A HIERARCHICAL BAYESIAN MODEL OF LEARNING AND DECISION MAKING IN ANXIETY

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Abstract

The effects of anxiety on various cognitive processes are of great interest in the field of neuroscience. Previous research has shown that anxious individuals have difficulties in updating their beliefs when the environment is unstable. (Browning et al., 2015). It has been known that anxiety can lead to learning deficits and suboptimal decisions (Huang et al., 2017). In this study, our main objective is to examine how state anxiety shapes learning and decision-making under uncertainty. For this purpose, a study consisting of two experimental groups was conducted. State anxiety was induced in the experimental groups. To manipulate anxiety levels, participants were told that they need to do a public speech and complete a mental arithmetic task after finishing the reward-based learning task. While 'Temporal Discount' (TD) group had a chance to get time discount in these tasks depending on their reward-based learning task performance, 'No Temporal Discount' (NTD) group had to do the all tasks in full. In the reward-based learning task, subjects learned the probabilistic relationship that varies over time between the visual stimuli and outcomes. Responses of participants were fitted individually using the Hierarchical Gaussian Filter (HGF) model which is a model within the context of Bayesian learning. Group differences in subject-specific variables estimated by the model were examined in the between-group comparisons. Although no significant between-group differences were found in the learning rates and subjective beliefs on different types of uncertainty, we observed some trends that are consistent with the current literature. Furthermore, our findings revealed the significant between-group difference in the anxiety measure, due to the manipulation. This thesis provides an important basis for further studies on the effects of state anxiety on learning and decision making.

Acknowledgement

First of all, I would like to express my sincere and deepest gratitude to my supervisor, Dr. Maria Herrojo Ruiz for her guidance, support, and patience. Thanks to her, I determined to continue to study on this exciting topic in the future.

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Chapter 1

Introduction

Anxiety is one of the most frequent mental disorders in the world with the highest economic burden to countries (Dreher & Tremblay, 2016). It has been reported that a budget of 42 billion dollars has been allocated for anxiety disorders in the USA (Kessler et al., 2012). In a scientific perspective, the word anxiety refers to a worrying emotional state in response to threats or uncertain events (Horikawa & Yagi, 2012). It is mainly known as a challenging experience and its effects on learning and decision making are one of the great areas of interest within the field of neuroscience. A frequent type of anxiety experienced by most of the people is state anxiety which can be described as an emotional condition caused by the probability of occurrence of an undesirable event in the future, thus it is related to uncertainty. High intolerance to uncertain events is characteristic of anxious individuals and resulted in suboptimal decisions (Grupe & Nitchke,2013). However, the question of how they experience different types of uncertainty during decision making remains to be understood completely.

Humans guide their decisions based on their beliefs about potential outcomes. However, it is usually not easy to predict the outcomes of our decisions in this uncertain world. Unexpected outcomes can be either due to noise (due to the probabilistic relationship between outcome and action) or change in the general structure of the environment. After deciding the reason for the surprise outcome, one should update his outcome expectancies for further actions. A recent study showed that individuals prone to anxiety showed less ability to update their outcome expectancies in a volatile environment (Browning et al., 2015). The prior study reveals that people with high anxiety tend to make suboptimal decisions under uncertainty compared to healthy participants. Although the underlying neural mechanism of these discordant behaviours has been examining by neuroimaging studies, computational models are fast becoming a key instrument to infer the internal models of individuals from their observed behaviours. According to the Bayesian brain hypothesis, the human brain uses sensory input to infer the structural model of the environment. In other words, the human brain acts like an inference machine that uses probability distributions to learn about the environment from sensory inputs (Mathys et al., 2014).

By implementing a hierarchical Bayesian learning model, we examined the between-group differences in various dependent variables (learning rate, two types of uncertainty and belief about volatility). It is aimed that the present study enhances our knowledge of how state anxiety shapes these variables which are related to the internal model (beliefs and uncertainty about them) of the individual.

1.1 Present Study and Hypotheses

Reward-based learning task was completed by all participants after the anxiety manipulation in the experimental groups. State anxiety was induced in two experimental groups by the anticipation of the public speaking task and mental arithmetic task. Spielberger et al. (1971) reported that future events such as public speech or exam increase the individual' state anxiety. We predicted a significant increase in state-anxiety levels in anticipation of doing a public speech. While the group TD had a chance to control the duration of the future tasks (speaking and mental arithmetic task) depending on their learning task performance, the group NTD had to complete all tasks without any discount on total-time of tasks. Control group did the reward-based learning task only and were not informed about any further task, thus was not state anxious. We fitted participants' responses using hierarchical Bayesian learning through perception which is a model within Bayesian brain hypothesis (Mathys et al., 2014). In addition to the learning rate, subjective volatility uncertainty, estimation uncertainty, and beliefs about volatility were compared between groups.

We hypothesized the group NTD would be more affected by state anxiety manipulation, because of the anticipation of future tasks that need to be done in full after the learning task. Based on previous findings given in the next chapter, we predicted that the group NTD would have lower learning rate and tend to underestimate the environmental volatility compared to control. On the other hand, the hypothesis about group TD was that their learning rate and belief on volatility would be higher than in controls since they were motivated to reduce the time of the public speaking task. This temporal discount was directly related to their reward-based learning task performance.

The main reason for studying this topic is my interest in the cognitive consequences of state anxiety which affects many people in their daily life. According to the report by the World Health Organisation (2012), %7.3 of the people in the world suffers from anxiety (Kessler et al., 2012). The current drugs for anxiety have been known for their strong side effects. Investigating new drugs that are overcoming these side effects is related to having better knowledge about behavioural patterns underlying anxiety as a first step. Using the advantages of computational models, we may provide quantitative measurements about the altered or attenuated beliefs about environment underlying the deficits seen in anxiety.

The general structure of the thesis takes the form of five chapters. Chapter two begins by describing the anxiety and continues by looking at the current literature that reported its effects on decision making and learning. Bayesian learning models and HGF are included in the last part of chapter two. The third chapter has described the methodology in detailed used for this study. The fourth section presents the findings of the study. The last chapter starts with the overall summary, continues with the comparison of our results and hypotheses in the light of previous studies and finishes with a discussion of the findings with the explanations of how to improve the present study for future research.

Chapter 2

Literature Review

2.1 Anxiety and Cognitive Deficits

State anxiety can be usually seen in the anticipation of an aversive future event and is associated with the tension feelings which increase the activity of the autonomic nervous system (Spielberger et al., 1971). Although trait anxiety is more general and represents the usual characteristic of a person (Spielberger et al., 1971), recent works had been reported that trait anxiety is positively correlated with state anxiety in a threatening condition (Leal et al, 2017; Horikowa& Yagi, 2012). Several human neuroimaging studies have been carried out to investigate the biological mechanism underlying anxiety (Chauret et al., 2019; Etkin & Wager, 2007). These studies which are using fear conditioning to induce anxiety may help us to identify activated neural patterns in the case of fear or anxiety. However, according to Grupe (2017), understanding the behavioural consequences of anxiety in the real world can be done by the studies examining the decision-making process.

Maladaptive behaviours during decision making under uncertainty are the key characteristic seen in high anxious individuals. (Browning et al., 2015; Grupe & Nitschke, 2013; Huang et al, 2017). Hartley & Phelps (2012) pointed out a behavioural reason with a neuroeconomic perspective, why anxiety and suboptimal decisions are related. They found that anxious individuals tend to avoid risk more and tend to choose a safe or known option. Furthermore, several studies have revealed that the suboptimal decisions are not just due to the tendency to avoid risk, but also, they tended to focus on the stimuli associated with the negative outcome rather than the stimuli associated with reward during an aversive learning task, in contrast to healthy control participants (Horry & Wright, 2009). Overall, there seems to be some evidence to indicate that anxiety caused to biased perception. A strong relationship exists between the perception and internal model of the environment (Mathys et al. 2014), thus by combining prior evidence and studies, we can state that in high anxious individuals the biased perception is caused by the altered hidden states. As we will point out later, this can be examined by the computational models which provide a quantitive measurement of the beliefs and subjective uncertainty within the internal model.

From another scientific perspective, the tendency to choose safe option can be interpreted as avoidance of an uncertain outcome and provides a link between anxiety and intolerance to uncertainty. According to the definition made by Grupe & Nitschke (2013), uncertainty and uncontrollability are related terms. Controllability of a future event can be described as an occurring change in the probability of occurrence of the event when the individual takes an action. If intolerance to uncertainty is one of the key features seen in anxiety (Grupe & Nitschke, 2013) and negatively related to controllability, we might predict that the individuals with a given chance to control the undesirable future event by their actions or decisions will be less state anxious.

On the other hand, another recent work indicated that healthy participants are more able to update their learning rates in an unstable environment and follow stimulus-outcome probability changes better than trait anxious individuals (Browning et al., 2015). In general, and regardless of anxiety, volatile and stable environments differ in learning rates. In volatile environments, participants tend to adapt their beliefs more quickly, this results in higher learning rates. In contrast, since there is not much to learn in stable environments (e.g the probability of a particular stimulus to be rewarded is %90), beliefs are not updated quickly (lower learning rates). In the prior study (Browning et al., 2015), an aversive learning task was used and there was no significant difference in learning rates between low and high trait anxiety groups when the environment is stable. This finding is supported by a recent study in which state anxiety and its effect on motor performance was examined using a hierarchical Bayesian model (Sporn et al., 2018). They found the first evidence for that the state anxiety led to suboptimal motor performance. Furthermore, they reported that belief on volatility is underestimated by anxious people, thus lead to deficits in belief update for this quantity.

There is a large number of volumes of published studies concerned with the role of anxiety in the various cognitive processes, yet there is still a discrepancy between the results. The relationship between anxiety and performance has been widely investigated. It has been demonstrated that individuals with high trait anxiety tend to get more state anxious compared to low trait individuals (Horikawa & Yagi, 2012) and high state anxiety is associated with lower performance in soccer players (Horikawa & Yagi, 2012). In contrast, trait anxiety can be served as a motivating factor in academic achievement and job performance when individuals understand their feelings clearly (Strack et al., 2017). While anxiety is known for its role in evolution in terms of preparing us to threats (Bateson et al., 2011), the number of studies which were reported the positive link between anxiety and increase in cognitive or motor performance is insufficient in the literature.

2.2 Learning and Decision Making Under Uncertainty

According to decision-making theory, individuals use previous experiences to make a decision which yields the maximum reward or desired outcome. However, the option which makes the reward maximum is not always explicit, since the uncertainty. One decides according to his prior beliefs about which option has a higher probability to be rewarded. A well-known functional magnetic resonance imaging study has revealed that the different forms of uncertainty are followed up by individuals during decision making (Iglesias et al., 2013). One type of uncertainty is the environmental volatility and the other type is estimation uncertainty which is caused by the missing knowledge about the probabilistic relationship between outcome and action. Uncertainty represents the subjective beliefs and when it is combined with new information, it shapes our internal model of the world. For instance, someone can believe that, if too many heads come during tossing a coin, tail will come soon (Dimitrakakis & Ortner, 2019). This belief is not consistent with classical probability theory in which tails and heads, regardless of how many times they come, have the same probability. This kind of subjective beliefs are consistent with the Bayesian approach which we will elaborate in the next section.

In the simplest case, learning can be described as updating our beliefs based on the old and new inputs we gathered. Combination of prior knowledge and noisy sensory stimuli allows to use previous experiences and improve our future decisions (Bennet, 2015). Humans learn by making decisions and observing the outcome of those decisions. Thus, to learn more, one needs to explore the world by making new decisions. For instance, one may choose the same way to go to the job every day and he knows everything about the way such as the busiest traffic times and other essential information. However, by choosing the same way every day, one may miss the better options. This is an exploration-exploitation dilemma (Dimitrakakis & Ortner, 2019). Choosing the safe and known decrease the risk, however, it limits the rate of exploration and learning. We can connect this information with the previous paragraph in which it was pointed out that anxious people tend to avoid risk. This connection allows to link the lower learning rates and anxiety.

2.3 Hierarchical Bayesian Model of Learning and Applications

Before the Bayesian learning models, this part will start with the Bayes' theorem which is the foundation of the Bayesian approach. Bayes' theorem is a probability theory to calculate the posterior probability of occurrence of an event given the model. According to the Bayes' theorem (Equation 1), the conditional probability of the model given the observed data is proportional to the likelihood and prior. The likelihood (denoted as p(D|M)) is the conditional probability of the data given the model and prior (p(M)) is the probability of the model before gathered the data. The denominator term is called marginal likelihood or normalization constant (p(D)) which is usually used to compare how well different models represents the data. Overall, Equation 1 shows a way to inference about the model from the data.

$$p(M|D) = \frac{p(D|M) * p(M)}{p(D)} \qquad (1)$$

This theorem, which was found by English mathematician Thomas Bayes in the 17th century was considered as probability theory, however, in recent years it has been getting more and more attention because it is seen as the base of the Bayesian brain hypothesis. A key function of the human brain is to model the external world by using sensory inputs. According to the Bayesian brain hypothesis, the human brain acts like an inference machine that uses probability distributions to learn about the hidden states of the environment from sensory inputs (Bennet, 2015).

There are different types of uncertainty which our brain must deal to guide our decisions and actions (Knill & Pouget, 2004). It is thought that our brain develops an internal model about the external world by representing uncertainty and its computations (Knill & Pouget, 2004). Bayesian inference is the updating this internal model with gathered new information in a Bayes optimal way which means the brain considers all observed information when inferring the hidden states of the environment. In various domains in neuroscience from the study of learning to decision making Bayesian theories have been used (Berker et al., 2016; Harle et al., 2015; Iglesias et al.,2013)

Models of Bayesian learning have become highly influential in the field of computational neuroscience. Hierarchical Gaussian Filter (HGF) introduced by Mathys et al. (2014) is a model of Bayesian learning. In the model, beliefs are stand for the inferences about hidden states of the environment. It is hierarchical as the different levels are connected with the precision (Equations will be shown in the Methods 2.5). Bayesian brain hypothesis is used as a framework of the model in which it has been assumed that every individual has a internal generative model of their sensory inputs. To reflect the internal generative model which represents the beliefs, one needs to assign probabilities to the sensory inputs (the likelihood) given the model, and parameters and combine with the prior distribution of these two (Bennet, 2015). While the main aim of the HGF is to anticipate sensory input derivation from the world (Mathys et al., 2014), it also represents the internal model of the individual about how inputs are generated. Hierarchical model derives update equations for the hidden states and their uncertainty over time since the hidden states of the environment changes with time (e.g., probability of getting a reward with same action), (Mathys et al., 2014). Gaussian distributions consisting of means and variances represent beliefs at the three levels of the probabilistic hierarchy. The mean of the distribution is our beliefs and variance of the distribution represents how much we uncertain about our beliefs, thus precision is the inverse of the variance. If the variance of the distribution too large, the uncertainty in the certain level about belief will be large, thus it means one is not certain about his belief. Beliefs are updated with the precision ratio at different levels weighted by prediction errors in the particular level (Mathys et al., 2014).

HGF was used in a recent fMRI study in which participants were administered an associative learning task and findings revealed that learning is a hierarchical process which rest on multiple prediction errors within the neural system engaged by task (Iglesias et al., 2013).

One of the important advantages in the model is that it captures variation between participants and does not assume a fixed learning rate, in contrast the Rescorla–Wagner learning model. Thus, it is ideal for observing individual learning differences by subject-specific parameters during the cognitive task. HGF was used in many studies and supported by empirical evidence (Iglesias et al., 2013, Berker et al., 2016; Diaconescu et al.,2017). HGF was used in a recent functional magnetic resonance imaging (fMRI) study in which was found that schizophrenic patients overestimated volatility and changed their decisions very quickly (Deserno&Boehme et al., 2017). In the prior study, the symptoms of schizophrenia assumed to have an incorrect inference about the extant world which is predicted to be the reason of maladaptive behaviours in the mental disorders. According to the Stephan et al. (2016), generative model of behavioural measurements can be called as ‘’computational assay’’ (p.3) and it may show a way to answer unknown questions about the underlying mechanism of behavioural differences in neuropsychological disorders.

To conclude, we reviewed the recent studies which were revealed the association between anxiety and various cognitive deficits such as lower learning rates, intolerance to uncertainty, tendency to avoid risk and limited exploration. After that, we examined the role of various types of uncertainty in learning and decision-making process. Lastly, the large number of studies in which Bayesian approach was used were investigated and it was highlighted that HGF can be used as an advantageous tool for examining individual belief differences.

Chapter 3

Materials and Methods

3.1 Participants

Procedure of the experiment was approved by Goldsmiths, University of London ethics commission. Informed consent was given by all participants before beginning of the experiment. Forty-five healthy subjects (30 females) aged 19 to 39 (mean 26.3) participated in this study. It was assured that there was no neurological and psychological disorder in the history of the participants. Power analysis was done to estimate the sample size. The estimated sample size was N=30. After the completion of State-Trait Anxiety Inventory (STAI), subjects were allocated to three groups randomly (n=15 for each group).

3.2 Reward Based Learning Task

In this study, binary reward based learning task in which participants learned the probabilistic relations between outcome and visual stimuli were administrated. Participants were familiarised with the experimental setup before the main task with practice trials. All participants were paid £ 10 at the end of the experiment and they confirmed receiving it.

The binary learning paradigm has similar features with the paradigm used in a recent study to examine the relationship between stress responses and uncertainty (Berker et al., 2016). The task consists of two visual stimuli (two fractals in different colors) presented on the computer screen and two outcomes. The aim of the task was different for each group. For the NTD and control group, the aim was to deduct the corrupted points as many as possible by choosing the correct (rewarded) stimuli. The outcome was either 3 deducted corrupted points (reward) or zero deduction (no reward). At the beginning of the task, all participants started with 1200 corrupted points. Differenly from other groups, for TD group, every correct decision yielded to 3 seconds deduction from the public speaking time and mental arithmetic task time. The total number of trials was 400 which is divided into 10 blocks.

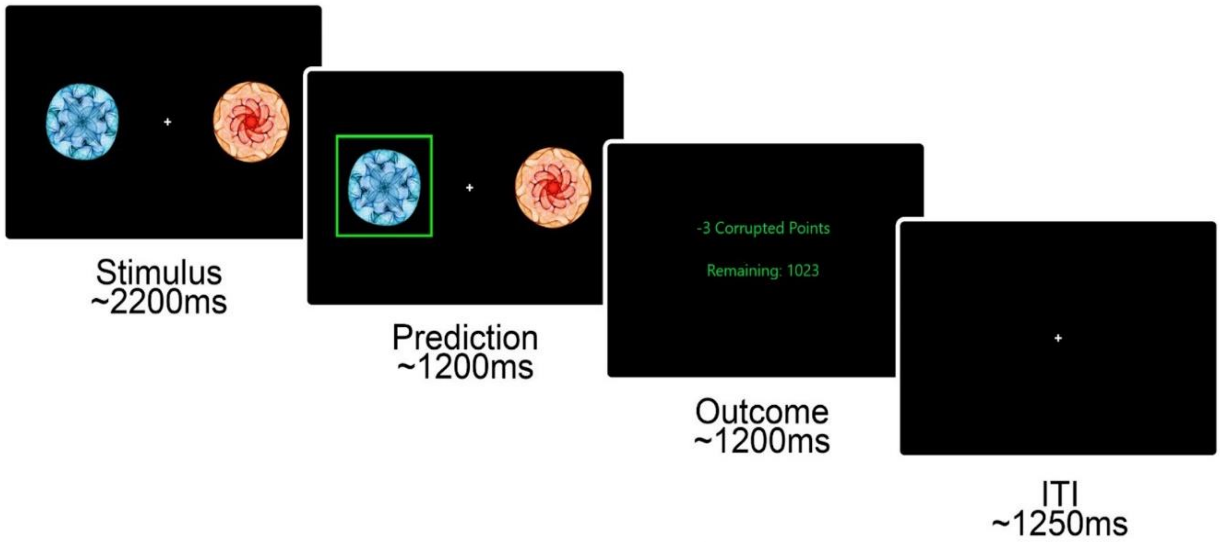

Figure 3.1: Reward-based learning task on the computer screen

The two stimuli were presented to the participants for 2200 ms on each trial. Participants should have made the prediction within 1200 ms according to their beliefs about which stimulus have a higher probability to be rewarded. After a certain waiting time, the outcome of the decision made by the participant was presented on the computer screen. If the decision was correct, the reward was either three deducted corrupted points (control and NTD) or deducted three seconds from the time of future tasks (TD). They have not received any reward in the case of incorrect guess (zero deducted points or zero time deduction). The probability relationship between two stimuli was explicitly told to the participants (Equation 2).

$$\mathrm{p(reward|\ stimulus1)} = 1 - \mathrm{p(reward|stimulus2)} \tag{2}$$

The main goal in the task was to correctly guess the most probable stimulus to be rewarded by using past outcomes. The probability-based link between the reward and stimulus varied in each block. Figure 3.2 shows the probablity relationships throughout the experiment. The participants were informed that the probability of receiving a reward from stimuli changed during the course of the experiment. It was expected that the participants would follow these changes in odds throughout the task.

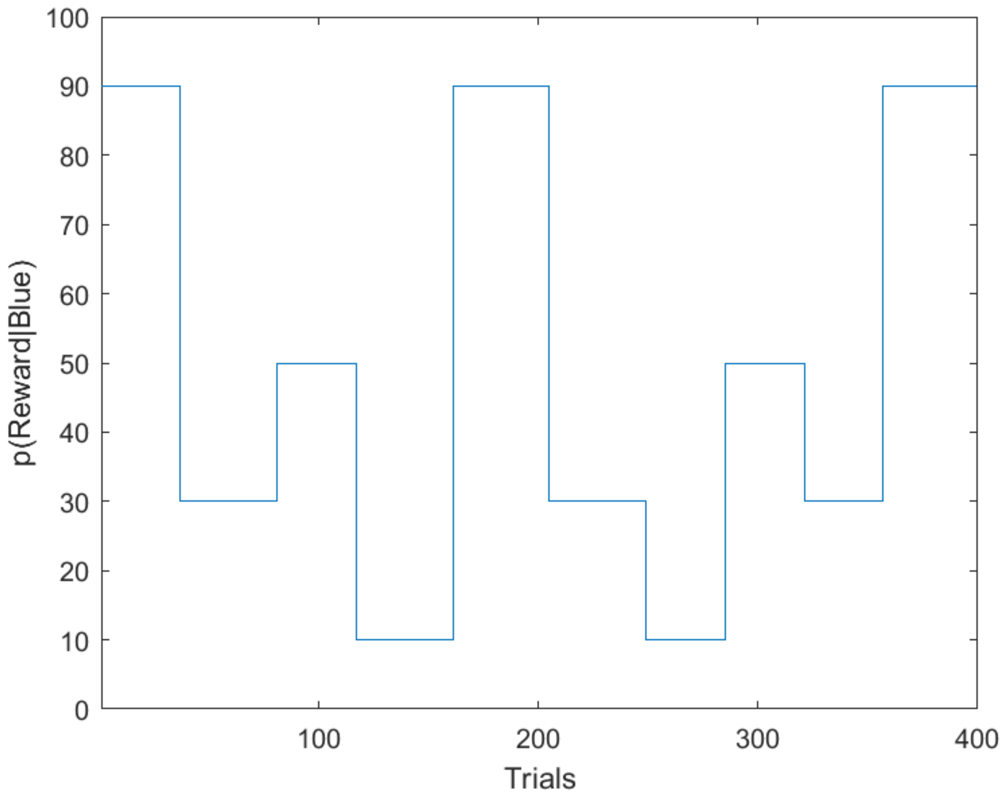

Figure 3.2: Figure 3.2: Example of the link between blue visual stimulus and reward outcome is illustrated. Probability relationship between the stimulus and outcome throughout the experiment were as follows: two blocks for 90/10 (high predictability), two blocks for 70/30 (moderately predictable), and two blocks 50/50 (random case). In addition, two blocks of 10/90 and two blocks of 30/70 were used. Order of the probabilistic blocks was randomized across participants.

3.3 Anxiety Manipulation

State anxiety was induced prior to the learning task in the experimental groups. The state anxiety manipulation method was similar to the method used in the recent study examining the link between anxiety and motor variability (Spouse et al., 2017).To induce state anxiety, second and third tasks were told to the participants in the experimental groups prior to the reward-based learning task. As a second task, participants were informed that they would need to complete a 10-minute mental arithmetic task with 5 second response time for each question. The third task in which participants need to prepare a 10-minute speech about a given art object to present to the experts was told. It was also mentioned that they would have a three-minute time period to prepare their speech and would see the art object before the preparation period. These tasks supposed to be done after the first task which was the learning task. As mentioned before, the main aim of the given tasks was to increase the state-anxiety levels of the individuals.

TD (temporal discount), one of the two experimental groups, could reduce the total time of the tasks (20minutes) depending on the number of correct answers in the reward-based learning task whereas no such temporal discount was given to the NTD (no temporal discount) group. On the other hand, the control group was asked to complete the reward-based learning task only and was not asked to perform other tasks. Before the beginning of the learning task, future tasks were explicitly told to the participants.

3.3.1 Experimental Group: Temporal Discounted Time (TD)

The participants in the TD group (n=15) were informed that their performance in the reward-based learning task would affect the total time of the second and third tasks. In other words, they were told that every correct prediction in each trial would yield a 3 second discount from the total time (20 minutes) of the tasks. Since the TD group was trying to reduce the total time as maximum as they can do, they were expected to be more motivated compared to other groups. After finishing the reward-based learning task, participants were informed about their performance. It was told to the participants that they would not need to perform the mental arithmetic task because they have succeeded to deduct enough time in the learning task but still need to prepare a presentation about a given art object. After the preparation time (3 min), participants have been told that the examiners were out of the office and they would not come back again. They were advised to present the art object in their own head for a minute.

3.3.2 Experimental Group: No Temporal Discounted Time (NTD)

In contrast, the NTD group (n=15) would need to complete all tasks in full without any discounted time. After the preparation time was over, they were told the same instructions with the TD group: ‘The experts are not available to listen to your prepared speech, please present it in your head for a minute.’’

3.3.3 Control Group

The control group (n=15) was asked to complete the reward-based learning task only and were not informed about future tasks, thus they were not expected to be state anxious.

3.4 Measures of Anxiety

All participants completed STAI (State-Trait Anxiety Inventory) prior to starting of the experiment. Mean values for the state and trait anxiety scores prior to the manipulation was calculated for each group: 34.7 (control), 35.93 (TD) and 33.8 (NTD) and mean values for trait anxiety: 40 (control), 47.6 (TD) and 41.4 (NTD).

Continuous rating of anxiety was assessed using HAD (Hospital Anxiety Depression) scale. Four questiouns from HAD (Hospital Anxiety Depression Scale) scale was asked throughout the experiment to track anxiety levels. The following four questions were scored from 1 to 4 by the subjects where '4' means 'Most of the time and '1' denotes 'Not at all': 'I feel stressed.' , 'I feel tired.', 'I have worrying thoughts going through my mind' and 'I feel bored'. Score 1 means 'I do not agree at all.' First HAD was given to all subjects before the practice trials (after the first 5 minutes resting state.). Second HAD was completed after the practice trials but before they were told they would do public speaking and maths task. Third HAD only completed by the individuals in the experimental groups. They were presented HAD questions 3 times over a 5 minute waiting period. In addition, during the first 200 trials of the reward-based learning task, participants completed HAD reports in every 40 trials. After a short break, participants started to second 200 trials and completed HAD reports in every 40 trials. Final HAD was given at the end of the task to the all participants.

3.5 Behavioral Data Analysis

3.5.1 Computational Model of Learning (HGF)

As mentioned in the literature review, Hierarchical Gaussian Filter (HGF) is a particular model within the Bayesian brain hypothesis. The HGF introduced by Mathys et al (2015), was implemented to each participant's responses to obtain belief trajectories individually. HGF uses maximum a posteriori parameter estimation (MAP) to estimate subject specific parameters. (Mathys et al ,2015). We implemented a three level HGF using the TAPAS Toolbox v2.1 (http://www.translationalneuromodeling.org/tapas) for MATLAB.

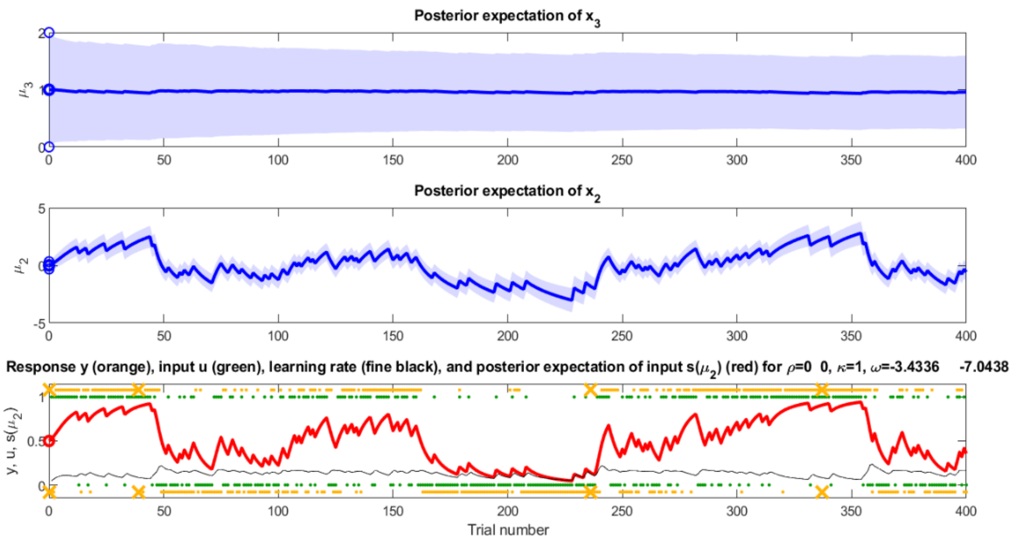

Figure 3.3: Example for the HGF belief trajectories which vary with time using TAPAS v.21 for participant number 11 is illustrated.

The example output of the HGF for a participant is shown in Figure 3.3. In the HGF, beliefs are represented as Gaussian distributions to capture the different types of uncertainty. Different types of uncertainty are estimated by the model individually: irreducible uncertainty in the first level, estimation uncertainty in the second level and volatility uncertainty in the third level. Irreducible uncertainty is due to pre-defined probability relationships in the experimental procedure. The equivalent reason of irreducible uncertainty in the real world scenario is the probability relationships between outcome and action (de Berker et al., 2016).

Estimation uncertainty is caused by missing knowledge of those relationships. The projection of environmental instability is volatility uncertainty (e.g: higher belief on environmental volatility when p(reward|stimuli1)=p(reward|stimuli2)). In the first level of the HGF output responses of the individual are shown as the orange dots and the black line in the bottom is the learning rate over time. As a note, the red line in the first level of given output represents the ideal Bayesian observer.Here, we focused on the second level and third level to capture the variations in beliefs and subjective uncertainty across participants.Beliefs about hidden states including belief about a tendency for a stimulus to be rewarding and belief about volatility were provided by the model HGF in which beliefs are represented by Gaussian distributions in each level. The model is hierarchical in terms of the interaction between levels. The variance of the Gaussian distribution at level 2 (σ_2) represents the estimation uncertainty, whereas the mean of the distribution shows the tendency for a stimulus to be rewarding. In the highest level of the hierarchy, the mean of the distribution represents the belief on volatility (μ_3) and the variance (σ_3) is the volatility uncertainty (Mathys et al., 2014).There are different learning rates at each level of the hierarchy. Here, we take into account the first level learning rate for our analysis. First level learning rate which represents the task performance can be seen in the equation. Approximation of belief update equation is shown in equation 3 in which the number of the level in the hierarchy is denoted by 'i'. Belief update equation is proportional to precision weighted prediction errors. We organized the equation 3 to show the belief update at level 3 and level 2 and prediction errors are denoted by PE and ('^') shows the pre-update values. Precision (π) is the inverse of the variance of the particular Gaussian distribution and variance represents the different types of uncertainty.

$$\Delta\mu_i \propto \frac{\widehat{\pi_{i-1}}}{\pi_i} (PE)_{i-1} \tag{3}$$

$$\Delta\mu_3 \propto \frac{\widehat{\pi_2}}{\pi_3} (PE)_2 \quad \& \quad \Delta\mu_2 \propto \frac{\widehat{\pi_1}}{\pi_2} (PE)_1 \tag{4}$$

3.6 Statistical Analysis

3.6.1 Between Group Comparisons

In the statistical analysis, the between-group comparisons were carried out between NTD vs control and TD vs control. The following dependent variables were used in the comparisons: μ_3 (belief about volatility), σ_2(estimation uncertainty which equals to variance at level 2), σ_3 (volatility uncertainty which equals to variance at level 3) and learning rate. We used the first level learning rate in HGF since it represents the task performance. The learning rates at level 2 and level 3 were not used in the comparisons.

Variables were averaged in bins of 100 trials for each participant and four mean values across time were obtained. For each group (n=15) and each dependent variable (four mean values in bins of 100 trials), a matrix with 15 columns and 4 rows was created using MATLAB.
Multiple comparisons between obtained matrices for each group were performed using non-parametric permutation tests. As a note, non-parametric tests do not require any assumptions including normality, thus it is more powerful than parametric tests when the assumptions do not meet. To control the false discovery rate (FDR) at the desired level (Q=%5), we used an adaptive linear step-up procedure which is introduced by Benjamini, Krieger & Yekutieli (2006). Results were judged against the adapted threshold p-value provided by the above procedure. All statistical analysis was performed using MATLAB.

Chapter 4

Results

4.1 Continuous Measure of Anxiety (HAD)

The continuous measure of anxiety (HAD) was administrated during the experiment in 13 times to track anxiety levels. HAD report which contains 4 questions were examined by excluding the answers to the two questions that were not related to anxiety. Those excluded questions were: ‘I feel bored’ and ‘I feel tired'. The individual mean scores of HAD were computed for the remaining two questions in each time point. Figure 1 presents the mean values obtained from the preliminary analysis of HAD scores for each group. The non-parametric permutation test between control and TD revealed the significant mean difference due to anxiety manipulation (p=.004). Group TD reported being more state anxious than the control group in one HAD report after the anxiety manipulation. Fig 4.1 shows the HAD number in which significant difference was found. Surprisingly, no significant mean difference was found between the group NTD and control. It is important to note that HAD 1 and 2 show the pre-manipulation mean scores. HAD 3 to 12 were obtained during the reward-based learning task and HAD number 13 was completed after finishing the task. Although not shown as a separate figure here, after preliminary analysis, each time series of HAD scores were corrected with their baseline average before the manipulation occurred. The aim was to question for each group how the scores vary over time from the baseline.

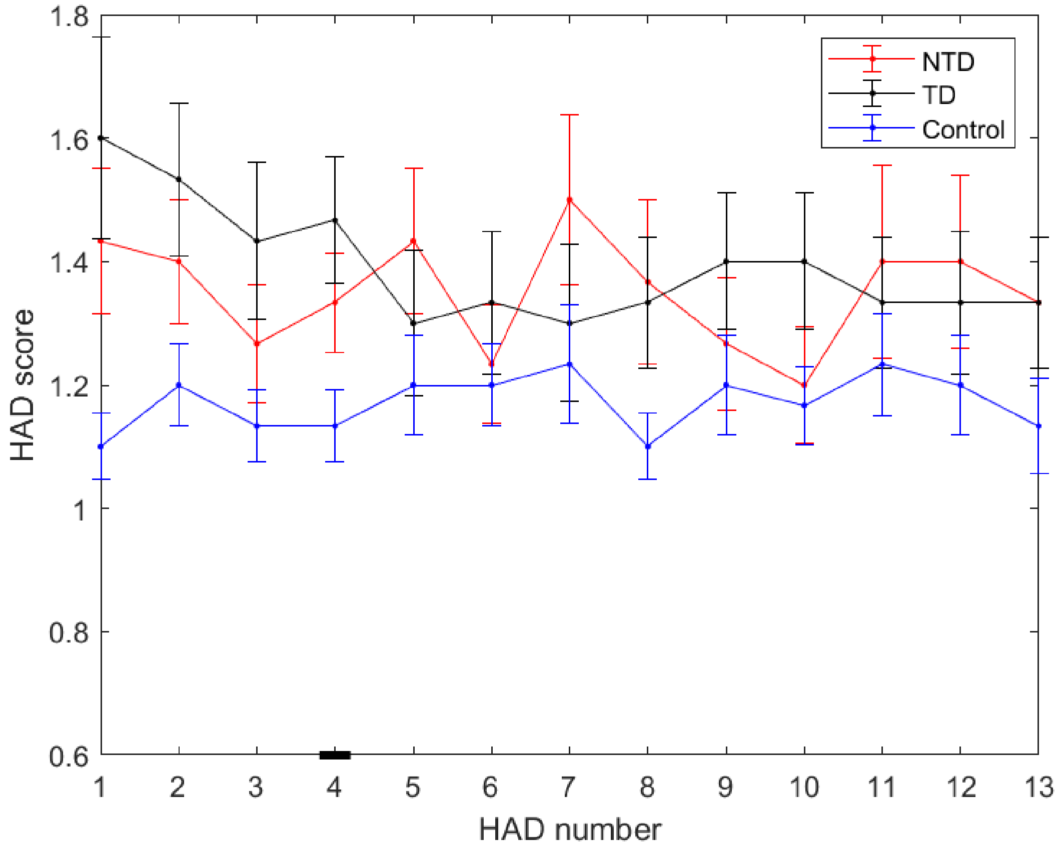

Figure 4.1: Mean values of each HAD report in each group are presented. 13 HAD were completed during the experiment. Error bars represent the standard error of the mean.

4.2 Dependent Variables

To test our hypotheses, we fitted three-level HGF to each participants' responses and obtained belief trajectories. The belief trajectories for a participant are shown in the previous section as an example (Fig. 3.3). In this study, dependent variables are learning rate, volatility uncertainty, estimation uncertainty and belief on volatility. Non-parametric permutation tests were carried out to determine whether the between group differences in these variables are significant.

4.2.1 Learning Rate

We hypothesized that the TD group would have higher learning rate as they were more motivated due to temporal discount directly relate to their task performance. Learning rate is proportional to the ratio of precisions at different levels of the hierarchy, where the precision is the inverse of the variance at the corresponding level and variance represents the uncertainty.

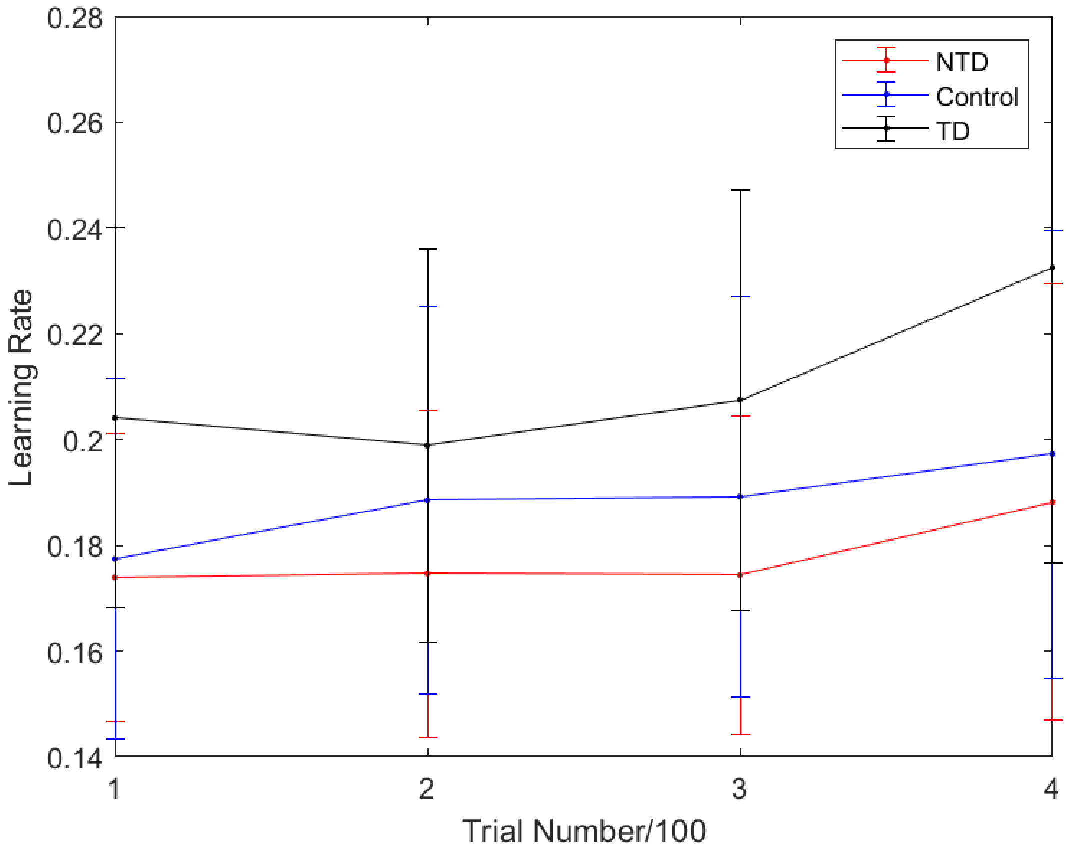

Figure 4.2: Mean values of the learning rate in bins of 100 trials is shown. Learning rate at the first level in the HGF is proportional to precision at level 2, thus inverse proportional to estimation uncertainty. Error bars represent the standard error of the mean.

The between-group non-parametric permutation test did not indicate a significant group difference in learning rates. However, there are clear trends in Fig 4.2. As predicted, the TD group have the highest learning rate compare to other groups. Group TD is followed by the control group. The group NTD have the lowest learning rate in each bin. Although the trends were aligned with our hypothesis, it is important to highlight again that a significant difference between groups was not found (p>.05).

4.2.2 Volatility Uncertainty

High belief on volatility means overestimation of the volatility, which resulted in higher learning rates and switching behavior patterns quickly. Not a significant between-group difference was found in volatility uncertainty (p>.05). In Fig.4.3 there is a clear trend of decreasing for each group over time. As a note, more uncertainty is interpreted as less precision about the belief.

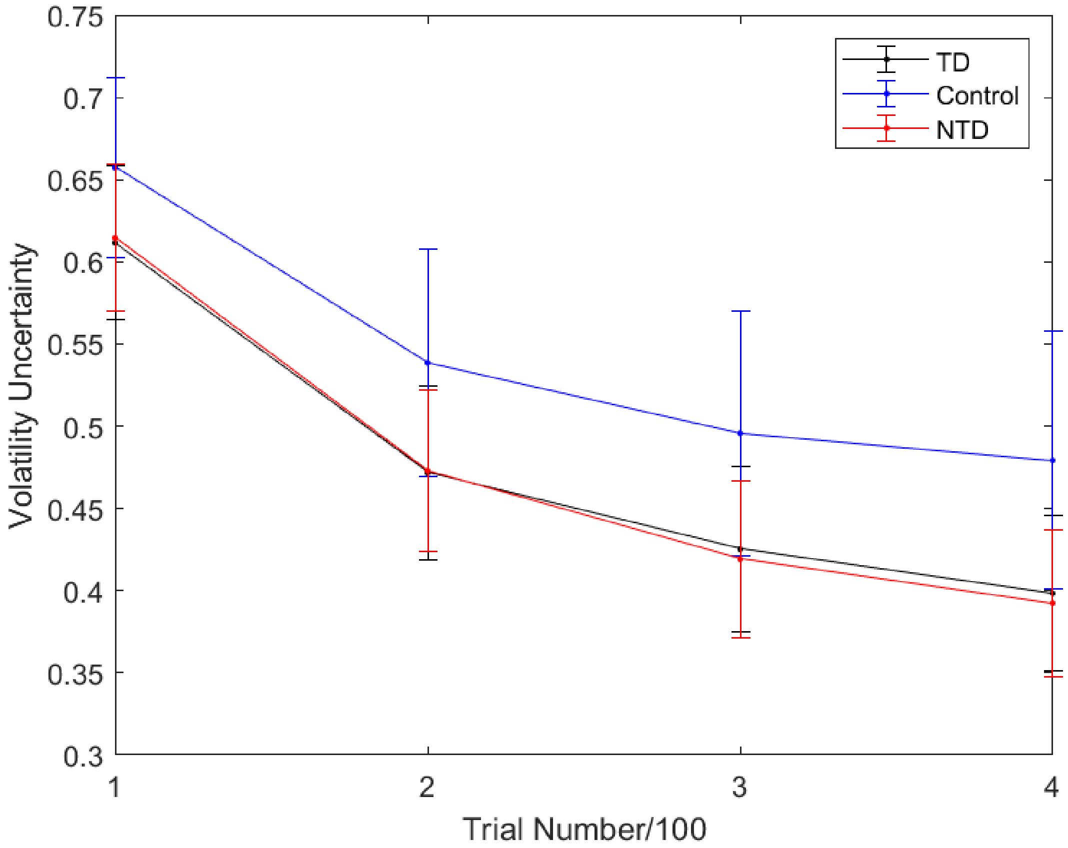

Figure 4.3: Volatility uncertainty (variance of the Gaussian distribution at level 2) is presented. The x-axis represents the bins of 100 trials. The y-axis shows the averaged values for the corresponding bin. Error bars represent the standard error of the mean.

4.2.3 Belief on Volatility

In the HGF, the mean of the Gaussian distribution at level 3 represents belief on volatility. Belief on volatility (μ_3) was compared using non-parametrical permutation tests between each experimental groups and control. Results did not indicate a significant group difference for both comparisons: NTD vs control and TD vs control. The change in belief on volatility over time for each group is highlighted in Fig 4.4 As a note regarding Fig 4.4, there are clearly different trends: the belief increases over time in TD and control group. In contrast, group NTD is out of that trend because of the continuous decrease.

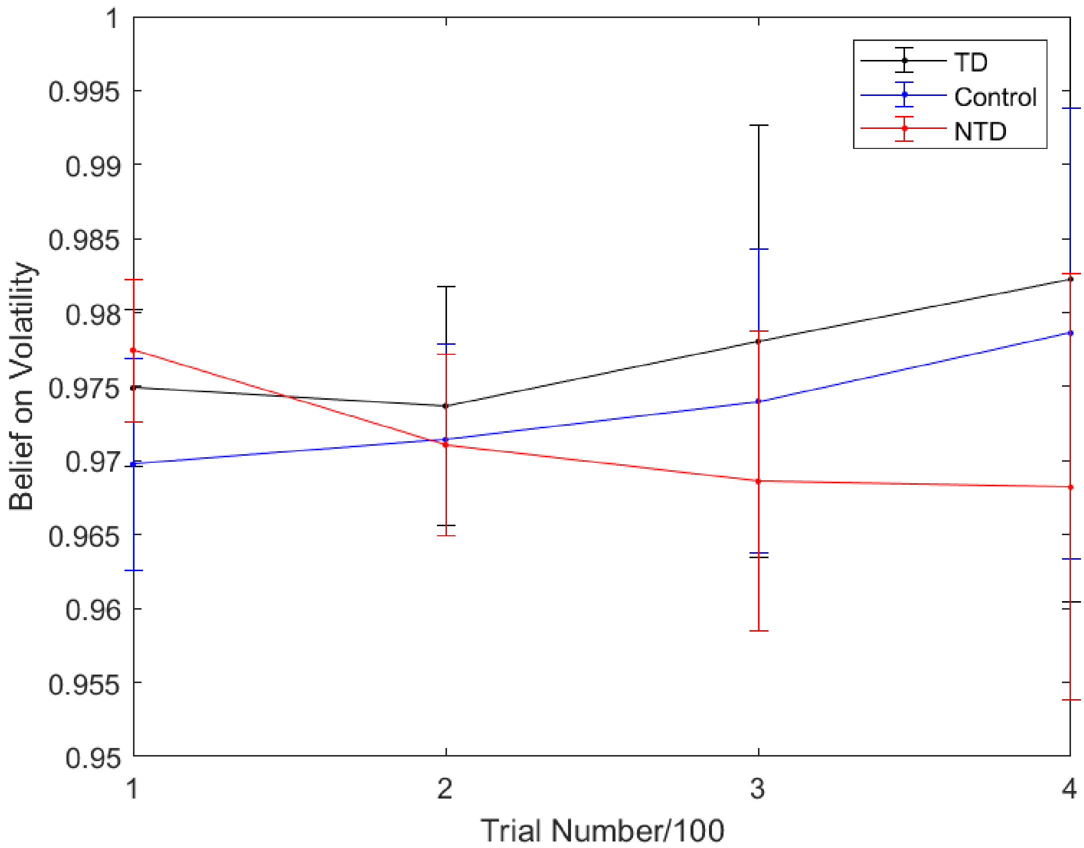

Figure 4.4: Belief on volatility (mean of the Gaussian distribution at level 3) is presented for each group. The x-axis represents the bins of 100 trials and the y-axis represents the values averaged in bins of 100 trials.

4.2.4 Estimation Uncertainty

The partial knowledge about the probability link between stimulus and outcome leads to estimation uncertainty. It is represented by the variance of the second level in the HGF. We compared the estimation uncertainty between groups using non-parametric permutation test in MATLAB. Although the observed trend in Fig 4.5 indicates that both experimental groups are more uncertain about the belief on the tendency for a stimulus to be rewarding, not significant between-group difference was found.

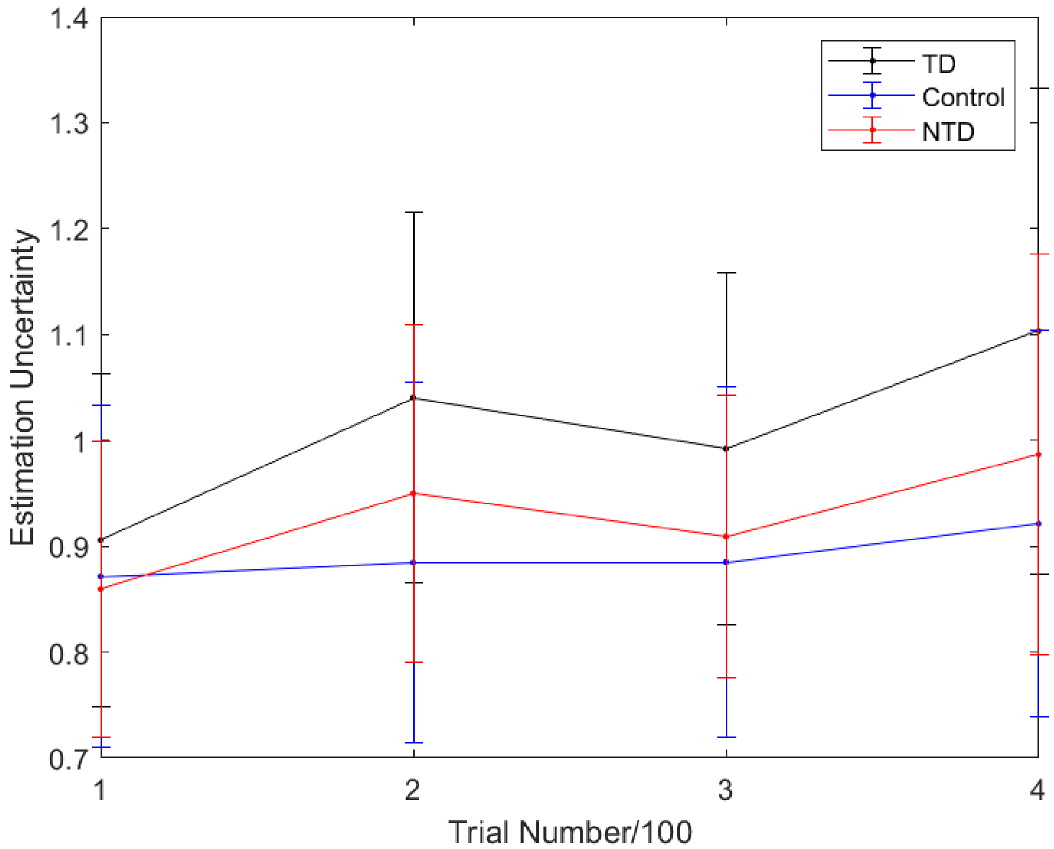

Figure 4.5: Mean values of estimation uncertainty (variance of the Gaussian distribution in level 2) is illustrated within the bins of 100 trials for each group. The x-axis represents the bins of 100 trials and the y-axis represents the values averaged in bins of 100 trials.

Chapter 5

Discussion

In the uncertain world in which we live, a choice rarely yields the same result. The ambiguous world was simulated as an uncertain environment in which the probability relationship between stimulus-outcome varies over time. The present study was designed to determine the attenuated effect of state anxiety on learning and decision-making using a hierarchical Bayesian learning model (HGF) which provides the individual belief trajectories about the environment. This chapter starts with the short summary of the experiment, continues with the comparison of our results and hypotheses in the light of previous studies and finishes with the description of limitations in the present study and plans for further studies.

At the beginning of reward-based learning task, the subjects did not have any information about the environment. Thus, exploration was needed to learn about the statistical structure of the ambiguous environment. They chose a stimulus and according to the limited feedback which was given after the decision, subjects were expected to update their beliefs about the stimuli-outcome relationship. However, they should have decided whether the surprise outcome was due to the estimation uncertainty or environmental uncertainty. For instance, in a stable environment where the probability of one stimulus being rewarded is 90%, the probability of rewarding the other stimulus is 10%. It is expected that the surprise result (e.g. rewarding of the 2nd stimulus with %10) arises from not knowing the probability relationships completely. Thus, in a stable environment (e.g. %90 to %10) past outcomes rather than the recent outcome should be considered; because the reason for the unexpected outcome is noise. With belief trajectories obtained through HGF, at level 2 of the hierarchy, we examined the belief on a tendency for a stimulus to be rewarding and how much they uncertain about this belief (belief about estimation uncertainty). Similarly, the environmental or volatility uncertainty is represented at the 3rd level of the model. Most volatile environments are the one with the stimuli-outcome probabilities were equal for each stimulus (%50). When the environment is volatile, the subject should decide based on the most recent outcome.

Firstly, it was hypothesized that participants in the NTD group would be more affected by state anxiety in anticipation of the public speech and the mental arithmetic task; because they supposed to complete these future tasks for 20 minutes without temporal discount. As mentioned in the literature review, Spielberger et al (1971) reported that future events such as public speech or exam increase the individuals' state anxiety. Surprisingly, no significant differences in mean values of HAD scores were found between NTD and control. Even though non-parametric permutation test did not reveal significant HAD scores difference between NTD and control, as consistent with Spielberger et al (1971), a trend was captured in fig 4.1 which shows that the experimental groups were more state anxious than the controls. Furthermore, differences in mean values of HAD scores were found to be significant between the group TD and controls at one time point. In the preliminary statistical analysis, there were other significant differences between each experimental groups and controls in more than one HAD however these could not survive against the correction for threshold.

Secondly, it was hypothesized that the group NTD would be less able to update their beliefs and would have lower learning rates than the control group. As mentioned in the literature review, our hypothesis about learning rates is based on the well-known study in which found that the high trait anxious participants were less able to update their beliefs in a volatile environment (Browning et al, 2015). Another recent finding which supports the link between suboptimal decisions and anxiety helped us to make our hypothesis stronger (Huang et al.,2017). Although our results did not indicate a significant difference in learning rate between NTD and control, there is a clear trend. In Fig 4.2, the NTD group is clearly below the control group in terms of learning rate during the task.

On the other hand, we predicted that the TD group would have higher learning rates than controls because of the motivation to reduce the total time of future tasks. It has been shown that dopamine is released in the brain when the subject is motivated to avoid future aversive tasks, thus results in higher learning rates (Westbrook &Todd, 2015). By comparing the groups TD and control, no significant difference was found in learning rates, however again in Fig 4.2 a clear trend is observed. Learning rates of TD in each bins of trials are higher than controls as predicted.

Higher belief on volatility leads to more explorative behaviors. It is found to be dopamine may lead to overestimation of volatility (Deserno et al., 2017). As a result, we expected that the motivated TD group has more belief on volatility or overestimation of volatility which is interpreted as the expectation of more surprise outcome. In contrast, anxious individuals tend to underestimate environmental volatility (Spoun et al., 2018). In light of the prior study, it was hypothesized that group NTD would have less belief on volatility than the control group. However, we did not find significant group differences regarding belief on volatility. Although no significant difference between groups was revealed in the results of non-parametric permutation tests ($p>.05$), there was a clear consistent trend in Fig 4.4. As a general note, these trends are consistent with our hypothesis and previous findings however we will discuss the reasons for not finding significant between-group differences. Lastly, for both types of subjective uncertainty (estimation and volatility) no significant difference was found in the between-group comparisons ($p>.05$): NTD vs control and TD vs control. We observed in Fig 4.3 that volatility uncertainty decreases over time for each group.

In a critical perspective, different computational learning models have not been implemented in order to determine which model explains our data in the best way. Most common learning models that are used in a large number of studies are Rescorla-Wagner and Sutton K1. Rescorla-Wagner model assumes a constant learning rate which prevents to capture how participants update their learning rates in response to change in environmental structure, in contrast to HGF. In a recent study, the modified version of Rescorla- Wagner (Vmax RL) which allows for updated learning rates only when the stimulus with the highest probability to be rewarded is changed was implemented (Huang et al., 2017). According to the study Berker et al. (2016) in which learning paradigm was similar to the present study, HGF was the best model in terms of explaining the data in comparison to Sutton K1 and Rescorla-Wagner. Although HGF was proved to be have many advantages, the model comparison is crucial to increase the accuracy of future studies.

Overall, this study has been unable to demonstrate the underlying behavioral and belief differences seen in state anxiety during decision making and learning. A possible explanation for this might be the inadequate sample size. Although the power analysis has been carried out to estimate the sample size for the desired level of power and found to be thirty (N=30), it was not sufficient for revealing significant difference. The second explanation for the non-significant results is that the high variance across participants in the same group. This problem can be solved in future studies with more participants.

In conclusion, the main goal was to identify the underlying beliefs that result in suboptimal choices in anxiety and in which way these beliefs are different than the control participants. Investigating the literature in detail concerning the characteristic behaviors of anxious subjects during decision making and learning and Bayesian learning models, the hypotheses were set out. Within the context of a Bayesian approach to learning, a three-level HGF was the main tool to obtain belief trajectories during the reward-based learning task. Surprisingly, rather than significant difference between NTD and control, induced state anxiety caused a significant difference in the continuous measure of anxiety scores between the experimental group (TD) and the control group. However, the non-parametric permutation tests did not reveal any significant difference in other dependent variables (the beliefs, different types of uncertainty about them and learning rate) between each experimental groups and control group. It is important to note again that there were clear trends consistent with the hypothesis in the given Figures. As mentioned in the results, these observed trends may be helpful in further work. Regarding future studies, considerably more work will need to be done to determine the most adequate learning model. Also, another power analysis to estimate the sample size need to be carried out by considering the results and limitations in the present work Even though this study has been unable to replicate previous findings and reveal new results because of the predicted reasons mentioned above, it has thrown up various questions in need of further investigation.

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