**Anhedonia sub-components and reward and effort learning for primary and
secondary rewards in young people with depression symptoms**

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Abstract:

Background: Anhedonia, a central depression symptom, is associated with impairments in reward processing. However how the sub-components of reward processing (anticipation, motivation, consummation and learning) are related to depression symptoms is not well understood. In particular, little is known about how effort cost and reward learning is related to anhedonia.

Methods: We recruited young people with high (N=50) and low (N=88) depression symptoms and assessed their learning, consummatory, anticipatory, and motivational responses within an effort and reward learning task. To increase the reward attractiveness, especially for younger people, we included not only money (secondary reward), but also chocolate tastes and puppy images (primary rewards).

Results: Across all participants, we found that self-reported willingness to exert effort positively correlated with actual effort exertion and negatively with effort completion times. We also observed higher accuracy for reward learning vs. effort learning. Additionally, effort expenditure differed between reward types, although no differences in reward liking were observed. Interestingly, we also found that higher anticipatory anhedonia was associated with lower reward learning accuracy.

Limitations: The study assessed only depressive symptoms, not clinically diagnosed major depression.

Conclusion: To our knowledge, this is the first study to examine reward and effort learning simultaneously in young people with depression symptoms. Our findings suggest a differentiation between motivational and consummatory responses, as well as between reward and effort learning. Moreover, we show that anticipatory anhedonia is related to reward learning. Understanding the link between objective reward processing and anhedonia sub-types could provide new targets for treatment development.

Key words: Anhedonia, depression, youth, learning, reward, effort.

Introduction:

Depression is the leading cause of illness and disability worldwide (World Health Organization, 2017). To develop new targets for treatment, a fundamental understanding of the mechanisms that underly depression symptoms is needed. Anhedonia, the lack of interest and pleasure in normally rewarding experiences, is one of the main symptoms of depression and is thought to be underpinned by dysfunctional reward processing (Argyropoulos and Nutt, 2013; Treadway and Zald, 2011) (Kaya and McCabe, 2019; McCabe, 2018; Rizvi et al., 2016).

It is thought that hyposensitivity to reward might be linked to dysfunctional reward learning in depression, and a number of studies report impaired reward learning in depressed individuals using decision-making tasks (Blanco et al., 2013; Cooper et al., 2014a; Herzallah et al., 2013) (Kumar et al., 2018; Kunisato et al., 2012; Pechtel et al., 2013; Robinson et al., 2012). However, little is known about how depression symptoms relate to learning about the effort cost associated with gaining a reward and whether learning in depression is differentially affected by primary and secondary rewards, which are partly supported by different neural mechanisms (Sescousse et al., 2013) (Graf et al., 2017).

Recent investigations using effort-based decision-making tasks find that depressed patients are less willing to expend effort for monetary rewards compared to controls and remitted individuals (Treadway et al., 2012) (Yang et al., 2014). In our studies, we extended the examination of effort expenditure to young people with a range of depression symptoms and found reduced effort exertion for primary reward in those with high vs low depression symptoms and reduced effort correlated with higher anhedonia scores (Rzepa and McCabe, 2019). However, little is known about how young people might learn about effort costs associated with obtaining rewards. To examine this question, we adapted a probabilistic monetary reward and effort learning task from Skvortsova et al. (Skvortsova et al., 2017; Skvortsova et al., 2014). In this task, participants are presented with different shape pairs and are asked to select a shape. All options are associated with a physical effort (high or low) leading to a reward (big or small). Depending on the shape pair, left and right options differ

either in the probability of needing to exert high effort (while the reward outcome is fixed) or in the probability of receiving a big reward (while the effort level is fixed). This design enables the comparison of mechanisms driving reward maximization and effort minimization, which may be differentially affected in depression. We extended this task by incorporating different reward outcomes, namely chocolate taste and images of puppies, as well as commonly used monetary rewards. This allowed us to examine if there are differences in learning from primary rewards (chocolate and puppy pictures) compared to secondary rewards (money), and whether the reward types have differential effects on learning from the associated effort costs. Additionally, the chocolate and puppy picture rewards may be more suitable and relevant to younger adolescents than monetary rewards, allowing for future investigations of the link between depression and reward and effort learning in younger populations.

Given our recent work showing that young people with depression symptoms experience anhedonia as reduced enjoyment and reduced motivation for effortful activities (Watson et al., 2020), we hypothesised that young people with depression symptoms would show blunted reward ratings and reduced willingness to exert effort, as well as decreased actual effort expenditure. Based on previous literature, we also expected reward learning to be impaired in young people with high depression symptoms compared to those with low symptoms (Admon and Pizzagalli, 2015). Given that effort may be considered a cost (Pessiglione et al., 2018) that is encoded in “aversive regions” of the brain (Skvortsova et al., 2014), and that in some tasks depression is associated with increased learning from aversive stimuli (Eshel and Roiser, 2010; Maddox et al., 2012; Rzepa and McCabe, 2019), (Beevers et al., 2013; Cooper et al., 2014b) we hypothesised that depression symptoms might be associated with better effort learning.

Methods

Participants

One hundred and thirty-eight volunteers between the age of 18 and 25 years were recruited from the student population via the School of Psychology research panel, online advertisements and posters throughout the university. The sample consisted of 50 participants with high (HD; Beck Depression Inventory scores ≥ 13 ; Beck et al., 1996) and 88 subjects with low (LD; BDI scores ≤ 12) levels of depressive symptomatology who were assigned to one of three reward conditions: chocolate ($N_{HD} = 20$; $N_{LD} = 36$), money ($N_{HD} = 15$; $N_{LD} = 23$), or puppy pictures ($N_{HD} = 15$; $N_{LD} = 29$). All participants were screened using an online version of the structured clinical interview for DSM-IV (SCID; adapted from First et al., 1996). Given that the current study was focused more generally on individuals with depression symptoms, rather than specifically on those with clinical levels of MDD, the SCID was not used for diagnostic purposes, but merely to determine if any exclusion criteria were met. Specifically, volunteers were excluded if they had ever experienced potentially clinical levels of symptoms of any Axis I disorder (besides depression or low levels of anxiety for HD subjects, with anxiety symptoms being secondary to depression).

The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008. This study was reviewed and given a favourable ethical opinion for conduct by the University of Reading Research Ethics Committee. After reading the information sheets, all participants provided informed consent. Participants were reimbursed for their time with course credits for the non-monetary reward tasks and with £10 for the monetary task. All participants received a debrief form which advised anyone concerned about their mood to contact their GP and which provided contact details for the Samaritans.

Procedure

Questionnaires:

After the screening, eligible participants filled in the following questionnaires online: Beck Depression Inventory - II (BDI - II; Beck et al., 1996), Snaith-Hamilton Pleasure Scale (SHAPS; Snaith et al., 1995), State and Trait Anxiety Inventory (STAI; Spielberger et al., 1983), Temporal Experience of Pleasure Scale (TEPS; Gard et al., 2006), and a demographics form. Additionally, subjects in the chocolate study answered the chocolate questionnaire and Eating Attitudes Test (EAT; Garner et al., 1982). Subsequently, participants performed the learning task described below on a computer in the psychology department testing cubicles using the software MATLAB and PsychToolbox. After the study, participants were given a debrief form explaining the hypotheses of the study.

Table I.

	HD (N = 50)		LD (N = 88)	
	Mean	SD	Mean	SD
Gender (N female/ male)	38/12	-	69/19	-
Age (years)	20.68	2.48	20.63	2.90
BDI	23.26	7.59	5.52	3.86
STAI	51.00	4.92	48.57	7.85
TEPS total	42.11	6.98	44.25	6.55
TEPS-A	34.32	7.06	36.18	5.52
TEPS-C	76.43	11.84	80.44	9.90
SHAPS	24.75	8.46	21.83	8.85
EAT*	12.95	11.00	5.74	3.78

Table I: Questionnaire data for participants with high (HD) and low (LD) depression scores.

*EAT scores were only collected from participants in the chocolate reward condition ($N_{HD} = 20$; $N_{LD} = 34$)

Learning task:

We adapted a probabilistic instrumental learning task based on a monetary reward and effort learning task by Skvortsova et al. (2014 & 2017). Our task was modified to allow for three different reward conditions to be included: money, pictures of puppies or chocolate taste. Participants were seated in front of a desktop computer running Psychtoolbox (psychtoolbox.org) implemented within MATLAB (MathWorks, USA). They registered their responses using a handheld dynamometer (Current Designs Inc), which was calibrated to each individual. The force participants exerted was represented, in real time, by a green bar moving up and down within a rectangle outline drawn on the computer screen. The same calibration procedure as described by Skvortsova et al. (2014) was used: to determine the maximal force a given participant was able to exert, subjects were asked to squeeze the handgrip as hard as they could for 15 seconds. Each participant's maximal force (f_{max}) was calculated by taking the average of the data points that lay above the median force of that person. The force required during the task was individually adjusted to each participant's maximal force by scaling the top of the rectangle outline to f_{max} . After the calibration trials and instructions, participants completed four practice trials. Before and after the task, subjects were asked to rate, on a visual analogue scale (ranging from 0% to 100%), how much they wanted to receive the rewards, how much effort they were willing to invest for the rewards, and how enjoyable they found it to receive the rewards. The experiment consisted of 50 trials (17 trials, short break, 17 trials, short break, 16 trials).

Figure 1: Illustration of the task using the example of a high-effort chocolate reward trial. For the other conditions, the image next to the effort bar (water glass, line drawing of a puppy/ dog, 10p/ 50p coin) and the picture shown during the outcome phase (water glass, photograph of a puppy/ dog, or 10p/ 50p coin) were adapted in line with the relevant outcome (and no 'swallow' cue was shown).

Every trial started with the option to choose between two shapes, shown on the left and the right side of the screen. Choices were made by pressing a key on the keyboard (z for the left and m for the right option). Each option was associated with both a reward and a physical effort, but the left and right options differed in the level of the associated reward or effort. On effort learning trials (shape pair 1), the effort level was probabilistic (80% vs 20% high effort for the left vs right option, sides counterbalanced) while the reward level was high for both options. On reward learning trial (shape pair 2), the reward level was probabilistic (80% vs

20% high reward for the left vs right option, sides counterbalanced) while the effort level was high for both options. Participants were instructed to choose those options that resulted in receiving high rewards and/or avoiding high effort levels. The high effort level was set to 80% of f_{max} and the low effort level to 20% of f_{max} . Depending on the reward condition, low rewards were either 10p, a picture of a dog, or a taste of water; and high rewards were either 50p, a picture of a puppy, or a taste of chocolate. The tastes were delivered in 0.5ml aliquots via long tubes to the participant who held the tubes in their mouth. This amount is perceived as rewarding and prevents habituation, similar to our previous studies (Rzepa and McCabe, 2019).

Once a choice was made, patients were informed about the outcome; i.e., the reward and effort levels were shown on the screen (reward: coin image, puppy line drawing, or chocolate image; effort: a visual target to reach within a black rectangle outline). Next, the rectangle outline turned white, signalling to participants to start exerting effort. Participants were required to squeeze the handgrip until the green bar reached the target (horizontal line) and to hold the target force for 1 second. Any force participants exerted beyond the target was not shown on the screen but was recorded to determine the maximum force invested on that trial. The two behavioural responses (choice and force exertion) were self-paced. Therefore, participants needed to produce the required force to proceed further, which they managed to achieve on every trial. After participants reached the effort target, they received the actual reward (winning 10p or 50p represented by a large coin image, seeing a photograph of a dog or a puppy, or receiving the water or chocolate taste).

The data generated consisted of reward and effort learning accuracy, choice reaction times (RT); effort completion times (started from the first initiation of the squeezing); effort force (the maximum amount of force the participants exerted on each trial, expressed as a percentage of their maximum effort); and ratings for reward "liking", "wanting" and "willingness to exert the effort" (collected at the start and the end of the task). All data were examined using Excel and SPSS.

Analysis

Differences between HD and LD participants in the questionnaire measures were assessed using one-way Analyses of Variance (ANOVAs; combined across all reward conditions).

Visual inspection of the task data, using box-and-whisker plots, revealed several clear outliers in the effort completion times and the effort force data. Therefore, values outside ± 2 standard deviations of the mean were removed from these datasets. Moreover, reaction times were log transformed due to a positive skew.

The task data were analyzed using mixed-measure ANOVAs, with group (HD or LD) and reward condition (chocolate, money, or puppies) as between-subject factors and rating type (liking, wanting, or willingness to exert effort), learning type (reward or effort learning), or effort level (high or low) as within-subject factors. Greenhouse-Geisser corrected results are reported where the sphericity assumption was not met.

In addition, Pearson's or Spearman's correlations were performed to examine the relationship between questionnaire measures and task performance.

Results

Demographics and questionnaire measures

One-way ANOVAs performed on the questionnaire data revealed that HD participants showed significantly higher BDI ($F(1,136) = 331.0, p < 0.001$) and EAT scores ($F(1, 52) = 12.32, p = 0.001$; chocolate reward condition only) than LD subjects. In addition, compared to LD participants, HD individuals demonstrated significantly lower total TEPS scores ($F(1, 132) = 4.36, p = 0.039$) and a trend for higher STAI scores ($F(1, 132) = 3.77, p = 0.054$), representing higher anhedonia and anxiety levels, respectively. Anticipatory ($F(1, 132) = 3.13, p = 0.079$) and consummatory ($F(1, 132) = 2.85, p = 0.093$) TEPS subscales and SHAPS anhedonia scores ($F(1, 132) = 3.46, p = 0.065$) did not differ significantly between groups.

Visual analogue scale ratings

Using mixed-measure ANOVAs (group [LD, HD] x reward condition [money, chocolate, puppies] x rating type [wanting, liking, willingness to exert effort] x time [before and after task completion]) we found a significant main effect of rating type ($F(1.53, 190.64) = 11.46, p < 0.001$), with higher liking than wanting ratings ($t(130) = 2.42; p = 0.017$), and higher wanting ratings than willingness to exert effort ($t(130) = 3.00; p = 0.003$) across all participants (as determined by a paired-sample t-test). In addition, a significant reward condition by rating type ($F(3.05, 190.64) = 3.56, p = 0.015$) and a group by reward condition by rating type ($F(3.05, 190.64) = 3.03, p = 0.030$) interaction was observed. All other main effects and interactions were not significant (all $F < 2.0$).

To follow up the three-way interaction, separate group x reward condition ANOVAs were performed for each rating type (using the average of the ratings from before and after task completion). There were no significant main effects or interactions for any of the rating types (all $F < 2.7$).

Figure 2: VAS ratings for participants with high (HD) and low (LD) depression scores in the chocolate (A), money (B) and puppy (C) reward conditions (error bars represent standard errors).

Task performance

A mixed-measure ANOVA (group [LD, HD] x reward condition [money, chocolate, puppies] x learning type [reward, effort]) performed on the task accuracy data revealed a significant effect of learning type, with better reward than effort learning across all groups and reward conditions ($F(1, 132) = 10.39, p = 0.002$). All other main effects and interactions were not significant (all $F < 1.7$).

Figure 3: Effort and reward learning accuracy across all groups and reward conditions.

Moreover, a mixed-measure ANOVA (group x reward condition x learning type) conducted on choice reaction times (RTs) demonstrated a significant main effect of learning type ($F(1, 132) = 9.44, p = 0.003$), with faster effort than reward learning RTs. Additionally, a significant main effect of reward condition ($F(2, 132) = 5.39, p = 0.006$), as well as a trend for a learning type by reward condition interaction ($F(2, 132) = 2.96, p = 0.055$), was observed. No other significant main effects or interactions were found (all $F < 0.7$).

To follow up the interaction, one-way ANOVAs were performed, which showed that both effort ($F(2, 135) = 5.63, p = 0.004$) and reward ($F(2, 135) = 4.58, p = 0.012$) learning RTs differed significantly between reward conditions. Bonferroni-corrected post-hoc tests revealed that effort learning RTs were significantly faster for puppy pictures than for chocolate ($p = 0.004$), while reward learning RTs were significantly faster for puppy pictures than for chocolate ($p = 0.043$) and faster for puppy pictures than for money ($p = 0.020$). None of the other comparisons were significant.

Figure 4: Effort and reward learning reaction times across all groups for the different reward conditions.

In addition, a mixed-measure ANOVA (group x reward condition x effort level) was run on the effort completion times. As expected, it was shown that low effort trials were completed significantly faster than high effort trials ($F(1, 125) = 275.08, p < 0.001$). All other main effects and interactions were not significant (all $F < 2.8$).

Further, a mixed-measure ANOVA (group x reward condition x effort level) performed on the effort force data revealed an expected main effect of effort level ($F(1, 127) = 845.51, p < 0.001$), with more effort force exerted on high than on low effort level trials, as well as a main effect of reward condition ($F(2, 127) = 5.55, p = 0.005$). Bonferroni-corrected post-hoc tests showed that participants exerted significantly more force in the money than in the chocolate reward condition ($p = 0.002$). No other significant main effects or interactions were observed (all $F < 1.5$).

Figure 5: Effort force (expressed as a percentage of maximum calibration performance) across all groups for the different reward conditions.

Anhedonia and task performance

Correlations were performed to examine the relationship of anhedonia questionnaire measures (TEPS-A, TEPS-C, SHAPS) with effort and reward learning accuracy, and effort completion time during the task. As the Shapiro-Wilk test indicated that the SHAPS scores were not normally distributed ($W_{HD}(47) = 0.881$, $p < 0.001$; $W_{LD}(86) = 0.796$, $p < 0.001$), Spearman's correlations were used for this questionnaire measure, while Pearson's correlations were run for the TEPS scores.

Across all participants, higher anticipatory anhedonia (as indicated by lower TEPS-A scores) was associated with lower reward learning accuracy ($r = 0.184$, $p = 0.034$).

This association appears to be driven by the LD group, which showed a significant positive correlation between anticipatory TEPS scores and reward learning accuracy ($r = 0.306$, $p = 0.004$). This association was not significant in the HD group ($r = -0.08$, $p = 0.595$).

No other significant correlations were observed across all participants or in either group.

Note that after application of the Benjamini-Hochberg correction for multiple comparisons (with a false discovery rate of 10%(Glen)), only the correlation within the LD group, not the one across all participants, remains significant.

Figure 6: Scatterplot of the association between reward learning accuracy and anticipatory TEPS scores for participants with high (HD) and low (LD) depression scores. Higher TEPS-A scores represent lower anhedonia.

Further exploratory analyses:

Given that our task included some novel aspects, it is important to understand how the subjective ratings relate to performance in our task. We therefore performed some additional exploratory analyses. As previous studies suggest that perception of effort and actual effort might be mismatched in depression (Clery-Melin et al., 2011), we examined how the subjective report of willingness to invest effort at the beginning of the experiment relates to actual effort exertion during the task. Using a Pearson's correlation, we found that willingness to exert effort positively correlated with actual effort on low effort ($r = 0.17$, $p = 0.055$) but not high effort ($r = 0.04$, $p = 0.641$) trials. Further analyses found that this was driven by a significant positive correlation in the HD group ($r = 0.32$, $p = 0.026$) but not the LD group ($r = 0.08$, $p = 0.434$). We also found that willingness to exert effort at the start of the experiment negatively correlated with the completion time on the low effort trials ($r = -$

0.168, $p = 0.053$), which shows that those who indicated that they would be willing to exert more effort were faster to complete these trials.

Discussion:

The aim of this study was twofold: to adapt a task sensitive to changes in reward and effort learning using secondary and novel primary rewards, and to examine if there were any differences in learning related to depression symptoms.

Firstly, we did not find any differences in the subjective ratings for wanting, liking or willingness to exert effort between the different reward conditions (money, chocolate and puppies) or between high and low depression groups. This might be expected given that our previous studies find that objective measures of reward processing are more sensitive to the subtle group differences between those with high and low depression symptoms compared to subjective ratings (McCabe, 2018; Rzepa and McCabe, 2019).

Further, we observed no significant effect of time (ratings collected before or after the task) on the ratings, which suggests that there was likely no habituation to the primary or secondary rewards. This supports our novel rewards as suitable for assessing reward behaviour over time.

Across all participants and all conditions, we found that subjective reward liking was higher than reward wanting and wanting was higher than the willingness to exert effort for reward. This supports the idea that liking and wanting can be dissociated (Berridge and Robinson, 2003), and that effort might be seen as a cost (Croxson et al., 2009), which some people may not be willing to invest, even if they want the reward.

When examining learning, we found that participants made significantly more correct choices (i.e., demonstrated higher accuracy) on reward than on effort learning trials, whilst reaction times were significantly faster on effort compared to reward learning trials. It is therefore possible that there was a speed-accuracy trade-off between the learning types.

It should be noted that in the studies on which we based our task (Skvortsova et al., 2017; Skvortsova et al., 2014) reward learning accuracies were also numerically lower than effort

learning accuracies, although this difference did not reach significance. It is therefore possible that there is a (task-induced or 'natural') bias in participants' allocation of attentional/cognitive resource towards reward learning, thereby reducing the resources available for effort learning. This effect may have been amplified in our task due to the use of primary rewards which, by their very nature, may be particularly salient. It is true that effort and reward learning trials were independent in the task, but, being unaware of this, participants initially needed to learn from both reward and effort contingencies on all trials. Therefore, effort and reward learning were initially competing for cognitive resources, and subjects' cost-benefit analyses may have favoured a focus on learning to achieve high rewards over learning to avoid high effort costs. In future studies it would be useful to ask participants about their strategy directly, e.g., examining whether they were more focused on achieving high rewards vs. avoiding low effort and if this differed between reward conditions. In addition, applying computational modelling to the data may provide insights into the relative reward and effort valuation/discounting.

We also observed that choice reaction times were faster in the puppy condition than in the other reward conditions. This may have been the case because, unlike in the other conditions, every outcome in the puppy condition was novel (a different puppy image). This novelty itself may have acted as a motivational signal, which in turn may have led to faster reaction times (Kakade and Dayan, 2002).

Moreover, in our exploratory analyses we found that the subjective willingness to exert effort at the beginning of the task positively correlated with actual task effort on low but not high effort trials. It should be noted that, although the bar visually representing the participants' effort did not rise above 20% on low effort and 80% on high effort trials, participant could squeeze the handgrip as forcefully as they wanted on every trial. This means that, on low effort trials, there was substantial room for individual differences to emerge, given that the required 'baseline' effort was low (20%) and the maximum force exerted (as a percentage of f_{max}) could vary widely, between 20% and 100%. On high effort trials, by contrast, the high 'baseline' force that was required from every participant (80%), and the reduced possible variability

(between 80% and 100%) may have prevented individual differences from becoming apparent. This may explain why we only observed a significant correlation between the 'willingness to exert effort' ratings and the actual task effort on low effort trials and not on high effort trials. Somewhat similarly, it has previously been found that during low, but not high, levels of required effort, individual differences in reward preference predict reward choice, in a task in which participants make choices between different reward and effort pairings (Vaughan and Gotlib, 2008) .

Finally, when examining anhedonia, we found that as anticipatory pleasure (TEPS A) increased, reward learning accuracy also increased across all participants. On closer inspection this was driven by the LD group. It is possible that HD subjects were motivated by aspects other than the rewards in this task, partly due to their high levels of anhedonia. To examine this possibility, follow up questions on task strategy and motivation would be useful in future studies.

In summary, our study suggests that novel primary rewards (chocolate and puppy images) are suitable for assessing reward and effort-related behaviour over time. We have shown that using rewards other than the commonly used secondary reward money may yield differences between reward and effort learning accuracies. In addition, we found that higher anticipatory pleasure correlates with increased reward learning, but that this relationship is absent in those with high levels of depression and anhedonia. Going forward, it will be important to ascertain in larger samples whether there are any differences in primary vs. secondary rewards on reward and effort learning. It will also be important to understand differences in participants' learning mechanisms, strategies and motivation that may account for the disconnect between anticipatory pleasure and learning in HD individuals.

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Declarations of Interest:

None

Contributors:

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