footnotes:

[1]The KDEF images included in the study were: F26SA, M17SA, F26HA, M17HA.

[2] The Bayes factor can be interpreted as a measure of the strength of evidence in favour of one model over another. In line with an influential classification scheme for interpreting Bayes factors, values greater than 3, 10, 30, and 100 are considered, respectively, moderate, strong, very strong, and extreme evidence (Lee & Wagenmakers, 2014; Jeffreys, 1961).

[3] A control analysis was performed to check whether the randomized assignation of the order of Cold and Hot versions of the task (ListOrder) might have modulated our results. This analysis revealed that a model including the interaction between ListOrder, Domain, and Condition provided a better fit to participants' data ($\chi^2_{(6)}$ = 80.46, p < .001). The ListOrder*Domain interaction ($F_{(1,31265)}$ = 48.05, p < .001) indicated that the Domain effect (i.e., longer RTs to emotional vs. non-emotional cues) was greater for participants who first completed the emotional task version. However, despite the ListOrder*Condition interaction was not significant ($F_{(1,31188)}$ = 1.65, p = .19), the ListOrder*Domain*Condition ($F_{(1,31184)}$ = 24.48, p < .001) indicated that the Domain*Condition interaction (i.e., the larger Domain effect in Single as compared to both Repeat and Switch conditions) was greater for participants who completed the non-emotional task version first. This result was also confirmed by post-hoc analyses performed on the two ListOrder groups separately (Cold first: $F_{(1,16367)}$ = 115.67, p < .001; Hot first: $F_{(1,14822)}$ = 11.34, p < .001). The inclusion of other higher-order interactions including the ListOrder factor was not justified (all ps > .23; all BF_{12} > 32).

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Table 1. Descriptive statistics for behavioural data.

	Single		Repeat		Switch	
	M	*SD*	*M*	*SD*	*M*	*SD*
COLD TASK						
Response times (ms)	503	93.2	685	198	763	232
Accuracy (%)	98	3.9	97	2.6	95	2.2
HOT TASK						
Response times (ms)	606	106	763	208	852	252
Accuracy (%)	97	6.1	97	2.1	94	2.6

Note. M = mean; SD = standard deviation; ms = milliseconds

Table 2. Estimated parameters of the final linear mixed-effect model of response times with a baseline of Single trials and Cold task version.

Fixed Effects	**Estimate (SE)**	***t***	***p***
Intercept	-2.210 (.055)	-40.000	**<.001**
Domain	.380 (.020)	18.790	**<.001**
Condition - Repeat	.359 (.013)	27.670	**<.001**
Condition - Switch	.521 (.013)	39.930	**<.001**
BDI	.000 (.004)	-.020	.986
Domain:ConditionRepeat	-.165 (.014)	-11.740	**<.001**
Domain:ConditionSwitch	-.174 (.014)	-12.250	**<.001**
Domain:BDI	.004 (.001)	3.870	**<.001**
ConditionRepeat:BDI	.004 (.001)	4.690	**<.001**
ConditionSwitch:BDI	.002 (.001)	3.200	**.001**

Note. SE = standard error; BDI-II = Beck Depression Inventory-II; Significant effects are displayed in bold.

Figures

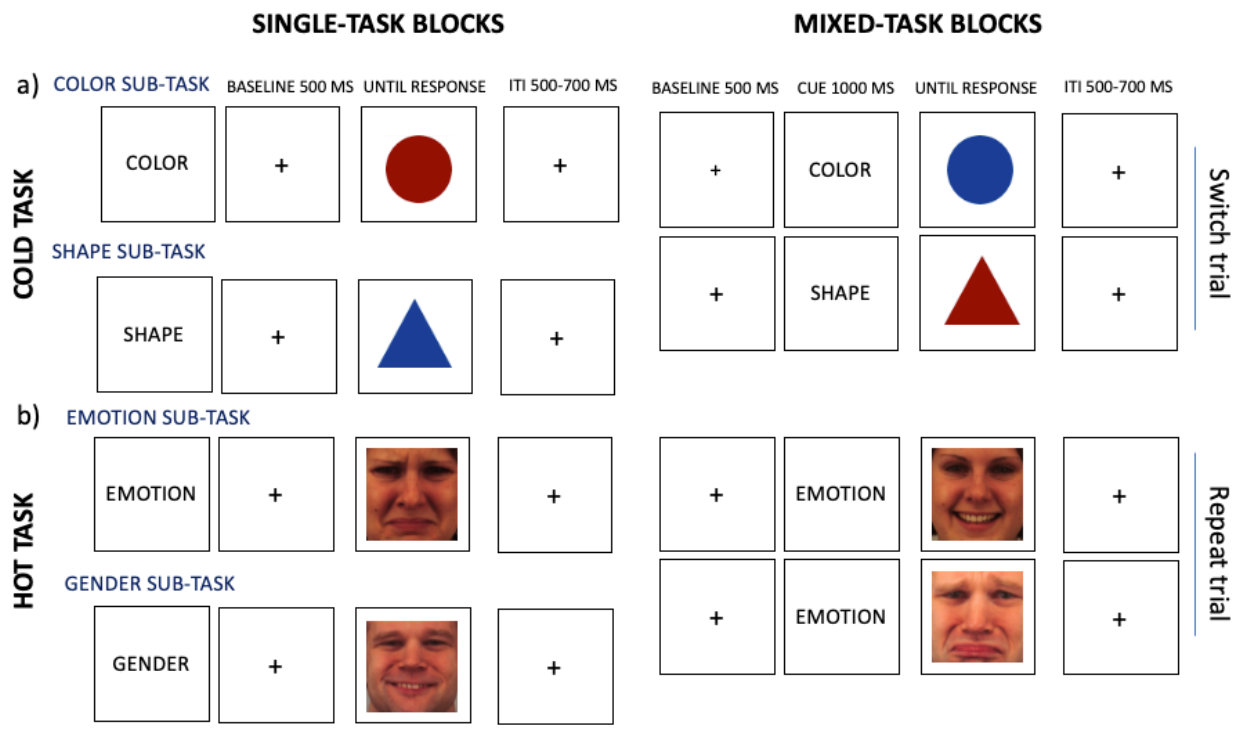

Figure 1

Task-switching paradigms. A) Non-emotional (cold) paradigm. On the left single-task blocks, where the categorization of the target is based on one feature (either colour or shape). On the right mixed-task blocks, where the task varies based on a cue presented for 1000 ms before stimuli onset and each trial can be either a repeat trial or a switch B) Emotional (cold) paradigm. On the left single-task blocks, where the categorization of the target is based on one feature (either emotion or gender). On the right mixed-task blocks, where the task varies based on a cue presented for 1000 ms before stimuli onset and each trial can be either a repeat trial or a switch.

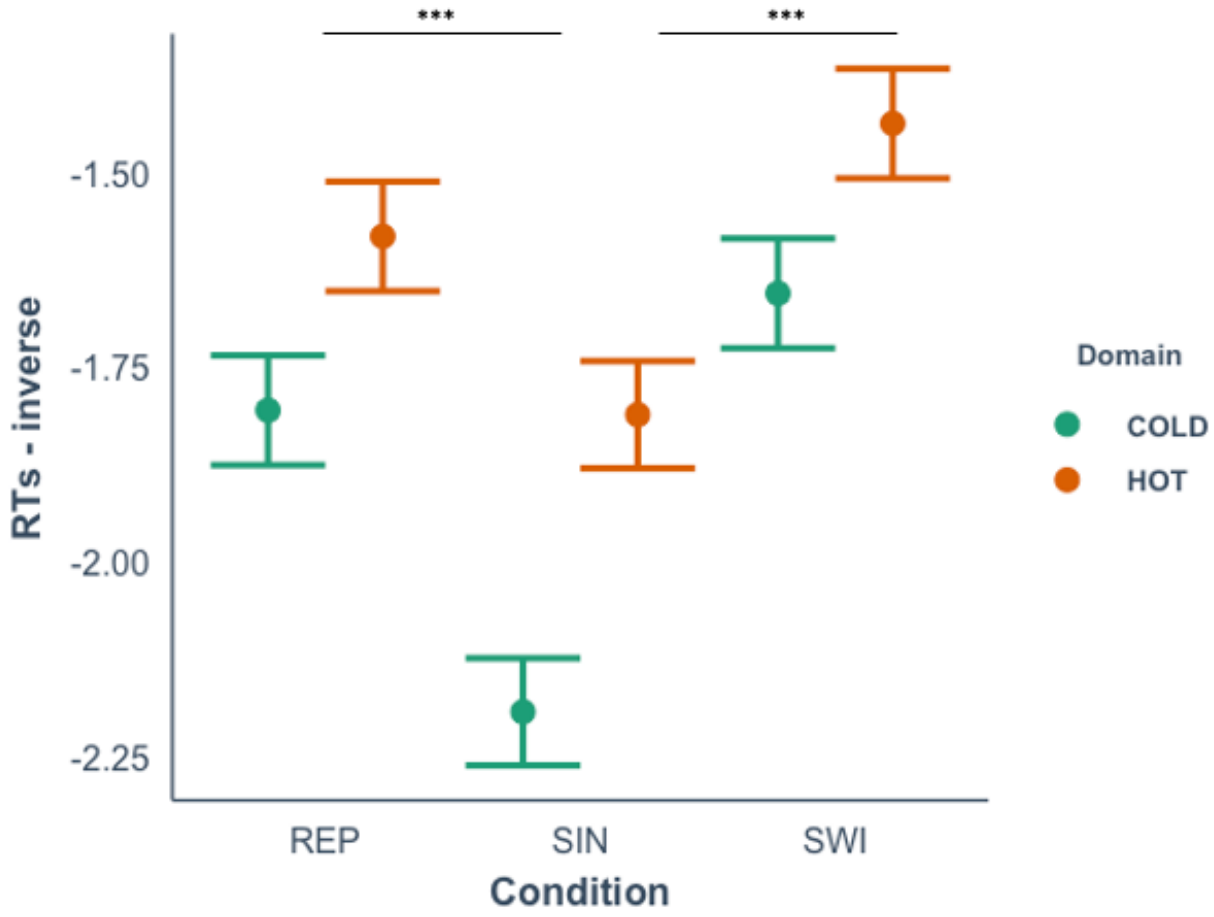

Figure 2

Interaction effect of Condition and Domain on response times (RTs). Error bars represent Ninety-five % confidence bands for each Condition. *Note*. SIN = single trials; REP = repeat trials; SWI = switch trials.

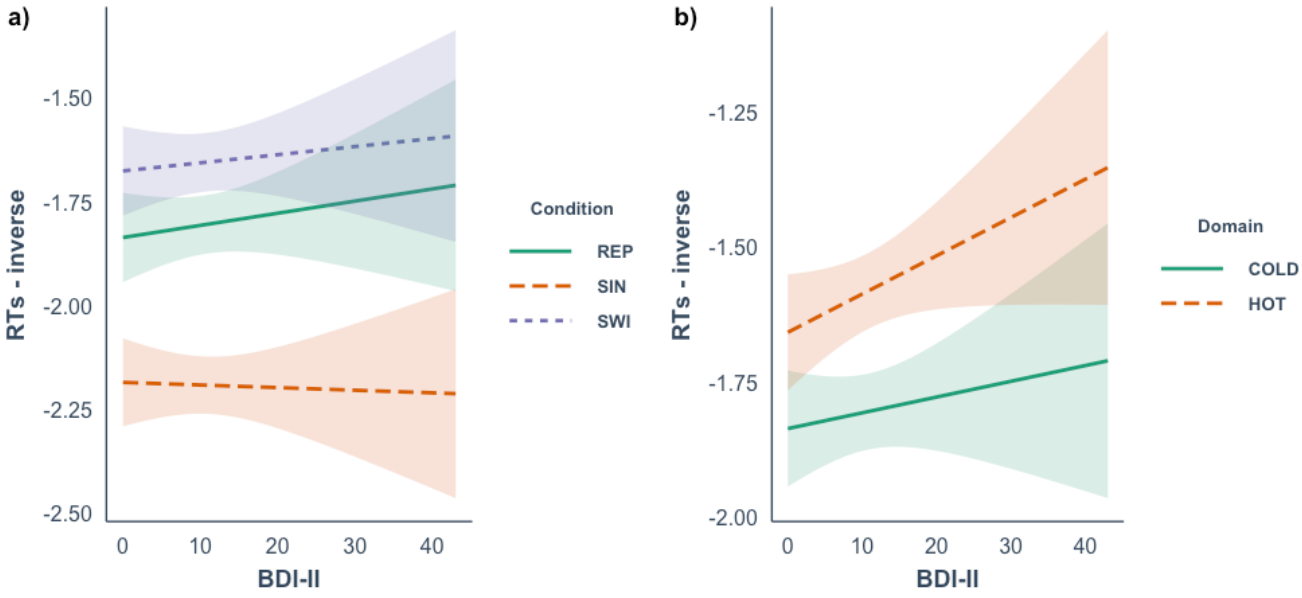

Figure 3

Panel a) Interaction effect of BDI scores and Condition (Single, Repeat, Switch) on response times (RTs). Ninety-five % confidence bands for each Condition are presented in different colours**.** Note. REP = repeat trials; SIN = single trials; SWI = switch trials. **Panel b)** Interaction effect of BDI scores and Domain (cold or hot) on response times (RTs). Ninety-five % confidence bands for cold and hot task versions are presented in different colours.