Comparing different cognitive mechanisms underlying depressive thinking

Bachelor's Project Thesis

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Abstract:

Some theories state that impairments in the Reward Learning mainly drive depression, whereas alternatives propose that a crucial factor in depression is the rigid, perseverative thinking involved in Rumination. Previous comparisons suggest that Reward Learning is a better cognitive mechanism for predicting an individual's subjection to be depressed. In this study, the performance of participants in two cognitive tasks, intended to target the cognitive functions was correlated with participant depressive thinking scores obtained from three questionnaires (BDI-II, RRS and PTQ). It was suggested that those who scored lower on self-reported Rumination (RRS) picked up on reward asymmetries earlier than those who scored higher, thus providing some comparable aspects to pre-pandemic scientific research in this topic. However, suspected issues that are yet to be rectified in relation to the processing of behavioural data of the depression (BDI-II) and perseverative thinking (PTQ) scores leave little to be concluded about both mechanism's ability to predict all three depression scores. It is suspected that issues in the calculation of questionnaire scores are eliciting suspiciously high mean scores, which cause a vast majority of participants to fall into the "mid to high" bracket of depressive thinking scores overall. Moreover, limitations such as new concerns impacting mental illnesses as a result of the COVID-19 era hint at the possibility that the results are not reflective of the typical underlying mechanisms believed to instigate and maintain depression in pre-pandemic studies. In sum, it is still unclear to what extent the cognitive mechanisms of Reward Learning and Rumination influence a person's subjection to be depressed, and to what extent they differ between pre-pandemic and peri-pandemic conditions. Both functions should be investigated further to find out more about their usefulness in predicting depressive thinking.

1 Introduction

"People are less happy when they are mind-wandering, no matter what they are doing. People do not really like commuting to work. It is one of their least enjoyable activities, and yet they are substantially happier when they are focused only on their commute than when their mind is going off to something else. When our minds wander, we often think about unpleasant things, and yet even when people are thinking about something neutral, they're still considerably less happy than when they are not mind-wandering at all. If mind-wandering were a slot machine, it would be like having the chance to lose 50 dollars, 20 dollars or one dollar." (Killingsworth, 2011). We as human beings spend a considerable amount of time thinking beyond our present reality, contemplating about events of the past, future, and even the imaginary. Our capacity to mind-wander is a remarkable evolutionary achievement that has enables us to learn, reason and plan, but it may seem to have an emotional cost (Killingsworth and Gilbert, 2010). How is it that mind-wandering can be so prevalent, yet so dictatorial in our tendencies to be unhappy?

Hammar and Årdal (2009) drew attention to the potential link between levels of mind-wandering and a person's subjection to be depressed during a study that investigated the cognitive functioning involved in major depression. Major depressive disorder is defined as a main subcategory of the more acknowledged psychological condition known as depression, one of the most common health issues in the world. The type of depression varies depending on the conglomerate presence and severity of symptoms as some may experience mild and temporary depressive episodes, while others endure more severe and ongoing depressive states. The study characterised depression as a prolonged sad mood, involving a loss of interest in daily life and feelings of worthlessness or guilt. These affective symptoms aside, cognitive symptoms were also

listed; indecisiveness, difficulty in concentration and increased (recurring) spontaneous thoughts particularly. These symptoms conceivably can interfere greatly with not only a person's outlook, but also, mere execution of daily activities. Moreover, recent suggestions show that certain cognitive functions may even be left impaired for much longer than the duration of a depressive episode. This highlights that there is indeed a link between levels of mind-wandering and a person's subjection to be depressed, which should be investigated.

On top of this, the current situation regarding the global outbreak of the COVID-19 virus has undoubtedly brought significant stress to the global population and people's mental health. Compared with an estimated prevalence of depression of 3.44% worldwide in 2017, our pooled prevalence now stands to be roughly 7 times higher at 25% (Bueno-Notivol, Gracia-García, Olaya, Lasheras, López-Antón, and Santabárbara, 2021), wherefore now more than ever, has the general awareness and academic study of mental health and depression been so ubiquitous. In light of this, to effectively address treatment to these matters, it is of primary importance to gather a profound understanding at the level of underlying cognitive mechanisms. Various theories about cognitive mechanisms have generated much discussion over what exactly instigates and maintains depression. Notably, several theories state that impairments in Reward Learning mainly drive depression, whereas alternatives propose that a crucial factor in depression is the rigid, perseverative thinking involved in Rumination.

Reduced Reward Learning causes depressed individuals to exhibit reduced ability in modulating behaviour guided by reward, thus depriving them from responding to positive reinforcers, leading to abnormal reward-based decision making and impairments in goal-directed behaviour (Vrieze, Pizzagalli, Demyttenaere, Hompes, Sienaert, de Boer, Schmidt, and Claes, 2013). This shortened capacity has also been associated to an inability to experience pleasure. Probabilistic learning tasks (where participants are trained to select between abstract stimuli associated with different probabilities of giving a reward) targeting Reward Learning are often used to measure said deficiencies by assessing participants' tendency to learn from positive versus negative outcomes (Tripp and Alsop, 1999). The general consensus is that healthy participants consistently develop a response bias towards the more rewarding alternative, while depressed participants tend to significantly delay or even fail in doing so.

Another symptom of depression, as stated earlier by Hammar and Årdal, is increased recurring spontaneous thinking. Rumination, a sub-type of spontaneous thinking (Christoff, Irving, Fox, Spreng, and Andrews-Hanna, 2016), can be defined as the repetitive, recurring tendency of self-related, spontaneous thoughts; distinctly those that are negative (Nolen-Hoeksema and Morrow, 1993). In practice, the Sustained Attention to Response Task (SART) is used as a common behavioural index of spontaneous thinking, where the aforementioned correlation between mind-wandering and depressive mood can be operationalised to target Rumination through thought probation, as thinking that is more self-related, difficult to disengage from and negative in valence. The general consensus is that depressed participants frequently answer to being subject to this type of spontaneous thinking *more* over the course of the task, compared to healthy participants.

A study of the direct comparison of these two cognitive mechanisms is currently ongoing, by Gupta, A et al, that examines their respective predictiveness towards individual differences in depression, ruminative and perseverative thinking. Initially, their goal was to perform a cross-national study between India and the USA that consisted of correlating the behavioural measures of three questionnaires intended to measure depression, ruminative and perseverative thinking to performance in two cognitive tasks targeting Reward Learning and Rumination. It was observed that Reward Learning was mostly correlated with the depression scores while Rumination was mostly correlated with ruminative and perseverative thinking scores. The Magnitude of Reward Learning (the development of response bias (over time) in participants to optimise reward) in particular, was found to be the cognitive mechanism that best predicted depression and perseverative thinking scores. The proportion of self-related thoughts was also a significant predictor for perseverative cognition scores. Regarding Rumination, the moment of Reward Learning was found to best predict the ruminative response score (RRS). Those suffering from Rumination noticeably took longer to pick up on the best strategy to optimise rewards. However, Rumination was also found to be significantly correlated with country. While in the USA, the moment of Reward Learning best predicted RRS scores and was significant in predicting depression scores, in India, the RRS score was best predicted by the constructs of the spontaneous thinking task. A possible explanation for such differences between the countries is the fact that the global conditions were not consistent throughout the data collection procedure.

With the onset of COVID-19, data collection in India took place during the midst of a pandemic,

unlike the US sample which was recorded before. It was argued that the India sample fell vulnerable to a multitude of external factors that may have caused some contamination regarding the reliability of the collected data. As a result, although together it is suggested that Reward Learning is a better cognitive mechanism for predicting an individual's subjection to be depressed, it can also be argued that the contrasts in results between India and US may not be due to cultural differences, but rather the presence of a pandemic. On these grounds, the following research question is formulated: **Do the cognitive mechanisms predicting rumination and depression in a Western sample differ between pre-pandemic and peri-pandemic?**

2 Methodology

To answer the research question, the performance of each participant in two cognitive tasks intended to target Reward Learning and Rumination was measured and examined for correlation with their depressive thinking score, measured over three questionnaires in a follow-up survey.

2.1 Participants

The data was collected from a total of 32 participants using Prolific; a distributive, data collection service that manages and recruits high quality, global research participants (see appendix for details on how to conduct an online (multi-part) study on Prolific). Participants eligible to partake in this study were pre-screened to only fluent English speakers. The demographics of the final participants is displayed in table 2.1 below.

Age (years)	29.1
Gender (F/M)	14/18
BDI-II (0-63)	44.1
RRS (22-88)	63.3
PTQ (0-60)	53.7

Table 2.1: Demographics of the participants (Mean age (years), Ratio of females to males, Mean depression score (BDI-II), Mean ruminative response score (RRS), Mean perseverative thinking score (PTQ)).

2.2 Tasks and Procedure

First, the participants were asked to list five concerns and achievements in their recent life, in the hope that this would stimulate ruminative thinking. Likewise and unbeknownst to the participants, the spontaneous thinking task used words indicative of general concerns in an attempt to also stimulate Rumination. This modification to the SART was inspired by McVay and Kane (2009) of whom made suggestions that, although the use of concerning words may not cause such a strong effect in terms of the specific trial in that moment in time, rather they may instigate ruminative or concern-related thinking more globally.

Reward-Learning Task The participant would subsequently perform the online experimental tasks; the Reward-Learning task, followed by the Spontaneous Thinking task and the survey. To test an individual's ability to modulate behaviour with respect to changes in rewards, a probabilistic learning task was used. The task consisted of briefly presenting simple, smiley faces to the participant with either a narrow or a wide mouth as illustrated in figure 2.1. For each trial, a fixation point was shown to the participant for 500ms followed by a mouthless face for another 500ms. Subsequently, a narrow (11.55mm) or a wide (13mm) mouth was overlaid on the face very briefly (100ms), to which the participant was then required to indicate as quickly as possible whether the mouth was narrow or wide, using corresponding response keys on the keyboard ('m' and 'z'). There was then a chance that the participant would receive a "reward", in the form of positive feedback, when correctly responding to a trial. Unbeknownst to the participants however, one of the responses was rewarded more frequently than the other. The correct response was rewarded with a probability of 75% for a wide (/narrow) mouth trial, and 25% for a narrow (/wide) mouth trial. The reward bias notably was randomised between participants to avoid complexities where the narrow mouth may have been more profitable than the wide mouth and vice versa. This bias in reward was expected to subconsciously adapt the response of a "healthy" participant by causing them to favour the more-frequently rewarded option when in doubt. The task included three blocks of 100 trials each, where 30 second breaks were given to the participants between blocks. The number of trials with wide and narrow mouths was equal and the total duration of the task was approximately 15 minutes.

Spontaneous Thinking Task The rumination task consisted of a GO/NO-GO SART task where participants were tasked with responding to frequently presented target stimuli as quickly as possible and refraining from responding to less frequent non-target stimuli. The simplicity and monotony of the task allows mind-wandering and spontaneous thinking to occur. To examine the type of mind-wandering the participants was subject to, thought probes were used randomly throughout the task. This is summarised in Figure 2.2. First, the par-

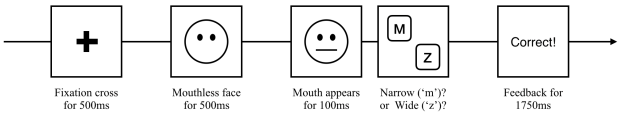

Figure 2.1: Schematic representation of the Reward Learning task (Pizzagalli et al., 2005). During each trial, the participant was required to decide whether a wide or a narrow mouth was shown to them by pressing the corresponding keys 'm' or 'z'. The reward was only given to the participant if, 1) they answered correctly, and 2) a reward was associated with the trial (with a probability distribution of 0.75 for narrow/wide mouth trial and 0.25 for the other wide/narrow mouth trial.)

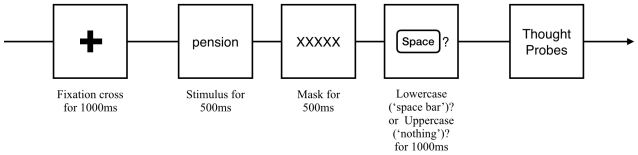

Figure 2.2: Schematic representation of the SART task. During each trial, the participant was required to indicate whether a word was presented in lower case by pressing the Space Bar. Some of the trials were followed by "thought probes" to measure Rumination levels of the participant.

ticipant was asked to recall the list of five recent concerns and goals. The participant was then told that this information would be needed for a later task. This was not actually true, yet deceived the individual in an attempt to stimulate rumination during the task once more. This also served as a way to motivate them to take the task seriously. For each trial, the participant was shown a fixation cross for 1000ms, followed by a stimulus word appearing for 500ms which was either upper case or lower case. The participant was required to press the Space Bar if the word was lower case (a target) and refrain from pressing anything if the word was upper case (a non-target). A mask of XXXX's was always presented for 500ms after the stimulus was shown, hence guaranteeing no chance of response if the participant was off-task and not paying attention. Next, an empty screen was displayed for 1000ms, giving the individual time to give their response.

More importantly, to test for levels of rumination, participants were required to report their thoughts randomly between trials. A generally-used measure of rumination is normally derived from responses to the RRS questionnaire, this cognitive task alternatively sought to operationalise it using the definition of rumination as construed by Nolen-Hoeksema and Morrow (1993). Participants would be presented with the same sequence of questions: "What were you thinking about just now?", "If you were not thinking about the task itself, what was the content of your thought?", and "How difficult was it to disengage from the thought?". Ruminative thoughts were identifiable by responses indicating that the participant was off-task, thinking about more self-related thoughts that are difficult to disengage from, and negative in valence. The ratio of target to non-target trials was 9:1; a key design modification to the SART initially implemented by Gupta, A et al. This change was made to facilitate the identification of legitimate data. Previously, the SART task trials were performed with a ratio of 1:1, which proved to demand extensive data analysis to filter participants that performed the task above chance level. It was realised that a participant could simply do nothing and technically still perform the task accurately to 50 percent. Therefore, a ratio of 9:1 between target to non-target trials forced rejection of participants that clearly under-performed (as the chance level is low), thus allowing easier data analysis and more reliable distributions of accuracy and response times. Finally, the task consisted of 540 word trials, 30 thought probes, and no breaks, making the total duration of this task approximately 20 minutes long.

OpenSesame (Mathôt, Schreij, and Theeuwes, 2011) was used to build both experimental tasks, which were then hosted on a JATOS server (Lange, Kühn, and Filevich, 2015) to collect participant data. OpenSesame is a software used to create psychological experiments and provides built-in support for creating trials and recording behavioural data. JATOS, or "Just Another Tool for Online Studies" is an open-source, cross-platform server used for hosting online studies. Both tasks ran on a server from the University of Groningen with JATOS software, which allowed the tasks to be accessed through a web browser. The ethical permission of the study was approved by the ethics committees and research institute of CETO and the University of Groningen, and informed consents were obtained from all participants.

Self-Report Measures Finally, the participants were asked to complete a survey hosted on the Qualtrics platform that contained the three questionnaires intended to measure depression, ruminative and perseverative thinking. These behavioural measures were assessed using the Beck Depression Inventory 2 (BDI-II) (Beck, Steer, and

Brown, 1996), Rumination Response Scale (RRS) (Bagby, Rector, Bacchiochi, and Mcbride, 2004) and Perseverative Thinking Questionnaire (PTQ) (Ehring, Zetsche, Weidacker, Wahl, Schönfeld, and Ehlers, 2011). The PTQ for one, was included due the transdiagnostic advantage it has over the RRS. The RRS exclusively isolates thoughts that are negative in valence, whereas the PTQ measures thoughts of all valences and therefore is more suitable for individuals who are not clinically depressed. The questionnaire names were not mentioned in the survey to avoid potential influences to the participants' answers.

2.3 Data Analysis

Assessment of Reward Learning To measure participants' competency at learning imbalances in reward, a number of variables were considered. These included Accuracy, Response Bias, ΔResponseBias (change in response bias) and Response Time. Response Bias was defined as an index of a participant's tendency to choose the more frequently rewarded stimulus, given by the following equation:

$$log\ \mathrm{b} = \tfrac{1}{2} log\left(\tfrac{(R_{correct}+0.5)(L_{incorrect}+0.5)}{(R_{incorrect}+0.5)(L_{correct}+0.5)}\right)$$

This equation was retrieved from research carried out by Pizzagalli et al. (2005) and produces a high response bias score when a participant gives a high number of correct responses to the "rich stimulus" (R) and a high number of incorrect responses to the "lean stimulus" (L), thus increasing the numerator and decreasing the denominator. The rich condition is associated to the more frequently rewarded stimulus (the wide mouth) and the lean condition is associated to the less frequently rewarded stimulus (the narrow mouth). A higher bias score indicates that the participant's learning is suggested to be facilitated by rewards. Moreover, to avoid calculations involving zeros in either the numerator or denominator, 0.5 was added to every factor in the equation (Pizzagalli, Iosifescu, Hallett, Ratner, and Fava, 2008). Next, these index scores could be devised to assess learning of response bias germane to the difference in index scores between trial blocks. The change in response bias score between Block 1 and Block 3 captures the overall development of a response bias and was described as the "Magnitude of Reward Learning". Comparatively, the change in response bias scores between *subsequent* trial blocks captures whether the participant developed the response bias "early" or "late" during the task. If the difference in scores between the 1st interval, Block 1 and 2, was greater than that of the second interval, Block 2 and 3, the "Moment of Reward Learning" was labelled as "early". Conversely, the "Moment of Reward Learning" was labelled as "late".

Assessment of Spontaneous Thinking Rumination on the other hand, was also measured on the basis of a number of variables. The main variables of interest were Accuracy, Response Time, Self-reported Attention, Valence and Stickiness. Self-reported Attention, Valence and Stickiness in particular were measured using responses to the thought probe. Self-reported Attention was recorded as a proportion of binarised choices for every trial of each participant. For example, if a participant indicated that they were on-task 18 times out of the 30 corresponding thought probes, Self-reported Attention would be quantified with a value of 0.6 (18/30). Valence expressed the general valence of the user (positive, negative, self-related) and was similarly recorded as a proportion of binarised choices also. For example, if a participant indicated that they were thinking about negative, self-related thoughts, 15 times out of the 30 corresponding thought probes, Valence would be quantified with a value of 0.5 (15/30). Lastly, Stickiness measured how difficult it was for the user to disengage from negative thoughts, and unlike Self-reported Attention and Valence, the choices for Stickiness were simply averaged over all the trials for each participant, using a scale from 1 (easy to disengage from negative thoughts) to 6 (difficult to disengage from negative thoughts).

Prediction of Depressive Thinking The object of this study was to distinguish the depression mechanisms of Reward Learning and Rumination, specifically to further inquire previous findings that suggested that Reward Learning is a better cognitive mechanism for predicting an individual's subjection to be depressed. Therefore, linear (multiple) regression was used to predict the three questionnaire scores (BDI-II, PTQ and RRS) with the help of the variables of interest identified in the Reward Learning and Spontaneous thinking tasks. The variables that best explained individual differences in the tendency to get depressed and the tendency to engage in ruminative thinking were revealed, and the model with the lowest AIC value was selected.

3 Results

3.1 Self-reported Psychometric measures

One could argue that the three behavioural measuring instruments used in the survey share related concepts. Therefore, pairwise Pearson correlation coefficients were calculated to examine to what

extent participants who score high on one questionnaire also score high on the other questionnaires. Table 3.1 indicates that the sample elicits significant positive correlation between the PTQ and RRS questionnaire scores. The BDI-II score's correlation with other scores on the other hand was insignificant.

	RRS	BDI-II	PTQ
RRS	1		
BDI-II	-0.09^b	1	
PTQ	0.51^a	-0.17^b	1

Table 3.1: Pairwise Pearson Correlation of self-report questionnaires ($^a p < .05, ^b p > .05$)

3.2 Manipulation Checks

Rejection techniques were applied to sanitise the data in accordance to those used in a study carried out by Pizzagalli et al. (2005). Trials with response times greater than 2500ms or less than 150ms were deemed abnormal and thus contaminative to the data. An unusually slow response time, generally speaking, suggested that the participant might have been completely disengaged from the task, whereas an unusually fast time alluded to the possibility that responses were made without allowing detection and identification of the stimuli. Furthermore, it was decided that participants with more than 10% outlier trials, or an accuracy of less than 65%, were also rejected.

3.3 Behavioural Predictors for Ruminative Thinking

To assess the predictability of participant Rumination (RRS score), a factor closely related to depression, the already identified variables of interest from both the tasks were used in a regression. It was indicated by the results of the regression that the Moment of Reward Learning (early or late development of response bias) was the behavioural variable that best predicted Rumination scores. Recall that the change in response bias scores between subsequent trial blocks captured whether the participant developed the response bias "early" or "late" during the task. If the difference in scores between the 1st interval, Block 1 and 2, was greater than that of the second interval, Block 2 and 3, the "Moment of Reward Learning" was labelled as "early". Conversely, the "Moment of Reward Learning" was labelled as "late". The participants were divided into these two groups based on the interval in which they experienced their highest response bias development (positive change). It is shown in figure 3.1 that participants scoring higher on the RRS scale appear to learn the reward contingencies later. The t-test however revealed an almost significant difference in RRS score between the subjects that developed their response bias early and late in the task (t(31) = -2.024, p = 0.051).

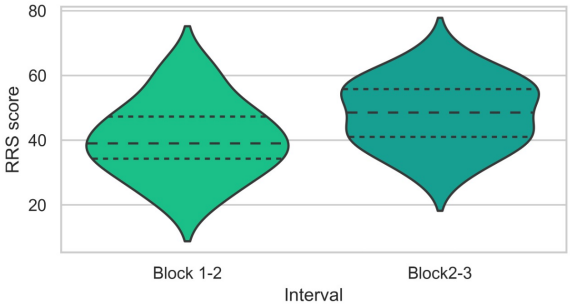

Figure 3.1: Difference in RRS score between participants who developed their highest response bias in earlier and later blocks of the Reward Learning task (number of subjects).

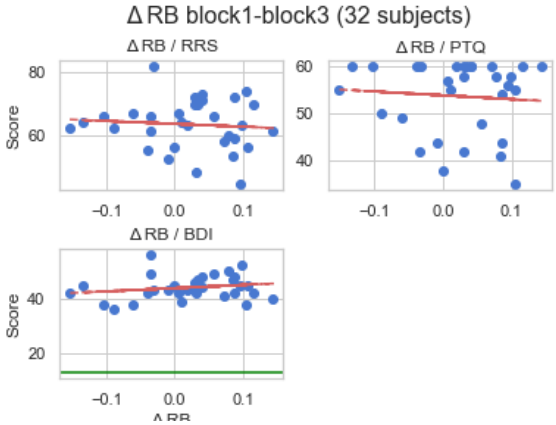

Figure 3.2: The relation between the RRS, PTQ and BDI-II score, and the overall change in response bias during the Reward Learning task ("Magnitude of Reward Learning").

Another identified variable of interest, the "Magnitude of Reward Learning", was conversely found to be insignificant in predicting depressive thinking scores across all three questionnaires. Recall that the "Magnitude of Reward Learning" captured the overall development of a response bias in the Reward Learning task, and was calculated as the change in response bias score between Block 1 and Block 3 (see figure 3.2. Pearson correlation tests revealed that no strong correlations exist between the "Magnitude of Reward Learning" and RRS score (r(31) = 0.286, p = 0.368), BDI score (r(31) = 0.055, p = 0.866), and PTQ score (r(31) = 0.277, p = 0.384), thus suggesting that the predictability of an individual's subjection to be depressed is not dependent on the size of the developed response bias, but the moment at which the response bias was developed instead.

3.4 Behavioural Predictors for Depression and Perseverative Thinking

Furthermore, variables of interest were also assessed for predictability with respect to participant Depression (BDI-II scores) and Perseverative thinking. Unfortunately, insignificant results were obtained, thus leaving little to be concluded about the correlation of cognitive performance to BDI-II and PTQ depressive thinking scores. To name a few, Pearson correlation tests revealed that no strong correlations exist between BDI-II and PTQ depressive thinking scores and accuracy (BDI-II score r(31) = 0.284, p = 0.370), PTQ score (r(31) = -0.020, p = 0.950)), response time (BDI-II score r(31) = 0.145, p = 0.653), PTQ score (r(31) = -0.111, p = 0.731)) or "Moment of Reward Learning" (BDI-II score r(31) = -0.225, p = 0.482), PTQ score (r(31) = -0.506, p = 0.094)) in the Reward Learning Task. It is suspected that there are issues regarding the processing of participant behavioural data. For example, the calculation of depressive thinking scores show that the mean scores are suspiciously high. Figure 2.1 indicates that the usual cutoff for BDI-II questionnaire scores are 0 to 63, and the average BDI-II score was 44.1. Moreover, the usual cutoff for PTQ questionnaire scores are 0 to 60, and the average PTQ score was a more extreme 53.7. By closely examining the data received from the survey, a vast majority of participants fall into a "mid to high" bracket of depressive thinking score overall.

4 Discussion

The aim of this study was to investigate the extent to which the cognitive mechanisms of Reward Learning and Rumination predict an individual's subjection to be depressed, and more specifically, if any difference in results are found to exist between pre-pandemic and peri-pandemic conditions. From the identified variables of interest in both the tasks, one key variable that proved to be the most influential in predicting Rumination scores (RRS) in particular, was the "Moment of Reward Learning". This variable was defined as the point (labelled as "early" or "late") at which participants developed their highest response bias in the Reward Learning task. Although it was found that participants scoring higher on the RRS scale *almost significantly* learn the reward contingencies later in the task, it is entirely feasible that this tendency could be significant.

First, this finding is comparable to pre-pandemic studies that suggest "healthy" participants perform better learning through rewards, implying that participants who score lower on the depressive thinking questionnaires are more competent at learning the imbalance in reward. Vrieze et al. (2013) reported that depressed individuals exhibit a shortened capacity in modulating behaviour guided by reward, thus depriving them from effectively responding to positive reinforcers, and hence explaining the delayed development of a response bias in participants scoring higher on the RRS scale. Therefore, given that the practice of using a p-value of 0.05 to test for significance is greatly dependent upon sample size and sensitivity analysis, perhaps repeating the study with a larger sample size would see a significant correlation between the "Moment of Reward Learning" and depressive thinking scores.

Second, these peri-pandemic findings also reinforce trends previously outlined by Winter (2020). Winter also found that participants with higher depression scores significantly expressed late response bias development compared to participants with lower scores. It was noted that participants subject to higher depression levels developed their response bias *later* rather than developing it *less*. Winter argued against theories stating that depressed individuals are not capable of developing the same response bias as "healthy" individuals, by suggesting that they are completely capable of developing the same response bias, but simply need more reinforcement. The insignificant correlation across all three questionnaires between a participant's subjection to be depressed and the "Magnitude of Reward Learning", displayed in figure 3.2, implies that Winter's statements could indeed be possible as participants were evidently, largely able to produce similar "Magnitudes of Reward Learning".

Although the results suggest to provide some comparable aspects to pre-pandemic scientific research, it is important to consider, not only the suspected issues mentioned in section 3, but also several limitations involved in this study. For instance, the use of online experiments draws reason to question the reliability of the data too. Prolific was used to recruit participants that were largely trusted to provide good quality and globally representative data very quickly. However, it cannot be ignored that participants were free to carry out the tasks in any location and at any given time, resulting in all tasks being made in uncontrolled environments. Both cognitive tasks required that participants would perform to the best of their ability and to react in a timely manner, where distractions coming from an uncontrolled environment could have influenced this, and hence, the outcome of the results. Lack of focus in the Reward Learning task may have caused participants to answer

incorrectly more often for example, thereby influencing the measured response bias. Distractions during the Spontaneous Thinking task on the other hand may have influenced answers to the thought probe, as the questions were directly related to distraction. The impact of this factor was reduced by carefully selecting participants for whom the data indicated that they performed the task correctly, consequently reducing the sample size from over 50 participants to the final 32.

A second concern is the role that the COVID-19 pandemic could have played in affecting patterns of thinking in the participants. Recent studies have discovered a slew of new concerns that are impacting and maybe changing the prognosis of mental illnesses as a result of the COVID-19 era. These include poor sleep quality, inattention (Mo, Wang, Chen, and Jiang, 2020), relationship quality (Pieh, O'Rourke, Budimir, and Probst, 2020), dread of infection or death, and unemployment or the prospect of unemployment (Bhattacharjee and Acharya, 2020), to name a few. One paper published by the Psycorona initiative examined the associations of risk perception of COVID-19 with emotion and subsequent mental health. It was discovered that higher risk perception of COVID-19 was significantly associated with less positive or more negative emotions. Specifically, regressions involving economic risk perception and negative emotions revealed stronger associations. Moreover, risk perception at baseline survey was inversely associated with subsequent mental health (Han, Zheng, Agostini, Bélanger, Gützkow, Kreienkamp, Reitsema, Breen, Collaboration, Leander, and et al., 2021), and as a result, it is possible that the results found in this study are not reflective of the typical underlying mechanisms believed to instigate and maintain depression in pre-pandemic studies, thus making comparisons difficult.

Lastly, it is important to consider addressing some other aspects in terms of the design of this study if future studies are to be carried out. Crucially throughout the Spontaneous Thinking task, the participant was given thought probes randomly, which proved to be a design flaw that could potentially have influenced the collected behavioural data. It was discovered that participants could be subject to answering subsequent thought probes very shortly after one another. For example, a participant could have been asked to report their thoughts, followed by only two decision trials before being another thought probe. Although this occurred sparingly, participants subject to few choice trials between subsequent thought probes may have not allowed mind-wandering and spontaneous thinking to even set in. Therefore, it is suggested that at least 8 or so choice trials should be presented between subsequent thought probes to rectify this issue in future studies.

In addition, the results obtained are dependent on the type of questionnaires used. The BDI-II, RRS and PTQ questionnaires were selected as they appeared most relevant to the objectives of this study. The results may indeed resemble something different if alternative questionnaires such as CES-D and HAMMS are used in future variations of this research.

In conclusion, it is possible that significant correlations that exist between the cognitive mechanisms of Reward learning and Rumination, and depressive thinking (during COVID-19). The results of this study suggest that self-reported Rumination (RRS) in particular was best predicted by the "Moment of Reward Learning", thus providing some comparable aspects to pre-pandemic scientific research. Despite this, it is suspected that there are issues that yet to be rectified in relation to the processing of behavioural data of the depression (BDI-II) and perseverative thinking (PTQ) scores that lead to insignificant results, therefore leaving little to be concluded about both mechanism's ability to predict all three depression scores through linear regression. It is suspected that issues in the calculation of questionnaire scores are eliciting suspiciously high mean scores, which cause a vast majority of participants to fall into the "mid to high" bracket of depressive thinking scores overall. Moreover, limitations such as new concerns impacting mental illnesses as a result of the COVID-19 era hint at the possibility that the results are not reflective of the typical underlying mechanisms believed to instigate and maintain depression in pre-pandemic studies. In sum, it is still unclear to what extent the cognitive mechanisms of Reward Learning and Rumination influence a person's subjection to be depressed, and to what extent they differ between pre-pandemic and peri-pandemic conditions. By the same token, both functions should be investigated further to find out more about their usefulness in predicting depressive thinking.

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A Performing a (follow-up) study through Prolific

A.1 Introduction

This guide offers a detailed look at the use of Prolific in not only the current study, but also other studies that could be followed up in the future. The guide will give an in-depth overview of the main Prolific components and is meant to serve as a tutorial for first time Prolific users from a researchers perspective. A summary of all of the steps taken during the conducting of the study will be provided, combined with an overview of all the valuable lessons learned along the way.

A.2 Why Prolific?

Prolific is a platform that is becoming increasingly popular among researchers to perform scientific studies for all kinds of data gathering online. The Prolific platform was favourable over alternative operators because of the many beneficial qualities that Prolific has to offer. These include:

- Good quality data (quality checks ensure that participants are engaged & trustworthy).
- Conducting experiments are not as time consuming as in-lab studies.
- Diverse, global, representative samples on-demand.
- Target audience can also be narrowed down to recruit niche samples on-demand.
- Pre-screening is flexible & free.
- Fast data turnaround (Within an hour of publishing from a personal computer in Groningen, 50 participants recruited).
- 75% of study costs goes directly to respondents.
- Possible to invite or exclude participants for follow-up studies.
- Easy & safe communication between study participants with in-app messaging system.
- Simple layout & user-friendly

A.3 How does it work?

A.3.1 New Study

After creating a Researcher account on Prolific, located on the left hand side of the home page is a tab divided into 5 sections: *New Study, Drafts, Scheduled, Active and Completed*. To setup a new study in Prolific, select *New Study*. Here you must provide all the specific details regarding your study. Give your study a title that will be visible to the participant, and another only visible to you. The internal name is perhaps useful to distinguish between similar studies published by yourself. For example, you might want to record a second batch of data for a new, improved version of your study. You will want to use the same title as you did previously, however, you will need a way of distinguishing this second study internally.

A.3.2 Study Description

Next, you must provide information about the study. Writing a good study description can improve participant motivation, instructional clarity and help you meet certain ethical requirements. Study descriptions can be complex to put together. Try to cover most of the following points for a good study description:

- The aim of the study.
- What the participant will be required to do.
- Any sensitive information participants will have to provide.
- Anything you think the participant might be uncomfortable doing.
- Any specific details necessary to perform your experiment, e.g downloading software or requiring headphones.
- Anything the participant must do to avoid their submission being rejected.
- An estimate of how much and how long it will take to receive a reward after submission.
- If you plan to use bonus payments, or if it's a longitudinal study with a payment schedule, then state this clearly.
- Information on how a participant can opt out of the study (and what will happen if they do).
- Information on whether a participant can remove their data from the data set.
- Information on whether anonymised data will be made accessible to other researchers.
- Your contact details in case of questions.
- If you have ethics approval, the contact details of the ethics board in question.

A.3.3 Study URL & Parameters

It is important that the URL to your survey or experiment administers the recording of participant ID's. In this study, JATOS was used to record participant data, of which a JATOS Worker ID was assigned to each. Notably, this ID is NOT the same as the Prolific ID of the participants. Therefore, it is crucial to set up your survey or experiment to record participants' unique Prolific ID's to thus match participants to the correct data so as to determine which ones deserve approval or rejection. Be aware that this is managed correctly as failing to do so can cause the process of matching JATOS Worker ID's to Prolific ID's to be rather troublesome. In these cases, data has to be matched manually based on specific information such as chronological data (i.e time started, time duration, etc), which is time consuming and more liable to error. It is recommended for this reason that the recording of ID's is done automatically. This is possible using URL parameters or by including a question in your study asking participants for their Prolific ID.

Automatic recording of Prolific IDs via URL parameters In this study, participants' Prolific IDs were recorded using a query string. This meant that, for the experiment tasks hosted by JATOS, participants did not have to copy and paste their IDs into a survey software, as the system automatically handled this.

```
if (window.jatos &&
    jatos.urlQueryParameters.PROLIFIC_PID) {
    console.log('Prolific information is
        available')
    vars.prolific_participant_id =
        jatos.urlQueryParameters.PROLIFIC_PID
    vars.prolific_study_id =
        jatos.urlQueryParameters.STUDY_ID
    vars.prolific_session_id =
        jatos.urlQueryParameters.SESSION_ID
} else {
    console.log('Prolific information is not
        available (setting values to -1)')
    vars.prolific_participant_id = -1
    vars.prolific_study_id = -1
    vars.prolific_session_id = -1
}
console.log('prolific_participant_id = ' +
    vars.prolific_participant_id)
console.log('prolific_study_id = ' +
    vars.prolific_study_id)
console.log('prolific_session_id = ' +
    vars.prolific_session_id)
```

To achieve this, you must first include the inline Java script displayed above at the beginning of your OpenSesame experiment. Next, export your OpenSesame file to a JATOS study. This can be found in the *OSWeb Tool*. Once you have done this, import your study into JATOS. Next, go to *Worker & Batch Manager* and activate the *General Multiple* worker. This generates a URL link to your experiment. Click on *Get Link*, copy the URL and paste it into the designated section of your new Prolific study. Finally, a query string of parameters must be added to your Study URL in order to successfully record the Prolific ID information. Tick the "I'll use URL parameters" option. This will add a query string to the end of the URL. Now, when a participant starts your experiment through Prolific, the system records their Prolific ID (which can be found in the data) at the beginning of the session. The final study link should look like the following:

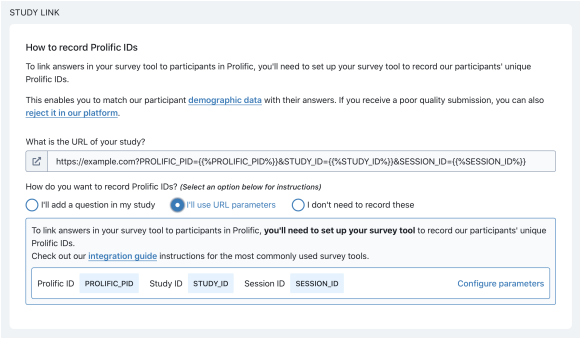

Figure A.1: Example study URL

Manual recording of Prolific IDs via a question in the study Alternatively, you may include a question in your study asking participants for their Prolific ID. In this study, a follow-up Qualtrics survey was given to the participants after they had completed the experimental tasks. A question was simply added at the start of the survey asking participants for their Prolific ID's.

A.3.4 How are participants paid?

To prove that participants have completed your study, it is important to redirect them back to a Completion URL (found on the study creation page), or provide them with a completion code to enter back into Prolific upon completing your study.

Redirecting participants Redirecting participants to a URL at the end of each submission is supported by a number of platforms. In JATOS, simply insert the "Completion URL" provided by Prolific into the "End Redirect URL" in JATOS, and participants will automatically be returned to Prolific once they complete the task. This can be found in the *Preferences* tab of your JATOS study.

A more detailed explanation of this and Prolific ID recording can be found here: `https://osdoc.cogsci.nl/3.3/manual/osweb/prolific/`

Custom end of survey message If it's not possible to redirect participants automatically back to Prolific, you can also manually include the completion URL/code at the end of the study, and instruct participants accordingly. Please show consideration towards participants when reviewing submissions using this format. The experiment in this study was initially set up to instruct participants to provide the completion code (displayed to them at the end of the task) in Prolific, however, many completed submissions were marked with an incorrect completion code (such as NOCODE). Please note that these submissions are not necessarily invalid and it is ultimately up to you to review their data and decide to either approve or reject them. `TIP: the "Preview" function can be used to check that everything is working smoothly before launching your study.`

A.3.5 Submission Approval/Rejection

During data collection, it is possible to view a list of all current submissions by clicking on an active study. Inspect your newly collected data to ensure it satisfies your expectations, and then decide which submissions to approve or reject. Remember, approved submissions pay participants automatically and cannot be reversed. Furthermore, Prolific automatically republishes rejected assignments thereby allowing your study to be completed by new participants, i.e if you have rejected the work of 5 participants, Prolific will immediately make your study available again for 5 new participants.

A.3.6 Audience and Pre-Screening (for longitudinal/multi-part studies):

One particular aspect of Prolific studies that you must pay attention to, is clearly defining what exactly is required of your participants, and planning your study suitably with Prolific in mind. Prolific only allows you to distribute one URL at a time, meaning multiple studies might need to be prepared if you plan to give participants more than one task. For example, this study required participation from the same individuals over multiple tasks; two experimental tasks followed by a survey. Two separate studies were set up on Prolific. The first study consisted of the two experimental tasks implemented into one OpenSesame file, and was distributed on Prolific (pre-screened to only fluent English speakers). Next, the same participants were invited back to a follow-up Prolific study (consisting of a link to a Qualtrics survey) using "Custom Allowlist" pre-screening. The *Custom Allowlist* parameter is a filter that can be applied to your target audience. It informs Prolific that only the provided Prolific ID's are eligible to realise this study. Therefore, only selected participants were emailed with an invitation to take part in the follow-up study when the study was published. Notably, Prolific ID's can be appended to the Allowlist dynamically. Simply select the active study, and the option "Add participants to allowlist" can be found in the *Action* tab located in the top-right corner.

Finally, the desired number of participants (can be increased once the study is active too), (rough) completion time and reward per participant must be determined. These parameters should be set to reflect what participants will be required to do within that stage of the experiment only. Therefore, if you're running a 2-part longitudinal study with an overall reward of £5.50, where one part takes 40 minutes to complete and the second part takes 5 minutes, you might set this up as follows:

- Study 1: Estimated Completion Time 40 minutes, Reward per Participant £4.00
- Study 2: Estimated Completion Time 5 minutes, Reward per Participant £1.50

When participants have completed both parts of the study, you can approve both of their submissions so that they are paid the full £5.50 reward. Make sure that you explain the full structure of your study clearly in the study description, especially when payment is contingent upon participation in follow-up stages. `TIP: Custom reminders can also be sent to specific Prolific ID's using the messaging system.`

Keep in mind that high drop-out rates can be seen in longitudinal studies. If the requirements of the full study are not made clear up front or the time between follow-up stages is too long, participants are likely to lose interest in your study. In this study, the major bulk of the experiment was carried out in the first Prolific study, paying participants £4.00 for 40 minutes of work. Then, participants were paid £1.50 to complete the follow-up survey, which only took 5-10 minutes of work. This further minimised attrition across the studies as participants would be more enticed to see the study through to the end. Nevertheless, when participants have a genuine reason for dropping out of a longitudinal study, you may wish to consider offering them partial compensation or approving their submissions in the parts they have completed. Please show consideration towards participants when reviewing submissions and deciding on a fair level of compensation.