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# Atypical Uncertainty Estimation Across Psychopathology: Insights from a Novel Learning Task

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# Atypical Uncertainty Estimation Across Psychopathology: *Insights from a Novel Learning Task*

by

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Thesis submitted in part fulfilment for the degree of Doctor of Philosophy

Cognitive Neuroscience

2023

# Acknowledgments

This thesis was not something I completed alone. I therefore want to take the opportunity to extend my sincere gratitude to all those people that played an integral role in this achievement. It would not have been possible without you.

I would first and foremost like to acknowledge the support of my supervisors, Dr Kelly Diederen and Dr Thomas Spencer, during this process. Thank you for offering me an opportunity I never expected to have. Your flexibility, encouragement, and guidance over the years has been essential.

I am also immensely grateful to those with whom I have collaborated. Without your support I would likely still be stuck looking at many dead-ends. Specifically, Dr Teresa Katthagen, thank you for your patience, persistence, and expertise. Also, to Dr Margret Westwater, and Dr Michael Browning, your direction was pivotal. Thank you for your time and insight.

To the students I have supervised, and that have worked on aspects of the research throughout this period, thank you for your interest and hard work.

To my friend, the talented Adam Wallis. A Senior Solutions Architect who programmed the novel learning task included throughout this thesis and continued to offer ongoing technical support.

Without your help the project would have looked very different. Thank you, I owe you a beer or two…

My family, my mum – Susie, my brother and sister Joshua and Victoria, and my family-in-law Jan and Axel. Thank you for supporting me to make it this far. Whether it was lending a supportive ear, offering a place to stay, or making me laugh, it all contributed enormously. Thank you especially, mum, for your belief in the power of education and dogged persistence that we follow its route despite having never experienced it yourself. The world I live in now is different from the one in which I grew up. I'm glad that this flexibility is possible, but I have not forgotten where I have come from, and I aim to use this privilege to do something useful.

Finally, my partner, Jake. Not to be too dramatic (!) but – quite literally, your encouragement and guidance through (some particularly difficult) times during this process was the only thing that enabled me to finish. You don't let me settle for anything less than you think I am capable of. Your belief in me has truly transformed the way I look at myself and continues to empower me to pursue bigger and better things. Thank you.

# Abstract

"*We sail within a vast sphere, ever drifting in uncertainty, driven from end to end".*

B. Pascal, 1852

***Background**:* To survive, humans and animals must adapt behavior in response to outcomes. However, a central question in cognitive science is how the brain learns from outcomes associated with different choices, given that outcomes can be highly uncertain. To account for the remarkable skill of optimal inference and decision making in the face of a capricious world, it is proposed that the properties of uncertainty itself must be accurately estimated. These properties include the changeability (or volatility) and noisiness of outcomes. Drawing on a normative account of learning, the joint estimation of noise and volatility is suggested to determine the speed of learning itself. Using (neuro) computational models, systematic deviation from normative learning has been linked to dysfunctional decision making in psychiatric illness. However, research to date has focused on properties of uncertainty in isolation i.e., noise *or* volatility. Although vital research, this approach fails to consider the full problem facing the learner: that learning involves the simultaneous estimation of both volatility *and* noise (i.e., stochasticity). Additionally, while aberrant uncertainty estimation has been linked to multiple psychiatric disorder categories, novel dimensional approaches to psychiatric nosology support the identification of commonly perturbed biobehavioral mechanisms as a route towards improved treatment. Computational psychiatry, the mechanistic description of maladaptive behaviour, used in conjunction with large-scale online populations, has emerged as a promising tool for capturing how cognitive deficits relate to the continuous, rather than binary (on/off; healthy vs. ill) nature

of mental illness. As such, this thesis aimed to develop, test, and implement a novel online learning task that was able to capture learning about multiple properties of uncertainty. This task was then used to test whether aberrant uncertainty estimation could represent a fundamental feature across symptoms of psychopathology.

***Methods:*** Firstly, a systematic review (patients/controls n=5371), assessed research that used (error-based) computational modelling to the question of belief updating in psychosis, depression, and anxiety disorders. Secondly, a novel learning task was developed. The task sampled from "ground truth" probability distributions that differed in their statistical configurations, designed to simulate different properties of uncertainty within the learning environment. The task included continuous response metrics that indicated the individuals' estimate of both the variance (noise) and the mean on a trial wise basis. Two experiments tested the task on feasibility, reliability, and construct validity (n=555; n=167). Post validation, the task was applied to an eating disorder group (n=116) and healthy controls (n=67); a general population group with natural variation in across psychosis, depression and anxiety symptomology (n=580); and a selected population of high (n=81) and low (n=66) schizotypy traits. Generalised linear mixed effects models were used for learning data. An extended version of the Hierarchical Gaussian Filter (HGF: JGET) that "learns" about (1) the current mean value and (2) its variance of the input stream, was also applied (Chapter 6).

***Results.*** The systematic review revealed both overlap and dissociation between disorder groups. For example, aberrant learning in response to the valence of feedback specifically was found in depression, and not anxiety disorder. Anxiety and psychosis disorders instead showed overlap regarding a difficulty in learning about, and adapting to, volatility. The novel task, built to specifications set out in the review, was demonstrated to be feasible in an online setting and

displayed good levels of reliability and construct validity across two studies (n=555; n=167). Experimental evidence showed partial evidence of a valence dependent deficit in depression only. Elevated psychosis and anxiety traits, and eating disorder patients (vs. healthy controls), overlapped in relation to an inflexibility in adapting to increases in volatility. Elevated psychosis traits were additionally associated with overall non-normative learning rates in isolated conditions of noise and volatility. Computational modelling applied to data from elevated schizotypy groups revealed a tendency to incorporate their belief about the noise into decision making when noise was irrelevant.

***Conclusion.*** This thesis demonstrates the ability for experimental design, and modelling approach, to explicitly test multiple dimensions of learning under uncertainty. In doing so, this research was able to provide insights into the simultaneous estimation of different aspects of uncertainty during learning. While further testing is required, a difficulty in adapting to increases in volatility may underlie multiple aspects of psychopathological symptomology, including eating disorder patients, and elevated trait anxiety and psychosis-related symptomology. However, elevated trait psychosis additionally showed a non-normative pattern of learning. In this case, it may be that difficulties in estimating the type of uncertainty e.g., mistaking noise for volatility, led to a trade-off effect in which estimates of volatility reached ceiling level. This could then lead to downstream impacts on both overall learning rates in volatility, and the ability to appropriately adapt to increases in volatility. Novel computational modelling approaches, for example the HGF: JGET were instrumental in capturing learning about the mean and variance independently and should be applied to future research interested in the joint estimation of uncertainty. Findings from the HGF: JGET suggest that schizotypy may be associated with an overloading of superfluous information when confronted with increased volatility, potentially due to a lack of confidence in a model of the world (i.e., volatility). Future research should build

on these findings by investigating the interdependence of inferences about volatility and noise, and their relationships to unique and cross cutting symptoms of psychopathology.

# Statement of work

The systematic review involved MSc students at points during the filtering and extraction phases. These individuals are acknowledged in the respective chapter. Alongside my supervisors, Dr Teresa Katthagen also provided guidance and reviewed the document pre-publication.

The novel task was inspired by a previously published task by Berniker et al., (2010). I went on to develop the "Space Task" and it was subsequently put to a Senior Solutions Architect, Adam Wallis, for programming in an online format.

The initial recruitment of the selected schizotypy groups was collected by Maite Arrabas. Maite used the platform Qualtrics (qualtrics.com) to collect 1000 participants and provided me with individuals who scored at the top and bottom 10% of the Schizotypy Personality Questionnaire. I then went on to contact and test these individuals using the novel learning task. Dr Margret Westwater collected the data from Chapter 4, in eating disorders and healthy controls.

Dr Margaret Westwater and Professor Michael Browning at the University of Oxford, both provided guidance regarding the analysis, including the idea to back contrast experimental blocks. Professor Michael Browning also provided the idea for using the beta coefficient in a model predicting the position change from the prediction error as a proxy for learning rate. While we worked together, the computational modelling using the Hierarchical Gaussian Filter in Chapter 6 was largely completed by Dr Teresa Katthagen. Additionally, we also consulted with Professor Christoph Mathys , given the novelty of the extended HGF package used.

# Table of contents

*Acknowledgments* ..... *2*

*Abstract* ..... *4*

*Statement of work* ..... *8*

*Table of contents* ..... *9*

*Table of figures* ..... *15*

*Table of tables* ..... *21*

*Chapter 1. Introduction* ..... *23*

**1 Reinforcement learning theory** ..... **23**

**2 Bayesian inference theory** ..... **25**

**3 Uncertainty** ..... **27**

**4 Measuring uncertainty estimation: models and tasks** ..... **30**

4.1 Computational modelling ..... 30

4.2 Experimental cognitive learning tasks ..... 32

**5 Computational psychiatry: uncertainty estimation in psychopathology** ..... **35**

**6 Novel experimental paradigms: the online context and transdiagnostic approaches.** ..... **40**

**7 A summary of gaps in current literature** ..... **42**

**8 Aims and hypotheses** ..... **43**

**9 References** ..... **47**

*Chapter 2. Belief updating in psychosis, depression, and anxiety disorders: a systematic review across computational modelling approaches* ..... 58*

**1 Abstract ..... 58**

**2 Introduction ..... 59**

**3 Methods ..... 66**

3.1 Belief-updating tasks ..... 66

3.2 Literature search ..... 68

3.3 Modelling procedures across the literature ..... 69

3.4 Outline of the review ..... 69

**4 Results ..... 70**

4.1 Modelling parameters ..... 72

4.2 Belief updating in stable environments ..... 73

4.3 Belief updating in volatile environments ..... 82

4.4 Change point detection modelling ..... 90

**5 Discussion ..... 95**

5.1 Learning rates and valenced feedback: a lack of overlap between depression and anxiety disorders ..... 95

5.2 Learning rates and valenced feedback: evidence of overlap between depression and psychosis disorders ..... 98

5.3 Learning under volatility is affected in anxiety and psychosis disorders ..... 99

5.4 Noisiness in decision-making ..... 104

5.5 Social bias in decision making ..... 107

5.6 Overview of non-error-based Bayesian learning literature ..... 108

5.7 Treatment implications and methodological considerations ..... 111

5.8 Limitations ..... 113

**6 Conclusion ..... 116**

**7 Author contributions ..... 118**

**8 Acknowledgement ..... 118**

**9 References ..... 118**

**10 Supplementary materials ..... 137**

***Chapter 3. Methods: development of a novel learning task ..... 141***

**1 Abstract ..... 141**

**2 Introduction ..... 142**

2.1 Aims, hypotheses, and outline ..... 148

**3 Part A. validation of a novel learning task - Version 1 ..... 149**

3.1 Methods ..... 149

3.2 Results ..... 160

3.3 Discussion of findings: Version 1 ..... 172

**4 Part B: validation of a novel learning task -Version 2 ..... 175**

4.1 Methods ..... 175

4.2 Results ..... 184

**5 Discussion ..... 195**

5.1 Limitations and future directions ..... 200

5.2 Conclusions ..... 200

**6 Acknowledgements ..... 201**

**7 References ..... 201**

**8 Appendix ..... 210**

***Chapter 4. Learning under uncertainty in eating disorders ..... 217***

**1 Abstract ..... 217**

**2 Introduction ..... 218**

**3 Methods ..... 221**

3.1 Participants ..... 221

3.2 Study procedure ..... 222

3.3 Experimental task ..... 223

3.4 Analysis ..... 229

**4 Results ..... 231**

4.1 Quality control ..... 231

4.2 Total score ..... 232
4.3. Beam width ..... 233
4.4 Total catch success ..... 233

**5 Discussion ..... 237**
5.1 Limitations and future directions ..... 241
5.2 Conclusions ..... 243

**6 Acknowledgements ..... 244**

**7 References ..... 244**

**8 Appendix ..... 251**
8.1 Task instructions ..... 251
8.2 Contingency distributions ..... 253
8.3 Identification of appropriate exclusion criteria ..... 255
8.4 Identification of potential thresholds for exclusion criteria ..... 259

***Chapter 5. Uncertainty estimation deficits across trait level psychopathology: overlap and distinction in psychosis, depression, and anxiety ..... 261***

**1 Abstract ..... 261**

**2 Introduction ..... 263**

**3 Methods ..... 267**
3.1 Participants ..... 268
3.2 Procedure ..... 268
3.3 Materials ..... 269
3.4 Analysis ..... 275

**4 Results ..... 280**
4.1 Quality control ..... 280
4.2 Task validation ..... 281
4.3 Task performance and acquisition of statistics ..... 292
4.4 Learning rates ..... 295

**5 Discussion ..... 303**
5.1 Limitations and future considerations ..... 308

5.2 Conclusion ..... 310

**6 Acknowledgements ..... 311**

**7 References ..... 311**

**8 Appendix ..... 318**

8.1 Instructions ..... 318

***Chapter 6. Belief updating in schizotypy: application of computational modelling to a novel learning task ..... 321***

**1 Abstract ..... 321**

**2 Introduction ..... 323**

**3 Methods ..... 327**

3.1 Participants ..... 327

3.2 Procedure ..... 328

3.3 Materials ..... 328

3.4 Analysis ..... 336

**4 Results ..... 343**

4.1 Quality control ..... 343

4.2 Acquisition of underlying statistics ..... 344

4.3 Performance (score) ..... 347

4.4 Learning rate ..... 347

4.5 Computational modelling – preliminary findings ..... 349

**5 Discussion ..... 354**

5.1 Limitations and future directions ..... 358

5.2 Conclusions ..... 360

**6 Acknowledgements ..... 361**

**7 References ..... 361**

**8 Appendix ..... 371**

***Chapter 7. General discussion, limitations, and future directions ..... 380***

**1 A summary of the aims, and findings of the thesis ..... 380**

**2 Interpretation and integration of results in relation to specific hypotheses .....388**

2.1 Anxiety and depression: a difference in uncertainty-based learning deficit .....388

2.2 Inflexible and maladaptive learning in response to uncertainty: overlap across symptoms .....391

**3 Methodological implications and considerations .....395**

**4 Limitations and future directions .....397**

4.1 The online experimental paradigm and cognitive tasks .....397

4.2 Symptom measurement .....399

4.3 Behavioural analysis and computational modelling .....400

**5 References .....402**

***Chapter 8. Conclusions*.....*414***

**1 References .....418**

# Table of figures

Figure 2.1. Showing a simple probabilistic learning task with stable and volatile contingencies using binary inputs.. .....67

Figure 2.2 PRISMA flow diagram for papers included in this study.....72

Figure 3.1 A-F: Figures showing scores between groups of people that displayed specific behaviours in at least 50% of trials, and those that did not.....162

Figure 3.2 Showing density of participants that fulfilled exclusion criteria relating to a lack of movement for the beam and rover stimuli, and those that did not,set at different thresholds (10%, 50%, 90%), against score from the space task. .....163

Figure 3.3 Plot A. shows the average rover position for each trial, across all participants in grey; the cumulative mean, using a rolling calculation across three inputs is shown in orange. .....166

Figure 3.4 shows the relationship between the participants rover positions and the inputs (input A i.e., the cue – in gold, input B in red. .....168

Figure 3.5 shows the average prediction error (Fig A) or performance error (Fig B) during block four (volatility only), at trials 1:11 after a mean change point.....169

Figure 3.6 Plot A. Showing the relationship between the cue (input A) and the location that participants placed their rover i.e., participant position, during conditions of high (green line) and low noise (purple line).. .....171

Figure 3.7 Showing that in version 2 of the task, the beam now has to be turned “on” to play the trial. Here we see the instruction slide informing participant to move the rover and adjust the power/beam to play. .....173

Figure 3.8 Showing the structure of trial inputs between versions 1 and 2 of the task. k.....175

Figure 3.9 A. Showing trial structure. ..... 178

Figure 3.10 Plot A. shows the average rover position for each trial (n=219), across all participants (grey line); and the cumulative mean (using a rolling calculation across three inputs) is shown in orange.. ..... 186

Figure 3.11 Plots showing prediction errors (purple), and performance errors (gold), at mean change points (dotted vertical lines). Grey vertical lines indicate blocks. ..... 188

Figure 3.12 Plot A. Showing the relationship between the cue (input A) and the location that participants placed their rover ..... 191

Figure 3.13 Showing LR averages for each trial across all participants. Dotted lines depict mean change points, solid grey lines indicate block changes.. ..... 193

Figure 3.14 Plots A and C shows the corrected (i.e., Nassar et al., () learning rates, with all LRs outside of 0 and 1 grouped at 0 and 1 (plot A), and excluded LRs (i.e., as above but with LRs outside of 0 and 1 removed from the analysis), averaged over trials after at a mean change (1) and in the subsequent trials (2 onwards). ..... 195

Figure 3.15 Showing the distributions of space junk inputs, for each combination of predetermined probability distributions (mean, and SDs).. ..... 214

Figure 3.16 Showing the distributions of space junk inputs, for each combination of predetermined probability distributions (mean, and SDs).. ..... 215

Figure 3.17 Showing the distributions of space junk inputs, for each combination of predetermined probability distributions (mean, and SDs).. ..... 216

Figure 4.4.1 A. Showing trial structure. ..... 226

Figure 4.2 Showing boxplots depicting the mean and interquartile ranges (IQR) of catch success across the entire task, for healthy controls (blue) and eating disorder groups (grey).. ..... 234

Figure 4.3 Showing boxplots depicting the mean and IQR of learning rates for each block (2-6), and for each group (healthy controls in grey, and eating disorder groups in blue). Individual

dots reflect average learning rates for each individuals, for each block. No significant differences between groups were found for any of the blocks (2:6).....236
Figure 4.4 Shows learning rate difference between blocks, for each group (healthy controls (HC) (light blue), eating disorder (ED) grey).. .....237
Figure 4.5 Showing the distributions of space junk inputs, for each combination of predetermined probability distributions (mean, and SDs). . .....253
Figure 4.6 Showing the distributions of space junk inputs, for each combination of predetermined probability distributions (mean, and SDs).. .....254
Figure 4.7 Showing the distributions of space junk inputs, for each combination of predetermined probability distributions (mean, and SDs). . .....255
Figure 4.8 Density plots showing differences in trial scores for individuals excluded and not excluded .....257
Figure 4.9 Top row: Density plots showing total scores for each block between individuals who have been excluded according to the 'strict' exclusion criteria. .....258
Figure 5.1 A. Showing trial structure.....276
Figure 5.2 Showing a flow diagram of the exclusion criteria used in this study, and the number of participants excluded for each criterion.....282
Figure 5.3 Showing learning rate across all participants, for each block.. .....284
Figure 5.4 Shows performance error (participant estimate – mean of the distribution) across trials where a mean change occurs (1), alongside subsequent trials after a mean change (2-11).. .....285
Figure 5.5A Showing the relationship between symptom scores on the MASQ depression subscales, and the Green Paranoia symptom scale, and performance errors across the task as a whole.....288

Figure 5.6 Shows the relationship between beam width and symptom scales for paranoia and depression. Each coloured dot in the plot represents the average beam width used by each participant, for each block..... 290

Figure 5.7 Showing the relationship between paranoia and depression scores, and the unexplained residuals of the fitted model, once all other covariates have had their variance explained i.e., depicting the effect of overall score as described by the model.. ..... 293

Figure 5.8 Showing the relationship between depression symptom scores, as measured by the MASQ, and scores on the task.. ..... 294

Figure 5.9 Showing the interaction found between SPQ scores (schizotypy personality traits), and averaged learning rates for each block. ..... 297

Figure 5.10A Showing the change in learning rates (beta coefficient) between conditions of high volatility (block 4), and stable conditions (block 2 small variance).. ..... 299

Figure 5.11A Showing the change in learning rates (beta coefficient) between conditions of high volatility (block 4), and isolated high noise conditions (block 2, wide variance). ..... 301

Figure 6.1 A. Showing trial structure. ..... 334

Figure 6.2 Showing a depiction of the Jumping Gaussian Estimation Task modelling process used in this study. ..... 341

Figure 6.3. Showing performance error (participant estimate – mean of the distribution) across trials where a mean change occurs (1), alongside subsequent trials after a mean change (2-11)..... 345

Figure 6.4 Showing average beam widths used in conditions of high (purple; SD=0.12) and low (green; SD=0.03) noise. The figure uses the unexplained residuals of the fitted model, once all..... 346

Figure 6.5 Showing learning rate across all participants, for each block. Learning rate is calculated as the beta coefficient of a model predicting signed prediction error from signed .....348

Figure 6.66 Showing a comparison between participant estimates, and estimates made via the model simulations, across blocks 3 to 6 (A to D). .....350

Figure 6.7 Plots showing $\beta_1$ value for each participate (dot) in blocks 3 (noise, low volatility), and 4 (high volatility, low noise), between high and low schizotypy groups.. .....353

Figure 6.8 Plot showing the associations between mean scores for each block and participant, and noise belief ($\beta_1$) for the overall by block.....354

Figure 6.9 Showing the noise belief parameter associated with the mean PE over the whole task (A), and by block (3:6, B). . .....374

Figure 6.10 Showing the kappa for the mean (kax) parameter associated with the mean PE over the whole task (A), and by block (3:6, B).. .....375

Figure 6.11 Showing the kappa for the variance (kaa) parameter associated with the mean PE over the whole task (A), and by block (3:6, B).. .....376

Figure 6.12 Showing the noise belief parameter associated with the mean score over the whole task (A), and by block (3:6, B).....377

Figure 6.13 Showing kappa for the mean (kax) parameter associated with the mean score over the whole task (A), and by block (3:6, B).. .....378

Figure 6.14 Showing the kappa for the variance (kaa) parameter associated with the mean score over the whole task (A), and by block (3:6, B). Correlation Pearson statistic and r2 value is for each relationship is plotted on each figure. The top statistic refers the low SPQ group, and the bottom statistic refers to the High SPQ group for all plots. .....379

# Table of tables

Table 2-1. Table showing parameter findings between groups when measuring belief updating in a stable environment using a PLT-S. ..... 77

Table 2-2. Showing reinforcement learning modelling to tasks measuring belief updating in volatile environments (PLT-V) including details, feedback, winning models and differences between groups for parameters ..... 85

Table 2-3. Describing parameters included in the HGF modelling process. ..... 89

Table 2-4. Showing Bayesian Learning modelling and Change Point modelling to behavioural data from tasks measuring belief updating in volatile environments (PLT-V) including details, feedback, winning models and differences between groups for parameters ..... 91

Table 2-5. Showing modelling procedures by study ..... 137

Table 3-1 Showing the details of the contingencies underlying the task for each block. ..... 156

Table 3-2 Showing exclusions given differing exclusion criteria and thresholds ..... 164

Table 3-3 Showing cumulative exclusions of participants in SPQ data using strict criterion (n=164) ..... 184

Table 3-4 Showing instructions given to participants in both versions 1 and 2 of the novel task. ..... 210

Table 4-1 Showing the details of the contingencies underlying the task for each block. ..... 228

Table 4-2 Showing planned backwards contrasts ..... 230

Table 4-3 Sample characteristics ..... 232

Table 4-4 Showing task instructions ..... 251

Table 4-5 Showing the outcome on the sample pool given different exclusion criteria. ..... 260

Table 5-1 Showing the details of the contingencies underlying the task for each block. .....273

Table 5-2 Showing planned backwards contrasts .....279

Table 5-3 Participant characteristics (N = 580).....282

Table 5-4 Showing the instructions and information given in the Space task for each screen. 318

Table 6-1 Showing the details of the contingencies underlying the task for each block. .....332

Table 6-2 Showing planned backwards contrasts .....337

Table 6-3 Participant Characteristics Table.....343

Table 6-4 Showing the instructions and information given in the Space task for each screen. 371

Table 6-5 Showing priors set for the HGF modelling by block. .....373

# Chapter 1. Introduction

In a simple learning scenario, learning refers to the formation of an association between a stimulus and an outcome/response. We feel hungry (stimulus), we eat an ice-cream (response), we feel sick (because ice-cream is not a suitable breakfast meal) (outcome). To utilise this information in an adaptive way i.e., in a way that supports our ongoing survival, the decisions that we make in response to stimuli are fine-tuned towards actions that keep us alive. Overtime, we become conditioned to make more sensible breakfast choices, that do not make us feel so unwell. On a personal and professional level, however, we know that people do not always appear to pick the adaptive choice. In fact, underlying many symptoms of psychopathology is this fact: on a behavioural (observable) level, some individuals continue to make maladaptive choices, choices that are self-destructive, choices that do not appear to promote survival. Why is this, and what part of the process is malfunctioning?

## 1 Reinforcement learning theory

To investigate these questions, we must firstly understand the mechanisms behind learning and decision making (LDM). "Learning", can be split into various subcategories. The type of learning described above is called *instrumental learning* – a naturally occurring general process that dictates the conditions under which behaviours are modified by their consequences (Skinner, 1963). This is a voluntary behaviour, as opposed to a reflex – which would instead describe Pavlovian learning or conditioning (Akpan, 2020; Pavlov, 2010). Reinforcement learning theory, an approach originally rooted in psychological theories of learning in animals,

has traditionally been used to capture learning using reinforcement learning models (RL). Broadly speaking, these models are designed to capture how individuals interact with the world: via the adaptation of behaviours in response to feedback from the environment. In turn, this theoretical and importantly, algorithmic, framework provides a structure to explore maladaptive LDM.

RL encompasses an entire family of models, from the simplest model form in which observations are explained by Pavlovian conditioning (Rescorla and Wagner, 1972), to more complex configurations that incorporate how feedback updates future decision making e.g., Q-learning models (Sutton et al., 1992). In these latter models an internal (hidden) decision variable, that represents the value of the action or behaviour previously performed, is assumed by the model. Central to these models is the concept of error-driven processing that emerges after an outcome is received. In other words, the choice or decision is updated in response to the difference between what you expected to happen, and what actually happened (termed prediction error (PE) (Schultz, 1998, 2022; Schultz et al., 1997). The PE is then weighted by an additional free parameter – the learning rate. The learning rate is formulated to quantify how much of the PE is incorporated into the update, i.e., given the size of the PE how much the value of the action or behaviour should be adapted or updated. When this value is 0, the value of the chosen option is not updated - likely the behaviour or action chosen previously elicited the expected feedback. Whereas when the LR is 1, the value of the chosen option is updated using the whole PE value, as the feedback was wholly unexpected. PEs allow individuals can keep track of violations to their expectations, and as such make improved decisions in response to incoming information. PEs have been shown to be related to dedicated neural signals that drive learning about outcomes in relation to perception, motor functions, and feedback (Den Ouden et al., 2012; Diederen & Fletcher, 2021). Within a RL framework, PEs can also be signed i.e., as well as engendering surprise, they additionally

indicate whether the feedback was positive or negative (Diederen & Fletcher, 2021). In such cases these PEs are often referred to as reward PEs (RPE). Here, decision making is optimal when rewards are maximised.

While the neurotransmitter dopamine is involved in many processes, it has been intensely studied for its role in RL, and specifically RPE coding. A wealth of research has shown that not only does the dopaminergic system (via the ventral segmental area/SN and striatum) signal RPEs about both direct and indirect rewards, but it also integrates information about other reward characteristics, including the expected type (e.g., food/money), magnitude, probability, and timing in the calculation of the RPE itself (Diederen & Schultz, 2015; Lak et al., 2014; O'Doherty et al., 2003; Tobler et al., 2005). As such, a dominant mechanistic theory is that dopamine is related to RL via RPE signalling (Schultz, 1998). Given that dopamine dysfunction has been shown to play an important role across a range of disorders, including Parkinson's disease, substance use disorders, depression, anxiety and schizophrenia, the precise role of PE coding in psychopathology is important to understand.

## 2 Bayesian inference theory

Importantly, alternative accounts of LDM, for example Bayesian inference theories, provide different accounts for the role of dopamine in LDM. While Bayesian inference theories also provide a framework to think about adaptive and maladaptive LDM, the models additionally include a measure of precision – or uncertainty, on the basis that neither sensory data, nor our prior knowledge of the world, is completely reliable. Here, its argued that dopamine in fact encodes the "precision" (other words that are used are un/certainty or reliability) of the PE. As

such, the brain must not only integrate both sources of information, but also take into account their inherent uncertainty.

To account for this uncertainty, Bayesian accounts of inference are probabilistic, postulating that the optimal combination of uncertain information is given by Bayes theorem. Here, our initial expectation of the state of the environment (the prior), is combined with the probability of the sensory information given the expectation i.e., the likelihood, to compute a posterior - an updated estimate about the state of the environment (Friston et al., 2014). Precision in this instance, refers to the tracking of the noise or variance in different sensory modalities. Incoming information that is precise is thought to afford a higher weight (Friston, 2009; Yon & Frith, 2021). For example, the success of the ventriloquists' act can be explained by the fact that visual information typically confers a more precise signal than auditory information. The illusion emerges because our perceptual systems infer that while the visual and auditory information come from the same source, the visual information is more precise, and as such will be weighted more strongly as we search for the source of the noise (Yon & Frith, 2021). This is called "precision-weighting" and provides an account of near-optimal cue integration in animals and humans.

Precision weighting can also account for the integration of beliefs/expectations, and sensory information. Influential Bayesian models of perception provide a framework that describes a hierarchical integration of bottom up (sensory information) and top down (expectations/beliefs) information as the primary way in which agents experience the world. These models make sense of inputs by inferring their causes (Helmholtz, 1867), via hierarchical generative models. Specifically, to make sense of extremely complex natural sensory information, hierarchical Bayesian inference models mirror the hierarchical structure of the environment, providing explanations for complex patterns of low-level sensory data in terms of more abstract (latent)

causes (Botvinick et al., 2009; Diuk et al., 2013; Huys et al., 2015). In error-based hierarchical Bayesian models, like the Hierarchical Gaussian Filter (HGF), PEs sit on a hierarchy where lower-level PEs signal violations in sensory expectations, and higher order PEs signal violations of beliefs about the probabilistic structure of the environment, including its changeability – or volatility. The precision/uncertainty of the incoming data then impacts the size of the update. For example, if you are highly uncertain about your belief, but the sensory information is highly reliable, then a belief update is required. Such theories go beyond the role of PEs in reward learning only and instead suggest PE processing is a general model for inference and learning across sensory and cognitive domains – in this context often termed belief updating. Here, behaviour is optimised when the PE is minimised, rather than when the reward is maximised. Theories such as the predictive processing account build on this rationale to propose specific mechanistic routes that Bayesian inferencing could be neurologically implemented (Friston, 2009; Friston et al., 2014; Sterzer et al., 2018).

# 3 Uncertainty

Uncertainty is a concept inherent in the Bayesian inference theories of LDM, via their use of probability to describe the nature of received information. However, RL modelling approaches are also commonly used to make inferences about participants estimates of uncertainty, often via changes to learning rate under differing learning environments (Pulcu & Browning, 2019). While the routes by which uncertainty itself is measured is discussed in more detail below, we first start with an outline of the concept of uncertainty and its importance in the LDM process.

Uncertainty is a phenomenon important to consider in the LDM process because of its ubiquitous nature in the information we receive. When we observe our environment, we perceive it incompletely. Consider these facts - our senses are vulnerable to illusions; we cannot observe another animal or persons intentions or processes directly; and we only perceive the world intermittently. Because of this, we must infer states of the world based on information and processes that are often changeable and hidden. These hidden processes, while not directly observable, can influence observations (Pulcu & Browning, 2019). As such, to make adaptive decisions, we must account for, and ideally, minimise, uncertainty.

It is important to acknowledge that incoming information can be uncertain in different ways. Firstly, information can be noisy such that while we know the probability of an event occurring, we can still not predict an outcome with complete certainty. Take the roll of a dice. While we can easily work out the probability of rolling a two, understanding this does not support our ability to accurately predict whether the next roll will in fact be a two. The subjective experience of this type of uncertainty is referred to as *expected uncertainty* and is irreducible. A second type of experienced uncertainty is *unexpected uncertainty*. This relates to the need to account for changes (volatility) in the environment i.e., if the stimulus-response association is likely to change between observations, say someone switched the dice for a weighted die with altered probabilistic outcomes, then it is necessary to compute the probability that a change has occurred over the learning period (Pulcu & Browning, 2017). In this case, the objective (statistical) uncertainty is referred to as volatility. Other types of uncertainty also exist, for example, information can also be uncertain due to perceptual ambiguity, however this is not focussed on here (Bach & Dolan, 2012; Gold & Heekeren, 2014; Summerfield & Tsetsos, 2012). Importantly, two independent agents may form differing uncertainty estimates for the same association. As

such, the way in which people learn and make decisions could be negatively affected by aberrant processing/estimation of uncertainty.

These different forms of uncertainty influence how relevant recent events are relative to more distant events, when learning about a hidden process (Pulcu & Browning, 2017). As such, within a normative account of learning we can expect opposing inferential responses to surprising events in response to different types of uncertainty. For example, if you have a belief that some surprising information you have just received is in fact generated by noise in the relationship between the hidden process and what you have observed, then this expected uncertainty means that you should use a lower learning rate, and rely more on/be more influenced by, prior events. On the other hand, if you consider that this surprising event is actually caused by a change in the hidden process being estimated, then this information is highly informative and predictive of future events, and as such learning rates should increase, alongside use of more recent information (Behrens et al., 2007; Browning et al., 2015; Pulcu & Browning, 2019; Soltani & Izquierdo, 2019).

To mitigate the impact of uncertainty on LDM one must accurately estimate the extent of the (correct type) of uncertainty and use it to inform our learning. Human studies confirm a normative account of LDM via evidence that individuals increase learning rates when exposed to unexpected uncertainty, in comparison to stable environments and potentially independent of the feedback valance (positive – e.g., a monetary reward, negative – e.g., monetary loss/electric shock) (rewarding: (Behrens et al., 2007, 2008; Nassar et al., 2012, 2021); punishing: (Browning et al., 2015; Pulcu & Browning, 2017). Regarding expected uncertainty, studies measuring the magnitude, rather than the probability of an outcome, have shown evidence that prediction errors, and by proxy learning rates, decrease as expected (Diederen & Schultz, 2015; Diederen et al.,

2016; Krishnamurthy et al., 2017; Nassar et al., 2010, 2012). Aside from human behavioural studies, neuroimaging findings also support the idea that humans maintain estimates of uncertainty and use them to refine the LDM process via evidence that the brain implements meta-control over its own rates of learning (Behrens et al., 2007; Browning et al., 2015; Nassar et al., 2012, 2021; Yu & Dayan, 2005).

# 4 Measuring uncertainty estimation: models and tasks

## *4.1 Computational modelling*

As discussed, successful learning requires learning rates to be adapted to both the noisiness and the volatility of the environment. This is achieved via inferences that are made based on a trial-and-error process during interaction with the environment. Modelling frameworks use differing algorithms to access how people learn to learn, or in other words, how individuals' learning rates adapt to uncertainty in its different forms.

To take error-based models i.e., that include PEs within their formal configuration, to start. The standard RW modelling process was described above, does not directly measure uncertainty in terms of whether learning rate should be changed in response to uncertainty. While these models provide an overall estimate of learning rate, these approaches are unable to directly capture how participants are quantifying volatility ascribed to different task conditions, or how changeable they believe the environment to be (Sandhu et al., 2023). This is because the RW keeps learning rate constant. However, more complex RL models, like the Pearce Hall (Pearce & Pearce, 1980), and the Kalman filter (Dayan et al., 2000) can include a dynamic learning rate, that can capture how learning rates change over time. These models adapt to changes in unexpected uncertainty

by estimating the surprise associated with the stimulus, and then adjusting the main LR using this estimate (Piray & Daw, 2021a).

Generative hierarchical modelling approaches on the other hand, are able to provide explicit insight into individualised volatility estimates on a trial wise basis. Here, learning takes place in a hierarchy. Upper-level beliefs reflect the estimated volatility informed by lower-level sensory errors. Learning rate in this case refers to a trade-off between the precision weights of the upper and lower precisions. More recently Bayesian "filters" have been used to provide estimates of higher order and/or expected uncertainty (Stephan & Mathys, 2014). While generative hierarchical models, like the hierarchical gaussian filter (HGF) are designed to measure continuous changes in the environment, other error based generative models like the change point detection model (CPD), measure learning in the context of discrete changes. The belief about how often the environment is thought to change is referred to as the hazard rate and informs the probability of a change point. The hazard rate is weighted against the relative uncertainty, and the estimated noise in the environment (Adams & MacKay, 2007).

While the models described thus far have included either none (RL) or partial (HGF) Bayesian inference, non-error-based modelling approaches i.e., those that do not include a PE in their algorithmic configuration, are technically "fully Bayesian". In other words, models like the Hierarchical Hidden Markov Models (HMM) track and weight the probabilities of different states against each other. Other non-error-based approaches, like the Ideal Bayesian Observer models, instead work to quantify the extent to which the agent's belief about a generative process is used to predict future outcomes, in response to an event change (Behrens et al., 2007). As such, outputs from this model include estimates of the effects of both expected and unexpected uncertainty on the information content of events. Using the Bayesian Ideal Observer, studies have investigated

how learning rate should adapt to uncertainty (Behrens et al., 2007; Payzan-Lenestour & Bossaerts, 2011; Yu & Dayan, 2005).

While the heterogeneity in modelling approaches that can be applied to the question on LDM under uncertainty provides a unique flexibility to the analysis of specific LDM questions, it has also been argued to be impacting the fields' ability to draw conclusions across the extant literature (Katthagen et al., 2022). Specifically, while various computational measures including parameter estimates, aim to characterise latent computational processes shaping behaviour, limited work has been done to establish whether they show convergent validity across studies and tasks (Browning et al., 2015; Karvelis et al., 2023). Additionally, there is evidence to suggest that a large proportion of studies using this type of modelling are yet to meet the "gold standard", in terms of for example, simulations and parameter recovery, argued to be necessary to the development of useful and informative models (Browning et al., 2023; Katthagen et al., 2022; Wilson & Collins, 2019). Finally, computational models can be skewed by general poor task performance, which can be reflected as high decision noise ("random" choosing). In turn this could impede the model identifiability and interpretability of model parameters, and generalisability across research. This highlights the importance of using the right task for modelling, specifically in terms being cognitively accessible, but maximally informative (Katthagen et al., 2022).

### *4.2 Experimental cognitive learning tasks*

Specific learning tasks are used to assess LDM under uncertainty. The task type and configuration can also impact the measurement of LDM under uncertainty. A typical experimental framework uses a probabilistic learning task (PLT) i.e., a binary (abstract) stimuli

and choice framework (a red or blue square). For example, the participant will be shown the abstract, neutral, stimuli (red/blue squares) and will be asked to choose the square that will lead to the better outcome. On a trial wise basis, the participant will then receive feedback about that choice (e.g., if correct they receive a pay-out). Typically, the link between choices and the feedback type e.g., reward, neutral, or punishment, is probabilistic i.e., red square = 80:20 reward; blue square 80:20 punishment. This probabilistic configuration induces expected uncertainty – while this type of uncertainty cannot be reduced, overtime and trial and error interaction, the agent will learn the likelihoods associated with each (De Berker et al., 2016; Feeney, 2017; Lawson et al., 2017; Pulcu & Browning, 2019).

Probabilistic reversal learning tasks (PRLT) on the other hand, reverse the "ground truth" contingencies over time. For example, the blue (worse) choice becomes less likely (20:80), and the red (rewarding) choice becomes more likely (80:20). These reversals are un-signalled and therefore surprising to participants, introducing volatility and an intuition of *unexpected uncertainty*, into the learning environment. In response, participants must re-learn the contingencies to continue receiving the better outcomes (Behrens et al., 2007; Soltani & Izquierdo, 2019; Yu & Dayan, 2005). Importantly, volatility manipulations can differ between tasks. For example, instead of a straight reversal, probabilities can themselves change, e.g., from 20:80 to 20:90. The timing and frequency of reversals can also differ between tasks. For example, reversals can be performance dependent i.e., they only occur once participants have successfully chosen the rewarding option in 9/10 trials (Reed et al., 2020). Alternatively, they can occur in a performance-independent way at regular intervals (Suthaharan et al., 2021), or sporadic intervals (Behrens et al., 2007; Browning et al., 2015; Cole et al., 2020; Deserno et al., 2020). Finally, these tasks can also differ in the stimuli used. While primarily content free i.e., abstract and neutral, given the interplay between for example symptoms of psychosis and delusions with

social components, stimuli can also integrate social information into the stimuli. Examples of this include the use of social avatars (Suthaharan et al., 2021).

As mentioned, within the PLT and PRLT framework, the majority of task designs are binary inputs (80:20), with binary choices (red/blue square). While these inputs capture expected and unexpected uncertainty in the sense that the goal is for the agent to estimate a changeable probabilistic relationship, one critique of this design is that real life is often not this straightforward. Within the frameworks described previously, incoming information is uncertain. That is to say, it is probabilistic – our brains are weighting information on its likelihood given certain parameters. Given the complexity of real life, the mathematical formulation of the probabilistic relationships underlying our estimates of hidden processes are unlikely to be binary, and more likely to be continuous. While the configuration is also unlikely to be a Gaussian, one-dimensional, distribution, novel tasks using continuous inputs sample from underlying Gaussian probability distributions in an attempt to better replicate the complexity of the real world (Haarsma et al., 2020; Katthagen et al., 2022; Nassar et al., 2021).

As described, LDM tasks with continuous inputs replicate uncertainty by sampling from a Gaussian probability distribution. Using standard mathematical descriptors of probability distributions – the mean and standard deviation (SD) - noise is manipulated by varying the SD, i.e., a probability distribution with a wider SD increases noise, and is inducing an increased sense of expected uncertainty. Whereas unexpected uncertainty, or volatility, is simulated by sampling from distributions that differ in their means and are switched in an un-signalled manner. Responses can also be continuous. For example, in the “helicopter task”, where participants must track the location of a hidden helicopter in uncertain and changing environments (Nassar et al., 2010, 2012, 2021). Here, participants had to give a continuous prediction of where the helicopter

might drop its bucket. Visual information was then shown that displayed an explicit prediction error i.e., how far the participant prediction was from the actual outcome.

While the use of continuous inputs and responses in experimental task design is likely to be more ecological valid, there are several other advantages. Firstly, it allows participants to dynamically infer the underlying statistics of the task – for example, to explicitly test whether participants can successfully differentiate noise from meaningful change on a trial wise basis (Katthagen et al., 2022). This can be tested for example, against the normative model of learning rates described above, where we expect LRs to increase when participants understand that the learning environment includes unexpected uncertainty (or volatility) and be relatively lower when learning under high expected uncertainty (noise) (Katthagen et al., 2022). Secondly, while learning rates can be calculated using RL and Bayesian Learning models (BL) described above, experimental task design with continuous measures additionally supports the extraction of directly observable prediction errors and learning rates (PE/position change). This precludes the need to infer such important measures as hidden states, as is done in computational modelling including RL and BL modelling (Katthagen et al., 2022).

# 5 Computational psychiatry: uncertainty estimation in psychopathology

While we see that LDM under uncertainty occurs in line with a normative account of learning in healthy individuals, it also stands to reason that the misestimation of uncertainty may be a candidate mechanism underlying psychopathological symptomology. In fact, the misestimation of uncertainty has recently been argued to potentially provide a mechanistic link between internal cognitive aspects of psychopathology, ranging from affective disorders, like anxiety and depression, to psychosis spectrum disorder, autism (Lawson et al., 2017) and stress

(De Berker et al., 2016), and external risk factors for mental health disorders – such as exposure to traumatic events (Eshel & Roiser, 2010; Mathews & MacLeod, 2004; Pulcu & Browning, 2019). Computational psychiatry has emerged as a field dedicated to examining dissociable information processing biases across psychopathology (Adams et al., 2016). By linking psychiatric symptoms, groups, or dimensions to deficits, computational approaches to studying learning under LDM have enabled the study of individual and group differences in the regulation of learning. In turn, research has revealed characteristic biases that help explain maladaptive LDM in psychiatry and could represent a novel route towards treatment (R. A. Adams et al., 2016; K. J. Friston et al., 2014; Huys et al., 2020; Montague et al., 2012; Nair et al., 2020; Schultz et al., 1997; Stephan & Mathys, 2014).

There are multiple ways in which uncertainty can be mis-estimated in psychopathology. For example, the degree of uncertainty can be over, or under, estimated. This can be tested using the normative account of learning (Behrens et al., 2007; Pulcu & Browning, 2019). One example would be where an individual was overestimating expected uncertainty (or underestimating unexpected uncertainty). In this case, and particularly in volatile and low noise environments, the individual would be relatively less sensitive to recent events, and as such, be slower to react (less flexible) and adapt to important changes. In contrast, underestimating expected uncertainty, or overestimating unexpected uncertainty, would lead to recent events having an increased influence. As such, in noisy learning environments, we would see an increased learning response to new information, when the information is spurious. Behaviourally, this would appear as though the individual is overacting to chance events (Pulcu & Browning, 2019).

One way of measuring how individuals are estimating the degree of uncertainty in the environment, is to measure the adaptation of LRs between conditions where uncertainty is

manipulated e.g., with high volatility, compared to stable (non-changing, low noise) conditions. One influential study using this method found that individuals with high trait levels of anxiety showed less adaptation of LRs to increases in volatility, during a learning task (Browning et al., 2015). This effect was mirrored in the pupil dilation of anxious individuals, showing that in response to unexpected uncertainty, pupil dilation was also found to be lower. Findings from this study suggest that individuals with trait levels of anxiety may show a deficit in ability to adapt learning appropriately when an environment changes from stable to volatile. Specifically, authors suggest that they show learning rates in individuals with trait levels of anxiety to be less flexible, specifically in relation to increases in volatility. Importantly, this finding was consistent with the putative role of altered norepinephrinergic responsivity in representing estimated unexpected uncertainty, linking neurological and behavioural theories of anxiety symptomology (Dayan et al., 2000). The behavioural findings from Browning et al., (2015) were replicated in a study that linked an internalising psychopathological dimension (shared anxiety and depression) to a reduced effect of volatility on learning rate (Gagne et al., 2020). The authors suggest that inflexible belief updating relates to an internalising symptom dimension (anxiety and depressive symptomology), potentially providing at least a partial explanation to the high comorbidity rates between these disorders (Kessler et al., 2005).

While there is still limited research available, assessment of learning rate adaptation has shown promise regarding our ability to probe important but subtle deficits in uncertainty processing. This has led to some surprising findings across mental health disorders such as anorexia. For example, while a general inflexibility in learning has traditionally been identified in eating disorders (Holliday et al., 2005; Roberts et al., 2007; Tchanturia et al., 2004, 2011; Wang et al., 2019), when investigating the adaptation of LRs to changes in volatility, the opposite effect has also been found (Pike et al., n.d.). Here, individuals recovered from anorexia were shown to

display an oversensitivity to volatility changes in the environment (Pike et al., n.d.). By isolating and comparing LRs to volatility in comparison to stable environments, a more detailed (and potentially accurate) picture of deficits was able to emerge.

Importantly, the misestimation of the degree of uncertainty in an environment is an error that can occur in relation to the valence of information specifically. In fact, research on this topic represents the route by which affective disorders have primarily been implicated in the LDM under uncertainty literature (Aylward et al., 2019; Pike & Robinson, 2022). Here, a tendency to overestimate the unexpected uncertainty to for example, negative (relative to positive) information, would mean that negative outcomes are more influential than positive ones (Pike & Robinson, 2022). From a clinical perspective this negative cognitive bias could quite straightforwardly link to symptoms of depression such as anhedonia i.e., a loss of ability to experience pleasure, but is believed to be causally linked to both depression and anxiety (Browning et al., 2010; Eshel & Roiser, 2010). While this mechanism would require humans to process and maintain separate estimates of uncertainties associated with positive and negative outcomes, recent research has not only provided evidence that these estimates are indeed independent, but they also appear to be used to modify the degree to which they update their beliefs in response to a particular valence of outcome (Pulcu & Browning, 2017). However, further research is required to establish whether learning in response to alterations in volatility is valence-dependent or independent, given findings of another study showing that high internalising symptomology (depression and anxiety), was not dependent on the valence of the information (Gagne et al., 2020). Differences in task design and modelling approaches may represent one explanation for the differences in findings (Katthagen et al., 2022).

There is also evidence to suggest that individuals with psychosis (at varying degrees of severity), are interpreting new information such that it suggests a change in the environment, even if there has been none i.e., are over-estimating volatility (Cole et al., 2020; Deserno et al., 2020; Gray et al., 1991; Kapur, 2003; Reed et al., 2020; Suthaharan et al., 2021). This mechanism is thought to underlie delusions (Sterzer et al., 2018). Multiple streams of research have conferred around several findings. Firstly, decision noise is repeatedly found to be higher in patients with psychosis i.e., the stochasticity of individuals' choice behaviour (not to be confused with the noise/expected uncertainty induced by the variance of the probabilistic distribution of outcome contingency). Overall, research shows a strong relationship between psychosis groups and a tendency for exploration (more random behaviour), over exploitation of acquired knowledge when learning under volatility (Katthagen et al., 2022). Secondly, studies using the HGF to extract individualised trial-wise volatility estimates show that parameters capturing an individual's initial belief about the volatility in an environment, are much higher in psychosis spectrum disorder compared to controls, suggesting they over-estimate environmental volatility (Cole et al., 2020; Deserno et al., 2020; Reed et al., 2020; Suthaharan et al., 2021). Finally, this increase in decision noise has been shown to interact with higher level beliefs about volatility (Culbreth et al., 2016; Kaplan et al., 2016; katthagen et al., 2020; Schlagenhauf et al., 2014; Waltz et al., 2013). One hypothesis integrating these findings suggests that the tendency not to stabilize beliefs, but to constantly update them (interpret as volatile), leads to a failure in reaching an equilibrium in higher level beliefs, which would enable these individuals to downplay noise (Katthagen et al., 2022). This would account for findings showing higher decision noise ("random" responding) because by downplaying noise in the incoming information, the individual is assigning it higher meaning, taking it more seriously, and as such needing to update their beliefs about the situation more readily.

One important factor to highlight here is that while multiple types of uncertainty exist in our environments, psychiatric research has currently only tested learning in response to (changes in) volatility or noise separately (and usually using a binary input/choice format). As such, research has not considered the full problem facing the learner: simultaneously estimating both the volatility and the noise during learning. In fact, it has been argued that given the interrelatedness of these dimensions of learning, inferences about volatility and noise would in fact be expected to exhibit compensatory trade-offs e.g., aberrant detection of noise would lead to a compensatory increase in inferred volatility (Piray & Daw, 2021b). As such, previous work purporting to show variation in volatility processing across different psychiatric groups, using models and tasks that do not vary noise, may by instead reflecting misidentified abnormalities in processing noise (Piray & Daw, 2021b).

## 6 Novel experimental paradigms: the online context and transdiagnostic approaches

A growing body of research within the field of computational psychiatry is looking to build upon the development of novel tasks in an online context to overcome well-documented issues with the categorical view of mental health (Haslam, 2003; Wise et al., 2023). Current categorical diagnostic frameworks show high levels of comorbidity, heterogeneity, and the increasing sense that, while clearly useful for clinical communication, dichotomous definitions of mental health are, by definition, unable to capture a continuous mental health space (Haslam, 2003; Markon et al., 2011). As such, transdiagnostic research has emerged in an attempt to capture a more dimensional sense of psychopathology.

One increasingly popular route to transdiagnostic testing is to use large-scale, unselected (general population) online samples of individuals, rather than small samples of patients vs. healthy controls (Gagne et al., 2020; Gillan et al., 2016; Wise et al., 2023). Such paradigms typically utilise a range of questionnaires to identify and capture psychopathology in the general population, gathered at a scale that enables robust exploration and replication. In relation to specific measures of interest, researchers can then either i) identify overlapping deficits that appear to exist in more than one symptom group and report on these; and/or ii) reduce dimensionality of the symptom data using data-driven approaches such as factor analysis, and relate task measures to symptom dimension. This latter approach additionally deals with potentially highly correlating symptom items across symptom scales (Gillan et al., 2016; Pulcu & Browning, 2019; Wise et al., 2023).

Given that several reviews have suggested that computational biases are not necessarily specific to a unitary disorder category, but cut across diagnostic boundaries, such online experimental paradigms have been used across a number of LDM constructs (Gagne et al., 2020; Gillan et al., 2016; Pike & Robinson, 2022; Seow et al., 2020; Wise & Dolan, 2020). For example, Gillan et al., (2016) tested an online sample of over 1400 participants, looking to disentangle model-based planning strategies from more reflexive learning styles. Correlations between parameters describing model-based planning and individual symptom scales were prominent in OCD groups, and also found for social anxiety, eating disorders and impulsivity items. Factor analysis was then carried out on the symptom data, which identified a dimension encapsulating compulsivity and intrusive thought, and its' strong and unique (in comparison to other dimensions tested) relationship to deficits in model-based control. Use of this paradigm to investigate LDM under uncertainty is a growing area of research. For example, Gagne et al., (2023) used a bifactor model approach in patient data (major depressive disorder and generalised anxiety disorder), and an

online cohort of unselected individuals. They found that a dimension representing combined anxiety and depression was related to an inability to successfully adjust learning rates from stable to volatile (unexpected uncertainty) environments.

## 7 A summary of gaps in current literature

The authors are unaware of any *systematic* review of literature assessing uncertainty estimation across disorders, and across computational modelling approaches. Aside from a study using a simulation approach across depression and anxiety: Pike, & Robinson, (2022), the remainder of reviews, though excellent and insightful overviews, are not systematic and/or not transdiagnostic (for example, see Lee, 2013; Huys et al., 2021; Kube et al., 2020; Rutledge & Adams, 2017; Katthagen et al., 2022; Barch et al., 2017; Sterzer et al., 2018; Voon et al 2017; Stephan & Mathys 2014; Maia and Frank, 2011; Heinz, 2019; Deserno et al., 2017). The lack of systematic overviews in this field is likely a direct result of the heterogeneity that exists in i) the algorithmic differences in computational modelling approaches that obscure/complicate direct comparisons between studies, and ii) the subtle differences in task types, and specific features. As such, a useful contribution to the field would be to publish a systematic review of the literature that attempts to account for these differences between studies, in order to draw overarching conclusions.

The importance of uncertainty in controlling the rate of learning has been highlighted in previous research. While research has investigated how such control depends on the agent inferring properties of the environment: noise and volatility, these have only been explored independently. This is problematic given the fact that learning rates are jointly determined by a comparison between estimates of the volatility and noise (Piray & Daw, 2021b). In turn, this limits the fields'

ability to comment on how uncertainty estimation may affect learning in psychiatry, and subsequently, our ability for this to inform and tailor more successful treatment options. Current task designs do not support investigation of joint uncertainty estimation and are often not ecologically valid (use binary choice formats). Development of a task that could capture the full problem facing the learner: simultaneous estimation of volatility and noise during learning, would shed light on the interrelationship, and where this may be malfunctioning. A recent review suggests that research would improve in its ability to measure subtle differences in LDM under uncertainty by designing a task that i) includes measurement and comparison of conditions where multiple types of uncertainty are captured; and ii) uses continuous inputs and responses allowing both raw measures of learning (PE and learning rate) and as a way to more readily disentangle noisy decision making form the over-updating i.e., to tell the difference between random responding or the interpretation of the information as highly meaningful (as a normative account would suggest happens under volatility) (Katthagen et al., 2022).

# 8 Aims and hypotheses

**Aim 1.** An aim of this thesis was to synthesise and organise the literature in such a way as to provide a meaningful systematic review of the literature in belief updating using computational modelling approaches in psychosis, depression, and anxiety disorders.

**Process.** To complete this, the literature was systematically searched with highly specific inclusion criteria. Each study had to include a task where the participant received probabilistic feedback on a trial-wise basis, as well as using an error-based modelling approach. To compare studies, free parameters extracted from the computational modelling within the study, were reviewed and compared. The literature was then categorised into computational modelling

approaches where extracted parameters were able to be sensibly compared, for example, RL and BL models.

**Hypotheses.**

- It was hypothesised that anxiety and depression disorders would reveal an overlap in LDM deficit that related to feedback responsiveness preferentially. Specifically, both groups will show increased learning in relation to negative feedback and reduced learning from positive feedback.
- Psychosis spectrum disorders will show no overlap with other disorders. Instead, individuals experiencing psychosis symptoms will show increased decision noise i.e., exploratory decision behaviours; as well as difficulties in learning under, and estimating volatility.

**Aim 2.** This research aimed to develop a novel task capable of capturing learning under different types of uncertainty, and to provide evidence of its reliability and validity in measuring learning under uncertainty. Given the development of novel experimental online paradigms that provide access to large scale populations and robust exploration (Wise et al., 2023; Wise & Dolan, 2020), the task was designed for an online format (Soltani & Izquierdo, 2019).

**Process.** To achieve this, a novel learning task was developed, specifically designed to probe LDM under multiple types of uncertainty, in isolated and combined conditions, and feasible for an online, and clinical context. The novel task used continuous inputs drawn from a "ground truth" gaussian probability distribution that had been statistically manipulated to simulate learning environments under different types of uncertainty. The task also used continuous parallel metrics that captured an individuals' estimates of both the mean and the standard deviation of the

underlying distribution on a trial-wise basis, enabling directly accessible (raw) measures of learning such as PE and learning rate. The task used a gamified, interactive interface, to increase engagement and support an intuition of uncertainty via the narrative to promote ecological validity (Soltani & Izquierdo, 2019).

**Hypotheses.**

- The task was hypothesised to be feasible in an online setting, shown via reduced exclusion rates during two large-scale online study (n555; n=167).
- The metrics included in the task were hypothesised to show construct validity i.e., they will be shown to measure what they are intended to measure, namely, the participants' continuous estimates of the mean and variance of an underlying distribution on a trial wise basis.
    - The rover position will closely follow the underlying mean.
    - The beam widths will closely follow the underlying variance.
- The task will be able to successfully replicate previous findings i.e., from the study that the task was developed from (Berniker et al., 2010).

**Aim 3.** A secondary aim of the thesis was to provide insight into the relationships between psychopathological symptoms, and deficits in the accurate estimation of statistical uncertainty in the environment. The research was interested in understanding whether traditional symptom groups (as described by the DSM/ICD) relate to specific uncertainty estimation deficits; or whether deficits in fact cut across traditional diagnostic categories, indicating the potential of LDM uncertainty to represent a common underlying issue and target for treatment.

**Process.** To accomplish this, the validated novel task was applied to unselected (general population) and selected large scale populations using a novel online testing paradigm, to provide i) insight into overlapping and unique uncertainty estimation deficits between symptom groups, and ii) to enable vigorous exploration into deficits. As such, the novel task was tested in a range of symptomatic groups:

1. Eating disorder patients (n=116) and healthy controls (n=67)
2. Unselected general population (n=580), with natural variation in depression, anxiety, and psychosis symptomology (paranoia, schizotypy, delusions) measured using questionnaires.
3. Selected general population sample with high (n=81) and low (n=66) schizotypy personality traits.

LDM was be tested against a normative account of learning, using two complimentary approaches:

1. To test the ability of groups to estimate the type of uncertainty inherent in the environment, analysis compared performance and learning metrics (learning rates, PEs) between learning conditions i.e., isolated noise condition vs. isolated volatility condition.
2. To test the ability of groups to estimate the degree of uncertainty in the environment, the analysis investigated the adaptation of LRs to different types of uncertainty using the learning rate difference between blocks (that differed in the statistical configurations of uncertainty).

**Hypotheses.** Overlapping and unique deficits in the estimation of uncertainty:

- Overlap was hypothesised to be found between anxiety, depression and eating disorder symptom groups in the inflexible adaptation of learning rate to volatility. Specifically, it was hypothesised that individuals scoring highly on depression and anxiety

questionnaires, and (in a separate experiment) ED patients, will show lower levels of flexibility in updating (via lower learning rate differences) between conditions of volatility and conditions of noise, compared to those scoring at the low end of symptomology scales and healthy controls.

- Overall learning (rather than adaptation) in response to conditions of uncertainty was also hypothesised to show some overlap between symptom groups. It was hypothesised that high scoring anxiety and depression symptomatic groups will show overlap in poorer performances between conditions where feedback policies change from reward only, to rewards and losses. Performance will be measured in terms of score, ability to learn the underlying statistics (PE and beam width), and learning rates.
- It was hypothesised that individuals high in psychosis symptomology will show a broader deficit across both the adaptation of learning rates to changes in volatility, and in overall performance differences between conditions. Specifically, individuals with elevated psychosis-like symptoms will over-estimate volatility, shown via differences in both the overall and adaptation of learning rates to changes in uncertainty. Particularly, these groups will show an over-adaptive effect, leading to higher learning rate differences when the learning environment increases in volatility.
- It was hypothesised that application of the HGF in selected high schizotypy groups will show that these individuals display higher estimates of trial wise volatility. In other words, their initial estimates of volatility in the environment will be higher than low schizotypy scorers. Exploratory analyses into how an individuals belief about the noise impacts decision making, will also be conducted.

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# Chapter 2. Belief updating in psychosis, depression, and anxiety disorders: *a systematic review across computational modelling approaches**

* *Publication of this chapter can be found here:*

Gibbs-Dean, T., Katthagen, T., Tsenkova, I., Ali, R., Liang, X., Spencer, T., & Diederen, K. (2023). Belief updating in psychosis, depression, and anxiety disorders: a systematic review across computational modelling approaches. *Neuroscience & Biobehavioral Reviews*, 105087. DOI: *10.1016/j.neubiorev.2023.105087*

## 1 Abstract

Alterations in belief-updating are proposed to underpin symptoms of psychiatric illness, including psychosis, depression, and anxiety. Key parameters underlying belief-updating can be captured using computational modelling techniques, aiding the identification of unique and shared deficits, and improving diagnosis and treatment. We systematically reviewed research that

applied computational modelling to probabilistic tasks measuring belief-updating in stable and volatile (changing) environments, across clinical and subclinical psychosis (n=17), anxiety (n=9), depression (n=8) and transdiagnostic samples (n=9). Depressive disorders related to abnormal belief-updating in response to the valance of rewards, evidenced in both stable and volatile environments. Whereas psychosis and anxiety disorders were associated with difficulties adapting to changing contingencies specifically, indicating an inflexibility and/or insensitivity to environmental volatility. Higher-order learning models revealed additional difficulties in the estimation of overall environmental volatility across psychosis disorders, showing increased updating to irrelevant information. These findings stress the importance of investigating belief-updating in transdiagnostic samples, using homogeneous experimental and computational modelling approaches.

# 2 Introduction

Individuals who meet criteria for a psychosis disorder, such as schizophrenia, frequently present with additional co-morbid symptoms and disorders, such as anxiety and depression (Green et al., 2003; Häfner, 2010; Peralta & Cuesta, 2009; Saha et al., 2007; R. S. Wilson et al., 2020). While anxiety and depression disorders are themselves highly comorbid (McKenna, 1990) they are additionally associated with all levels of the psychosis spectrum, from subclinical experiences, through to symptom development, maintenance, and relapse (Cosoff & Hafner, 1998; Dai et al., 2018; Garety et al., 2001; Morrison, 2001; R. S. Wilson et al., 2020). In fact, these concurrent symptoms are found to relate to the severity of psychosis symptomatology, the level of distress, and even the content of symptoms, such as delusions (Dominguez et al., 2011; Freeman & Garety, 2003; Hartley et al., 2013; Kiran & Chaudhury, 2016). While a causal direction is yet to be established around this phenomenon, the importance of accounting for these

commonly co-occurring symptoms has been demonstrated, due to its impact on prognosis and treatment (Birchwood et al., 2005; Freeman et al., 2007; Michail et al., n.d.; Siris, 2000).

The categorical approach to symptom classification reinforced by nosology's like the Diagnostic and Statistical Manual of Mental Disorders (DSM), in large part, contributes to the field's lowered awareness of the role of anxiety and depression symptoms in psychosis disorders (Cuthbert & Insel, 2013; Insel et al., 2010; Nuckols & Nuckols, n.d.). This in turn affects researchers' ability to successfully identify whether observed deficits relate to a unique symptom or disorder, or if the deficit represents a more fundamental underlying mechanism. In concordance with a move away from a categorical approach to nosology, research is beginning to support the identification of biobehavioural dimensions of individual variation, that are persistent across established disorder categories, and enable a more specific disaggregation of deficits. Computational psychiatry has emerged as one way to support identification of such candidate biobehavioural dimensions.

The field of computational psychiatry uses modelling to elucidate a more mechanistic understanding of behaviours thought to underlie symptoms of psychopathology, such as belief updating. Belief updating refers to the constant integration and weighting of expectation and novel information, with disturbances in this fundamental process suggested to sit at the heart of psychopathology. Prominent computational models fundamentally rely on prediction errors i.e., the difference between what the agent expected and what (feedback) was observed. For example, psychotic symptoms such as delusions are described as an over-weighting of expectation, and an underweighting of novel observations – the latter being vital in the disconfirmation of the abnormal belief (Adams et al., 2013; Gray et al., 1991; Heinz, 2002; Kapur, 2003; Maia & Frank, 2017). While some evidence suggests that depression and anxiety disorders relate more

specifically to the valance of the feedback received e.g., reduced reward sensitivity (Aylward et al., 2019; Beevers et al., 2013; Huang et al., 2017; Q. J. Huys et al., 2013; Mathews & MacLeod, 2005; Pulcu & Browning, 2019).

However, due in part to methodological heterogeneity between studies in the field, as well as an overall lack of transdiagnostic samples, it remains largely unclear which alterations in belief-updating are shared between symptoms of psychosis, depression, and anxiety, and which are symptom - or disorder - specific. Disaggregating unique and shared deficits in belief updating would improve understanding of fundamental mechanisms involved in these disorders, supporting the vital development of effective, and importantly, targeted, treatments.

This study aims to systematically review the extant literature on belief-updating as described by computational modelling across clinical and subclinical anxiety, depression, and psychosis. More specifically, the objective is to provide analysis of belief updating in response to i) probabilistic valenced feedback i.e., positive/rewarding, or negative/aversive/loss, and ii) changes in the environment. As such, studies using probabilistic learning tasks are compared using extracted modelling parameters, with a focus on learning rates, as well as parameters that describe noise in decision making.

We addressed methodological heterogeneity by synthesising research using several key criteria. Firstly, to provide a logical comparison of parameters extracted from modelling approaches of differing theoretical origins, the review focusses on computational models that are algorithmically similar, i.e., that include belief-updating as a function of prediction error (see Box 1 and 2). However, a discussion of non-error-based Bayesian learning models is also included. Secondly, the review separates probabilistic learning tasks measuring belief updating

in stable environments, from learning under changing - termed volatile – environments. Finally, in addition to a systematic comparison of parameters across modelling approaches and disorder groups, we provide detailed information on the quality of modelling procedures used across studies.

**Box 1**. *Reinforcement Learning Models (RL)*

An important difference between modelling approaches is the way in which they deal with the learning rate. For example, the simplest RL model, the Rescorla Wagner model (Rescorla and Wagner, 1972), has a constant learning rate α. This prevents the learning rate from getting too low and is computationally efficient and simple to use.

$$[1]\ y^t = \mu^{t-1} + \alpha\, x\, \delta^t$$

Here, μ refers the reward value (or in instrumental paradigms: the "Q-value" for the anticipated reward associated with choosing stimulus x), which is updated iteratively (*n* for trial index) as a function of the size of the prediction error δ in response to a reward – termed reward prediction error (RPE). A constant learning rate (*a*) then determines the weight attributed to the RPE and drives learning. When the RPE equals zero no learning occurs (Diederen & Fletcher, 2021).

However, a constant learning rate cannot change and adapt with a changing environment making it suboptimal for providing a detailed mechanistic explanation of observable behaviours. There are multiple ways that modelling approaches define learning rates. For

example, within the Pearce-Hall model, learning rates are dynamic, and as such are highest when a novel stimulus is first perceived (Pearce & Pearce, 1980).

$$[2]\ \alpha^t = \gamma \parallel \delta^{t-1} \parallel + \quad (1-\gamma)\,\alpha^{t-1}$$

Here, the learning rate is allowed to decrease across trials ($\alpha_n$) as a function of the absolute, previous PE ($\parallel \delta_{n-1} \parallel$). This provides a signal of the extent to which the previous trial is wrong. As well as the learning rate on the previous trials, and an individual determined discount factor ($y$). This recursive process in initialized with a starting learning rate $\alpha_0$.

$$[3]\ \sigma(\overrightarrow{z})_i = \frac{e^{z_i}}{\Sigma_{j=1}^{K} e^{z_j}}$$

Given the Q values, a SoftMax rule is used to estimate the associated probability of selecting each action. This SoftMax rule includes the (sometimes inverse) temperature β that denotes the choice stochasticity (Sutton et al., 1992).

**Box 2.** *Error Based Bayesian Learning Models*

In Bayesian learning posterior beliefs are characterised as probability distributions, representing inferences about hidden states of the environment. The Bayes-optimal approach utilises an algorithm designed to perform optimally given a model of the environment and the

task (Bayes, 1763). This computationally heavy approach led to the development of probabilistic modelling approaches, that use error-update approximations to a Bayesian learner, such as the Hierarchical Gaussian Filter (HGF) (Mathys et al., 2011; Mathys et al., 2014); and change point "normative" models, that impose constraints such as limitations on computational resources for the ideal observer agent (Collins & Frank, 2012; Nassar et al., 2010).

**Hierarchical Gaussian Filter**

Beliefs within the HGF can span any number of levels, however commonly 3 levels are used, and these are continuously updated using random gaussian walks with a constant step-size ω. Each level describes different types of beliefs about the state of the world. Level 1 ($\mu_1$) is the belief about the state of sensory input. Importantly, this is only relevant where there is output uncertainty i.e., perceptual ambiguity about the input. With binary inputs, this is instead a sigmoid transformation of the second level belief. The second level belief ($\mu_2$) represents the probability ($x_2$) of state $x_1$ being true. For example, that the stimulus led to a reward. This is associated with expected uncertainty ($\sigma_2$) i.e., the uncertainty that is able to be predicted by the model. The third level relates to the belief about environmental volatility ($\mu_3$).

$$\frac{\hat{\pi}_1}{\pi_2} = \frac{\hat{\pi}_1}{\hat{\pi}_{2+}\hat{\pi}_1} = \frac{\hat{\pi}_1}{\frac{1}{\sigma_2^{(t-1)} + \exp\left(\kappa\mu_3^{(t-1)} + \omega_2\right)} + \hat{\pi}_1}$$

[4]

The top-down influences within the HGF are represented by higher level beliefs determining the extent to which lower-level (bottom-up) PEs influence beliefs. Precision weights, an

equivalent to a dynamic learning rate, are used to weight the influence of PEs on the updates. To achieve this precision weights use the predicted precision from the level below (e.g. $\hat{\pi}_1$) (numerator) and the same-level precision (e.g. $\hat{\pi}_2$ ) as the denominator.

Additional free parameters to be fitted include $\omega_2$, $\omega_3$and $\kappa$. These relate to the levels described above with $\omega_2$representing the fixed proportion of the dynamic learning rate on the respective level. A coupling parameter ($\kappa$) can also be used as a free parameter, representing the coupling influence of the high level belief on the level below e.g. the influence of the third levels belief on the second level.

**Change Point Detection Models**

Central to change point detection theory, and in line with probabilistic views of belief updating, is the idea that a belief can be formalised as a distribution – using the mean to represent the current prediction. Here, volatile environments are changing action-outcome contingencies, where beliefs are required to shift discretely rather than evolve gradually. This model dissociates whether a participants' prediction in response to a deviating input is due to noise (reflected in the variance), or due to an actual change in the generative distribution (reflecting environmental volatility).

$$a^t = \Omega^t + \tau^t \times (1 - \Omega^t)$$

[5]

In the same format as the previously described modes, this is an error-based account of learning, with PEs being updated and weighted by dynamic learning rates. In this case learning

rates can be affected by the change point (Ω) probability and the relative uncertainty (τ). When there is no environmental change, learning rates (*a*) are scaled by the current uncertainty belief. When a change point has occurred, this can be overridden, allowing for rapid increase in the learning rate. A set level of environmental volatility feeds into this – termed "hazard rate". Assuming that there are few change points leads to a low hazard rate, meaning the agent can tolerate larger PEs without increasing the learning rate and assuming a true change point.

# 3 Methods

## *3.1 Belief-updating tasks*

Research in this field commonly uses probabilistic learning tasks that require dynamically updating beliefs via trial-and-error learning. Crucial aspects where tasks can differ are (1) the use of binary or continuous task inputs, (2) the stability of the task environment, and (3) the valence of the feedback, described below:

(1) *Binary vs. continuous inputs.* Here continuous beliefs can represent cue-outcome-associations of binary inputs e.g., stimulus x leads to feedback x by probability 0.8, as found in probabilistic reversal learning tasks. Alternatively, for continuous inputs in prediction tasks, beliefs can be represented by the mean of (hidden) underlying distributions also tracking the variance of these inputs.

(1) Environmental stability. A probabilistic learning task with binary rewards can probe learning in stable versus volatile environments via its stimulus outcome contingencies.

The task structure simulates volatility by manipulating (A) changing cue-outcome contingencies (a stimulus leads to 80% reinforcement first, which then changes to 60% reinforcement), or (B) the frequency of reversals (see Figure 2.1. Please note that Figure 2.1 is a visualisation of only binary inputs).

(2) *Feedback valance.* Belief updating tasks aim to encourage new and more adaptive behaviours in individuals. This necessitates the existence of external feedback that can be i) rewarding (e.g., a gain in money/points), ii) neutral, and/or iii) punishing (e.g., loss of money/points, or an aversive stimulus such as electric shock).

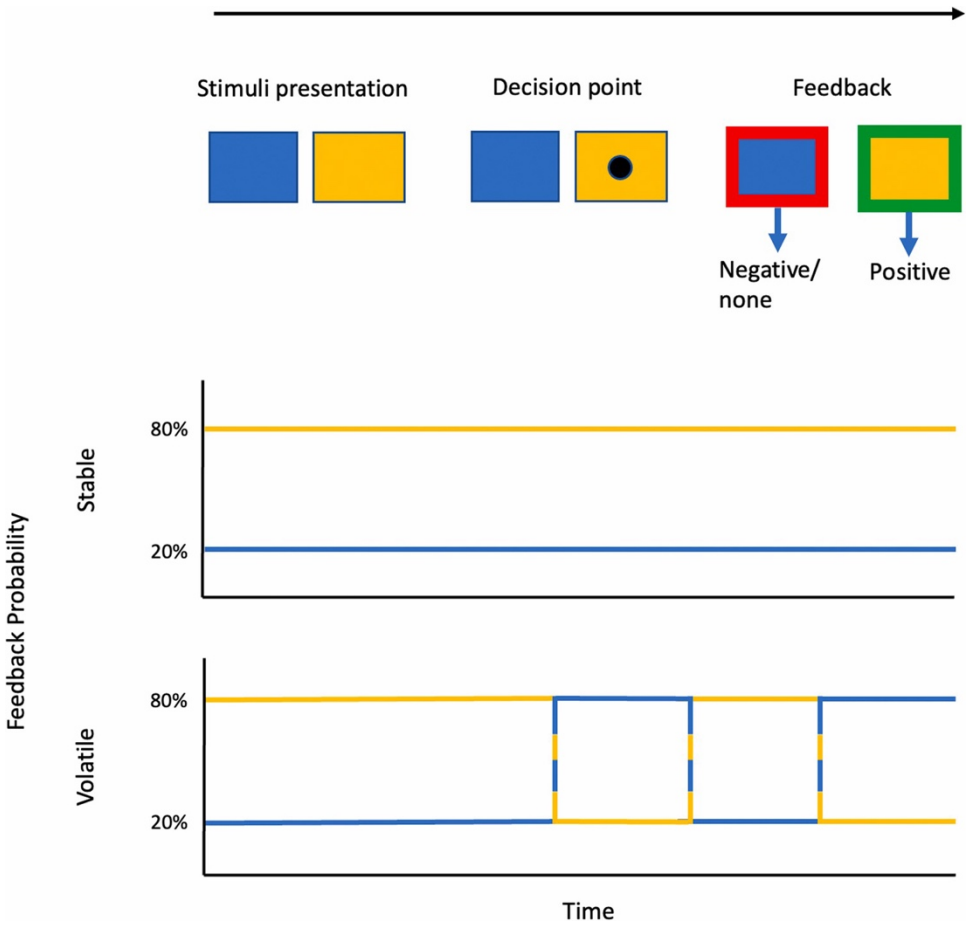


**Figure 2.1.** *Showing a simple probabilistic learning task with stable and volatile contingencies using binary inputs. In the stable condition, the orange choice remains at an 80% likelihood i.e., 80% of the time the participant will receive a reward if this choice is picked, however 20%*

*of the time no reward will be given. Similarly, the blue choice will only be rewarded in 20% of cases, and no reward will be issued in the remaining 80% of trials. In the volatile condition these contingencies are switched, without warning, and participants must re-learn which is the most likely rewarding choice.*

### *3.2 Literature search*

Searches of Web of Knowledge, PubMed and Ovid databases were carried out using a web browser on 01/01/2021 and 01/06/2022. Searches used keywords: phobia or anxiety or psychosis or schizo* or depressi* or major depressive disorder or bipolar disorder and computational-model* and prediction error and learning, not review. Additional papers were added to the search results from the references of the papers found (described in Fig 2). Duplicates were removed and screening of papers was carried out on the remaining papers by two independent researchers. The full text articles were then reviewed. Papers were rejected if they failed to meet all the inclusion criteria listed below:

Inclusion criteria for articles:

1. Human participants
2. Study must include either/or i) at least one clinically diagnosed group using the DSM or ICD; ii) At least one group defined by a set of subclinical symptoms derived from a questionnaire.
3. Modelled behavioural data using a computational modelling approach that included an error-based measure of belief updating.
4. Included a comparison between groups using parameters extracted from the computational modelling.

5. Used a probabilistic learning and decision-making task, with or without a volatility component, that included trial-wise choices, and trial-wise feedback (points, money, feedback, electric shock etc.).

### 3.3 *Modelling procedures across the literature*

To provide a benchmark for assessing modelling procedures across studies, we utilized published work detailing a set of rules for achieving a so called methodological "gold standard" (R. C. Wilson & Collins, 2019). This approach primarily aims to provide a full picture of the modelling space and comparison approaches, with a focus on some key criteria for achieving the gold standard. For details, please see Table 2.5 in the supplementary materials.

A modelling quality (MQ) score (out of 4) is provided based on whether data was 1. simulated, 2. whether parameters were recovered, 3. whether sample changes were reported if the model was a poor fit to some individuals, and finally, 4. whether the study compared models. While the scoring system is a crude method of assessment, it has enabled the findings of this review to be contextualised, giving at least a sense of the reliability and validity of the findings discussed. Importantly, where a study does not score a point for a given criteria, this can be because of a lack of reporting, rather than an absence of process. Where we were unable to locate the information in the text, this is indicated as "not reported". Using this approach, each finding from the review is discussed with reference to a MQ overall score presented as a percentage across the studies in the relevant category.

### *3.4 Outline of the review*

The review will firstly provide analysis on the quality of modelling procedures used across the literature, using recently published guidelines (Wilson & Collins, 2019). The review will then go on to provide results for studies measuring belief updating in stable and volatile environments separately. A range of modelling approaches are used within the studies measuring belief updating in volatile environments, and as such, this section is divided up into these modelling approaches: reinforcement learning models (RL), Bayesian learning models (BL), and change point detection models (CPD), for sake of a cleaner comparison.

A range of free parameters are used across the models in the literature. Where there are significant differences between groups for any free parameter (such as outcome sensitivity, decay, mixing etc.), these are listed in the relevant associated tables. However, learning rates and parameters capturing noisiness of decision making, such as temperature, have been extracted and described specifically, due to their continuity across error-based algorithms, and therefore similarity in phenomena being described. While learning rates play an important role in moderating the relationship to belief updating, they can be formulated differently according to the algorithm chosen. For RL modelling, formulas can use a single learning rate (measuring overall learning), or multiple learning rates, often 2 valenced learning rates that are used to distinctly measure learning from positive and negative rewards. These approaches have been disentangled in the review in order to provide an overview of overall learning rates and those specifically focussed on feedback learning.

# 4 Results

Data was extracted from 44 studies containing 5,371 participants overall (experimental groups n=1,756). Studies investigating clinical groups (n=33) included psychosis disorders:

schizophrenia (n=11), first episode psychosis (FEP) (n=1), clinical high risk for psychosis (CHR) (n=1); depressive disorders: major depressive disorder (MDD) (n=10); and anxiety disorders: generalized anxiety disorder (GAD) (n=1); obsessive compulsive disorder (OCD) (n=1); posttraumatic stress disorder (PTSD) (n=1). Studies investigating subclinical populations included subclinical psychosis (n=4), subclinical anxiety (n=7), subclinical depression (n=1). Several studies also looked at these disorders transdiagnostically across clinical groups (n=8), with one additional study investigating both subclinical populations: anxiety and depression (see fig. 2). Of the 44 studies, 35 used RL modelling, while 7 used BL modelling, and 2 change point detection modelling.

The distribution of disorders across the RL literature was relatively even, with a slight tendency towards an increased frequency of psychosis disorder research, and decreased frequency of anxiety disorders (psychosis disorders: n=19 (including four transdiagnostic studies); depression disorders: n=13 (including five transdiagnostic studies); anxiety disorders: n=9 (including two transdiagnostic studies)). BL modelling was more frequent in psychosis disorder research (psychosis disorders: n= 6 (including one transdiagnostic sample); depression disorders: n= 1 (transdiagnostic); anxiety disorders: n=2; Figure 2.2).

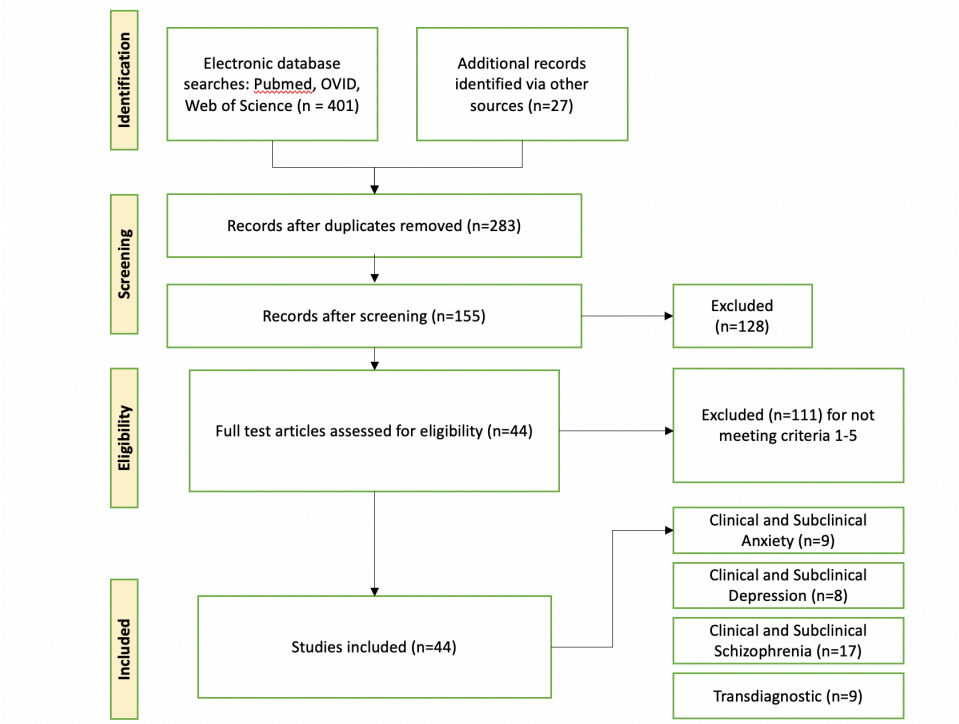


**Figure 2.2** *PRISMA flow diagram for papers included in this study*

## *4.1 Modelling parameters*

Given the recency of the publication for suggested guidelines in computational modelling (R. C. Wilson & Collins, 2019) it was not expected that all research would use all the recommended steps, and that more recent research may be more successful in achieving this. Overall, there were less BL and CPD modelling studies than RL modelling studies. MQ findings showed that overall, RL modelling studies completed less recommended steps than studies using BL or CPD modelling, shown as percentage completed (RL: MQ=41%, BL: MQ=71%; CPD: MQ=66%) (please see: Table 2-5).

Specifically, for RL/CPD modelling (n=37), there was a lack of reporting for any simulation of data (n=3), of implementing parameter recovery (n=14), or both (n=16) (see Supplementary Table 2-5). Several studies additionally did not include any model comparison, instead using one

model (n=10), usually a Q-learning model, in their analysis. In studies that successfully included parameter recovery, simulation, and model comparison (n=10), only one study also included reference to whether their sample had changed due to poor model fit, scoring the full four points. This criterion remained unreported in the remaining studies. Further reference to MQ overall percentage scores will be made in relation to specific findings discussed in the review.

### *4.2 Belief updating in stable environments*

Overall, the review found 24 studies that used stable probabilistic learning task (PLT-S) to evaluate belief updating in a stable environment (Table 2-1). All PLT-S task designs were analysed using RL modelling approaches. As studies often included more than one comparison, for example, when multiple disorder groups were included, a total of 38 comparisons were compared using extracted parameters. Disorders were not evenly distributed across these comparisons, with 14 comparisons including a depression group (including 5 studies using bipolar disorder populations); 20 comparisons including a psychosis related disorder such as schizophrenia, FEP, or CHR; and 4 comparisons using an anxiety-related disorder for example GAD, OCD or PTSD.

When looking across all free parameters, significant differences between groups of interest were found in 15 out of 24 studies (Albrecht et al., 2016; Cavanagh et al., 2019; Cooper et al., 2014; Dowd et al., 2016; Geana et al., 2021; Gold et al., 2012; Haarsma et al., 2020; Hernaus et al., 2018; Montagnese et al., 2020; Murray et al., 2005; Myers et al., 2013; Reinen et al., 2016; Strauss et al., 2015; Waltz et al., 2018; White et al., 2017). These differences were found in relation to a variety of parameters including for example, learning rate (valenced and non-

valenced), temperature, mixing, and decay parameters. While full details of all differences are listed in Table 2-1 learning rates and temperature parameters have been extracted and discussed below, given their presence across all reinforcement learning models.

Studies that did not find a differences between groups (n=9) can be split into those that did not find differences between *any* free parameters (Bakic et al., 2017; Ermakova et al., 2018; Gradin et al., 2011; Kumar et al., 2008; Moutoussis et al., 2018; G. K. Murray et al., 2008; Rothkirch et al., 2017; Rupprechter et al., 2020), and those where at least one comparison between groups was non-significant. Out of all comparisons that included a depression related disorder compared directly to a healthy control group (n=14), over half (53%) did not find any differences between groups. This is compared to comparisons that included a psychosis-related disorder compared to a healthy control group (n=20), where 15% of comparisons did not find a significant difference with healthy controls, and anxiety comparisons (n=4), where all studies found at least one significant difference. Note that anxiety comparisons were much rarer than the other categories.

### *4.2.1 Learning rates in stable environments*

Modelling approaches using a single, non-valenced learning rate in conjunction with a PLT-S (n=18), showed consistency in the direction of effect, but with a limited number of cases. For example, every study that found a difference between groups in overall learning rate found that symptomatic groups (schizophrenia with high negative symptoms, clinical high risk for psychosis (x2), obsessive compulsive disorders (OCD)), showed significantly lower overall learning rates in response to learning in a stable environment. However, this effect was found in

only 4 out of the 18 studies included in the category (Albrecht et al., 2016; Haarsma et al., 2020; Montagnese et al., 2020; G. K. Murray et al., 2019).

Modelling approaches that used multiple, valenced, learning rates in conjunction with a PLT-S (n=6), also showed some consistency in their direction of effect. In total 4 out of 6 studies in this category found a significant difference between groups (Cavanagh et al., 2019; Cooper et al., 2014; Dowd et al., 2016; Waltz et al., 2018). Subclinical depression groups showed i) an increased learning rate for negative feedback, displaying the highest discrepancy in their learning from negative feedback relative to positive feedback, compared to controls (Cooper et al., 2014); and relatedly, ii) a deficit in learning from positive feedback when compared to individuals identified to be low in subclinical depression (Cavanagh et al., 2019). A deficit in learning from positive feedback was also identified in individuals with schizophrenia, when compared with healthy controls (Dowd et al., 2016; Waltz et al., 2018). The remaining studies using the same approach, did not find any significant differences between groups for learning rate in response to either positive or negative feedback. These included two studies investigating MDD, and PTSD groups (Kumar et al., 2008; Myers et al., 2013).

### *4.2.2 Decision making noise in stable environments*

The majority of reinforcement-learning studies that captured learning in stable environments included a parameter designed to capture decision noise (n=23). In most cases this was the standard or inverse temperature parameter, described as beta in the softmax algorithm (see Box 1). In some cases, this response parameter was described as capturing phenomena such as exploration/exploitation behaviour and/or lapse rate, all of which also determine how

randomly, or how noisily the individual is making each decision. While disorder groups were slightly biased towards an increased frequency of psychosis related disorder types, each disorder category contained at least nine studies (psychosis disorders n=19 (including four transdiagnostic studies); Depression/MDD/BPD n= 13 (including five transdiagnostic studies; anxiety n=9 including two transdiagnostic studies).

Of these 23 studies, 4 found a significant difference between symptomatic and healthy groups for this parameter. These studies were all investigating psychosis spectrum disorders including schizophrenia (Geana et al., 2021; Reinen et al., 2016; Strauss et al., 2015), and CHR and FEP groups (Montagnese et al., 2020). One study included a transdiagnostic patient sample, and found significant differences between a BPD group and SCZ in terms of the temperature parameter (Strauss et al., 2015).

All four studies found the same direction of effect. Individuals with diagnoses of schizophrenia, both with and without medication, were found to display higher levels of noise in their decision making compared to healthy controls (Geana et al., 2021; Reinen et al., 2016; Strauss et al., 2015), and individuals with BPD (Strauss et al., 2015), when learning in a stable environment. The effect of higher randomness in responses was also found to increase with clinical severity from healthy individuals, through those at CHR, to individuals who have had a FEP (Montagnese et al., 2020), potentially implying increasing noise in decision making as symptom or illness severity increased.

**Table 2-1**. *Table showing parameter findings between groups when measuring belief updating in a stable environment using a PLT-S.*

| Author | Population | Feedback | Winning Model | Significantly Different Parameters | Direction of Effect |
|---|---|---|---|---|---|
| Albrecht et al (2016) | SCZ (48); HC (32) | Money | RL model (6 parameter) | Learning rate | Correlation: high negative symptoms = lower learning rate |
| Bakic et al., (2017) | MDD (35); HC (60) | Feedback | Q-learning model with separate learning rates | None | NA |
| Cavanagh et al., (2019)* | High subclinical depression (46); Low subclinical depression (75) | Feedback | RL model with separate learning rates for gain and loss | Positive learning rate | HC >DEP |
| | High anxiety scorers within the subclinical depression group** | Feedback | RL model with separate learning rates for gain and loss | None | NA |
| Cooper et al., (2014) | Self-reported depression (22); HC (33) | Points | Extended RL model (7 free parameters) | Negative learning rate | Placebo trained subclinical depression > no depression |
| Dowd et al., (2016)* | SCZ only + affective SCZ (38); HC (37) | Money | Q-learning model with separate learning gain and loss learning rates | Positive learning rate | HC > SCZ |
| Ermakova et al., (2018) | CHR (30); HC (39) | Money | Q-learning model | None | NA |
| | FEP (14); HC (39) | Money | Q-learning model | None | NA |
| Geana et al., (2021)* | BPD (+psychosis) (60); HC (72) | Money | Hybrid Q-learning – actor critic model | None | NA |

| | | | | | |
|---|---|---|---|---|---|
| | | | including decay and epsilon-SoftMax | | |
| | SCZ (+med) (120); BPD (+psychosis) (60) | Money | Hybrid Q-learning – actor critic model including decay and epsilon-SoftMax | Decay | SCZ(+med) > BPD (+psychosis) |
| | SCZ (+med) (120); HC (72) | Money | Hybrid Q-learning – actor critic model including decay and epsilon-SoftMax | Decay | SCZ(+med) > HC |
| | | | | Mixing | HC > SCZ(+med) |
| | SCZ (-med) (44); BPD (+psychosis) (60) | Money | Hybrid Q-learning – actor critic model including decay and epsilon-SoftMax | Decay | SCZ(-med) > BPD(+psychosis) |
| | SCZ (-med) (44); HC (72) | Money | Hybrid Q-learning – actor critic model including decay and epsilon-SoftMax | Decay | SCZ(-med) > HC |
| | | | | Temperature | SCZ(-med) > HC |
| | | | | Mixing | HC > SCZ(-med) |
| Gold et al., (2012)* | SCZ high-negative symptom (25); HC (28) | Money | Hybrid actor-critic augmented with Q-learning model | Mixing | SCZ high-negative symptom <HC |

| | | | | | |
|---|---|---|---|---|---|
| | SCZ low-negative symptom (22); HC (28) | Money | Hybrid actor-critic augmented with Q-learning model | Mixing | TREND: SCZ low-negative symptom < HC |
| Gradin et al., (2011) | MDD (15); HC (17) | Juice/water | Temporal difference model | None | NA |
| | SCZ (14); HC (17) | Juice/water | Temporal difference model | None | NA |
| Haarsma et al., (2020) | CHR (24); HC (30) | Money | Pearce-Hall model with precision-weighting of signed and unsigned PE | Learning rate | HC + CHR > FEP |
| | FEP (20); HC (30); CHR (24) | Money | Rescorla-Wagner | None | NA |
| Hernaus et al., (2019)* | SCZ (29); HC (38) | Money | Hybrid actor-critic augmented with Q-learning model | Mixing | HC>SCZ |
| Kumar et al., (2018) | MDD (-med) (28); HC (26) | Money | Q-learning model | None | NA |
| Liu et al., (2017) | MDD (-med) (24); HC (21) | Points | Q-learning standard RL model | None | NA |
| Montagnese et al., (2020) | CHR (23); HC (29) | Money | Go/nogo RL model (4 parameter) | Sensitivity to reward + punishment | HC > CHR |
| | CHR (23); FEP (11) | Money | Go/nogo RL model (4 parameter) | Temperature | CHR >FEP |
| | | | | Learning rate | CHR >FEP |
| | | | | Sensitivity to reward | CHR< FEP |
| | | | | Go bias | CHR > FEP |
| | | | | Pavlovian bias | CHR > FEP |

| | | | | | |
|---|---|---|---|---|---|
| | FEP (15); HC (29) | Money | Go/nogo RL model (4 parameter) | Temperature | HC > FEP |
| | | | | Sensitivity to reward | HC > FEP |
| | | | | Sensitivity to punishment | HC > FEP |
| | | | | Go bias | HC > FEP |
| | | | | Pavlovian bias | HC > FEP |
| Moutoussis et al., 2018 | MDD (39); HC (22) | Money | Go/nogo RL model (6 parameter) | None | NA |
| Murray et al., (2008) | FEP (13); HC (12) | Feedback | Q-learning temporal difference model | None | NA |
| Murray et al., (2019) | OCD (18); HC (18) | Money | Q-learning model | Learning rate | HC > OCD |
| Myers et al., (2013) | Veterans with PTSD (48); Veterans without PTSD (39) | Points | Q-learning model | No feedback (R0) | PTSD < HC |
| Reinen et al., (2016) | SCZ (-med) (16); HC (23) | Feedback | Q-learning model | Inverse temperature | SCZ > HC |
| Rothkirch et al., (2017) | MDD (35); HC (33) | Money | Q-learning model | None | NA |
| Rupprechter et al., (2020) | HC + 20 MDD (475) | Points | RL model assuming learning at different rates on choice versus no-choice trials (3 parameters) | None | NA |
| Strauss et al., (2015)* | BPD (+psychosis) (24) + BPD (-psychosis) (23); Healthy controls (24) | Feedback vs. no feedback | Hybrid actor-critic augmented with Q-learning model | None | NA |

| | | | | | |
|---|---|---|---|---|---|
| | BPD (+psychosis) (24) + BPD(-psychosis) (23); SCZ (29) | Feedback vs. no feedback | Hybrid actor-critic augmented with Q-learning model | Beta/temperature | SCZ>BPD(+/-psychosis) |
| | | | | Mixing | SCZ<BPD(+/-psychosis) |
| | SCZ (29); Healthy controls (24) | Feedback vs. no feedback | Hybrid actor-critic augmented with Q-learning model | Beta/temperature | SCZ> HC |
| | | | | Mixing | SCZ< HC |
| Waltz et al., (2016)* | SCZ (+med) (27); HC (27) | Money | Q-learning model with separate learning gain and loss learning rates | Positive learning rate | HC >SCZ |
| White et al., (2017) | GAD (46); HC (32) | Money | RL model (2 parameters) | Correlation between expected value and observed behaviour | HC>GAD |

*ARMS = at risk mental state (psychosis); BPD = bipolar disorder; CHR = clinical high risk for psychosis; GAD = generalized anxiety disorder; HC = healthy controls MDD = major depressive disorder; OCD = obsessive compulsive disorder; PTSD = post-traumatic stress disorder; RL = reinforcement learning; SCZ = schizophrenia. (+/- med)= medicated/non-medicated; *Used an acquisition-test task design, see appendix for further discussion. **undisclosed number in sample.*

### *4.3 Belief updating in volatile environments*

Overall, 20 studies were found that investigated belief updating in volatile environments using a probabilistic task that manipulated the underlying volatility (PLT-V). Studies in this category used a mixture of modelling approaches. Modelling approaches included: RL (n=11), BL (n=7), and CPM (n=2) (Table 2-2). A number of studies compared both RL and BL modelling approaches, using model comparison techniques (Cole et al., 2020; Deserno et al., 2020; Diaconescu et al., 2020; Henco et al., 2020). All of the studies that used this approach found that the HGF model included in the modelling comparison was the winning model, these have therefore been characterised as BL studies.

Within PLT-V tasks using RL models, 9 out of 11 studies found at least one parameter that was significantly different between groups. The exception to this was a study looking at depressed individuals with suicidal tendencies (Dombrovski et al., 2019), and another comparing subclinical PTSD with controls (Howlett et al., 2021), where no parameters were found to differ between groups. The distribution of research across disorder categories was relatively even (anxiety disorders: n = 5; depression disorders: n = 4; psychosis disorders: n=4). All BL studies found at least one parameter that significantly differed between groups (Table 2-2). The majority of research in the BL modelling category related to disorders of psychosis (anxiety disorders: n = 1; depression disorders: n= 1; psychosis disorders: n= 6) and used an HGF modelling approach (n=8). Finally, the CPD modelling studies were less frequent in the literature (n=2) and did not include any data on depression disorders (anxiety disorders: (OCD) n=1; depression disorders: n= 0; psychosis disorders: n=1). The following sections describes results from PLT-V tasks by separating studies into which modelling approach was used (RL, BL, CPD).

### *4.3.1 Learning rates in volatile environments*

Studies using a RL model with one learning rate (n=7) in conjunction with a task measuring belief updating in a volatile environment (PLT-V) revealed that anxiety and psychosis groups may show differences in their ability to adapt or modulate overall learning rates to changing environments, leading to a difficulty in inferring the statistical regularities of an environment (n=3) (Browning et al., 2015; Hernaus et al., 2018; Huang et al., 2017). For example, whether comparing between volatile and stable blocks (Browning et al., 2015) or within a volatility block (Hernaus et al., 2018), individuals with subclinical anxiety showed an inability to flexibly update their learning rate in response to changes between volatile and stable conditions i.e., to learn faster when volatility was high and more slowly when stable. Instead, learning rates for sub-clinically anxious individuals remained the same across both stable and volatile conditions. Importantly, this effect was shown for both positive (Huang et al., 2017), and aversive (Browning et al., 2015) stimuli. Similarly, individuals with a diagnosis of schizophrenia were unable to demonstrate dynamic changes in learning rate modulation as a function of environmental volatility (Hernaus et al., 2018).

In relation to learning from feedback in a volatile environment, overall learning rates in response to a PLT-V task were shown to be lower for individuals with schizophrenia, when in response to positive feedback (Li et al., 2014). Relatedly, when valenced learning rates were included in the RL modelling approach to PLT-V data, subclinical socially anxious groups displayed lower learning rates in conditions where a 'rewarder' had become a 'punisher', compared to when the punisher did not change (Beltzer et al., 2019). Whereas learning rates for negative/punishing

feedback trials were found to be significantly lower for individuals with depression, leading to an updating difficulty after unfavourable outcomes had been received (Takano et al., 2019).

### *4.3.2 Decision noise in volatile environments: reinforcement learning modelling*

All 11 RL studies measuring learning under volatility used a parameter designed to capture decision noise, predominantly the (inverse) temperature. Research in this category was evenly distributed across disorder types (anxiety n = 5; depression/MDD/BPD n = 4; schizophrenia n=4). In total, 3 out of 11 studies found a significant difference between groups. Again, all studies that found a significant difference were investigating psychosis disorder groups (Culbreth et al., 2016; Katthagen et al., 2020; Li et al., 2014). The direction of effect was consistent across these studies and was additionally displayed across the spectrum of severity within psychosis disorders, including subclinical symptomatology (high and low subclinical groups) (Li et al., 2014), individuals with schizophrenia who were unmedicated (Katthagen et al., 2020), and individuals with a diagnosis of schizophrenia who were described as chronically unwell and on medication (Culbreth et al., 2016). In each case, the temperature parameter indicated that individuals with symptoms of psychosis displayed noisier decisions, i.e., more exploration than exploitation of learned values.

**Table 2-2.** *Showing reinforcement learning modelling to tasks measuring belief updating in volatile environments (PLT-V) including details, feedback, winning models and differences between groups for parameters*

| Author | Sample | Task Inputs | Feedback | Winning Model | Significantly Different Parameters | Direction of Effect |
|---|---|---|---|---|---|---|
| Beltzer et al., (2019) | Subclinical ANX identified from general population sample (222) | Binary | Receiving the ball | Q-learning model with single learning rate | Learning rate (after 'rewarder' change) | High social ANX<low social ANX |
| Browning et al., (2015) | Subclinical ANX (33 | Binary | Electric shock | Adapted Rescorla-Wagner | Learning rate | High anxiety = reduced change in LR between volatile and stable blocks |
| Culbreth et al., (2016) | SCZ (86); HC (57) | Binary | Feedback | Q-learning model | Beta/temperature | SCZ < CTL |
| Dombrovski et al., (2019) | Non-suicidal depressed; suicide ideators; suicide attempters (92); HC (33) | Binary | Money | RL model with separate learning rates for rewards/omissions, decay of unchosen values and no choice autocorrelation (stickiness) parameter | None | NA |
| Hernaus et al., (2018) | SCZ (+med) (26); HC (23) | Binary | Money | Dynamic learning rate RL model | Learning rate modulation | HC>SCZ |
| Howlett et al., (2021) | Subclinical PTSD (20) (correlation) | Continuous | Money | Rescorla-Wagner model | None | NA |

| | | | | | | |
|---|---|---|---|---|---|---|
| Howlett et al., (2020) | High fear scorers from MDD, GAD, BPD, SUD (306) (correlation) | Continuous | Points | Rescorla-Wagner model with bias and drift | Perceptual learning rate | High fear scorers =low perceptual learning rates |
| Huang et al., (2017) | High subclinical ANX (77); Low subclinical ANX (45) | Continuous | Points | Vmax RL model with constant learning rate - does not allow learning rate adjustment to adapt to changes in the environment (3 parameters) | Baseline learning rate | High subclinical ANX > low subclinical ANX |
| Li et al., (2014) | High SCZ (PANSS) (26); Low SCZ (PANSS) (19); HC (24) | Binary | Money | Q-learning-temporal difference model | Beta/temperature: | HC and Low SCZ> high SCZ |
| | | | | | Positive learning rate | HC < high SCZ |
| | Low schizophrenia (PANSS) (19); HC (24) | Binary | Money | Q-learning-temporal difference model | Positive learning rate | HC < low SCZ |
| Katthagen et al., (2020) | SCZ (-med) (19); HC (23) | Binary | Money | Single update learning with one learning rate | Beta/temperature: | HC >SCZ |
| Takano et al., (2019) | Subclinical DEP (23) (correlation) (negative to positive task condition) | Binary | Money | Q-learning model | Negative learning rate | Correlation: high subclinical depression + rumination = lower learning rates for negative memories |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Subclinical DEP (23) (correlation) (positive to negative task condition) | Binary | Money | Q-learning model | None | NA |

*ANX = anxiety; DEP = depression; OCD = obsessive compulsive disorder; PTSD = post-traumatic stress disorder; PANSS = positive and negative symptom scale; RL = reinforcement learning; SCZ = schizophrenia; (+/- med)= medicated/non-medicated.*

### *4.3.3 Bayesian learning modelling*

Parameter descriptions for HGF modelling are described in Table 2-3 and further details are provided in Table 2-4, describing research findings. Psychosis disorder groups were found to perceive relatively higher environmental volatility across studies. The effect was seen in subclinical general population high paranoia individuals (Reed et al., 2020; Suthaharan et al., 2021); individuals at CHR for psychosis (Cole et al., 2020) – mean reverting HGF; and individuals with a diagnosis of schizophrenia (medicated and non-medicated) (Deserno et al., 2020). Reduced estimates of tonic volatility weightings alongside increased estimates of phasic volatility weightings were also identified in two studies investigating individuals with high subclinical paranoia symptoms (Reed et al., 2020; Suthaharan et al., 2021). Such findings may indicate that these individuals confuse probabilistic errors and task volatility as a signal that the task has fundamentally changed.

Belief updating in response to social information was also perturbed in high paranoia (subclinical) individuals. Diaconescu et al., (2020) found that low subclinical paranoia individuals showed more rapid belief updating in their beliefs about an advisor when the advisor was more likely to be a potential source of incorrect advice (Diaconescu et al., 2020). Whereas high paranoia individuals displayed consistently lower omegas on the second level i.e., the fixed proportion of the dynamic learning rate, independent of the condition (please see Table 2-3 for further description of this parameter). In agreement with the above results, this suggests that high paranoia individuals were more resistant to changing beliefs in response to underlying contingency changes.

Estimates of tonic volatility (but not phasic volatility) were found to be significantly reduced in healthy individuals with induced high subclinical state anxiety, while learning under volatility (Hein et al., 2021). As such, participants in an induced anxious state estimated the outcome tendency to be more precise, such that new information had a more limited influence on the belief updates on that level. Estimates of phasic volatility (but not tonic volatility) were found to be altered in one study. Schizophrenia patients showed increased coupling between higher and lower levels of learning leading to enhanced lower-level belief updating about action-outcome contingencies (Deserno et al., 2020).

Differences were also identified in how individuals with psychosis disorders process social information. Evidence showed that individuals with subclinical paranoia symptoms weighted social information differently to controls given the condition of the experiment. For individuals with high paranoia, less differences were found in how they took advice into account across the conditions compared to controls suggesting they were less likely to use the social information (Diaconescu et al., 2020). In contrast to this, BL in a second study revealed that schizophrenia patients weighted their social domain predictions more strongly than healthy controls and individuals with MDD. This indicated an overreliance on social cues (Henco et al., 2020).

**Table 2-3.** *Describing parameters included in the HGF modelling process.*

| | **Parameters (HGF)** | **Description** |
|---|---|---|
| **Hidden states (underlying distribution)** | *x2* | Stimulus-outcome associations |
| | *x3* | Phasic volatility |
| **Perceptual parameters** | Kappa (*k*) | Coupling strength between levels 2 and 3 – i.e. phasic volatility coupling |
| | Omega 2 | constant - governing speed at which 2nd level belief changes |

| | | |
|---|---|---|
| | Omega 3 | constant - governing speed at which volatility belief changes |
| **Response/decision parameters** | Decision noise | Choice stochasticity (sometimes inverse) |
| **Estimates** | *mu2* | belief about stimulus outcome association |
| | *mu3* | belief about environmental volatility |
| | Sigma 2 | uncertainty about level 2 belief |
| | Sigma 2 | uncertainty about level 3 belief |

### *4.4 Change point detection modelling*

CPD modelling findings revealed that levels of perseverance or repeating behaviour were higher in individuals with schizophrenia (Nassar et al., 2021). This study suggests that patients were lacking in the ability to integrate new and old information properly, being more prone to completely ignoring new information and therefore perseverating on previous responses. This study found that individuals with SCZ used moderate learning updates less frequently than controls and as such were more likely to either update completely or not at all in response to new information. In contrast, individuals with symptoms of OCD were also found to display abnormalities when it came to integrating past experiences, finding that those with more severe symptoms assigned a lower weight to prior experience, leading to over-exploratory behaviour (Fradkin et al., 2020).

**Table 2-4.** *Showing Bayesian Learning modelling and Change Point modelling to behavioural data from tasks measuring belief updating in volatile environments (PLT-V) including details, feedback, winning models and differences between groups for parameters*

| Author | Sample | Task Inputs | Feedback | Winning Model | Significantly Different Parameters | Direction of Effect |
|---|---|---|---|---|---|---|
| Cole et al., (2020) | CHR (13); HC (13) | Binary | Money | Mean-reverting HGF (3-level) | Mu3 | CHR>CTL |
| Diaconescu et al., (2020) | Subclinical high paranoia (70); Subclinical low paranoia (81) | Binary | Money | HGF (3-level) | Omega 2 | Low paranoia > high paranoia |
| | | | | | decision noise - social bias parameter | High paranoia < low paranoia |
| Fradkin et al., (2020) | Subclinical OCD (58) (correlation) | Binary | Feedback | Bayesian Change Point | Transition uncertainty (h) | Correlation: high subclinical OCD > low OCD |
| Henco et al., (2020) | Borderline PD (28); HC (31) | Binary | Money | HGF (3-level) | Psi2 (Kappa) | BPD<CTL |
| | | | | | Psi3 (Kappa) | BPD>CTL |
| | | | | | social weighting decision parameter | BPD>CTL |
| | Borderline PD (28); MDD (28) | Binary | Money | HGF (3-level) including subject specific decision noise and volatility estimate | social weighting decision parameter | BPD>MDD |

| | | | | | | |
|---|---|---|---|---|---|---|
| | MDD (28); HC (31) | Binary | Money | HGF (3-level) including subject specific decision noise and volatility estimate | None | NA |
| | SCZ (29); HC (31) | Binary | Money | HGF (3-level) including subject specific decision noise and volatility estimate | Social weighting decision parameter | TREND: SCZ>CTL |
| Deserno et al., (2020) | SCZ (+med) (46); HC (43) | Binary | Money | HGF (3-level0 | Kappa | PSZ>CTL |
| | | | | | Mu3 | PSZ>CTL |
| Nassar et al., (2021) | SCZ + SCZ (+affective) (108); HC (33) | Continuous | Points | Change point | Perseverence Max | SCZ>CTL |
| | | | | | Perseversence width | SCZ>CTL |
| Reed et al., (2020) | Subclinical high paranoia (73); Subclinical low paranoia (234) | Binary | Points | HGF (3-level) | Kappa | HP>LP |
| | | | | | Mu3 | HP>LP |
| | | | | | Omega 2 | LP>HP |

| | | | | | | |
|---|---|---|---|---|---|---|
| | High paranoia from clinical groups: ANX, DEP, BPD, SCZ (11); Low paranoia from clinical groups ANX, DEP, BPD, SCZ (21) | Binary | Points | HGF (3-level) | Kappa<br>Mu3<br>Omega 2 | HP>LP<br>HP>LP<br>LP>HP |
| Suthaharan et al., 2021) | Pre-pandemic: high paranoia subclinical (16); pre-pandemic: low paranoia subclinical (56) | Binary | Points | HGF (3-level) multi-armed bandit configuration | Kappa<br>Omega 2<br>Omega 3<br>Mu2<br>Mu3 | HP>LP<br>LP>HP<br>LP>HP<br>HP>LP<br>HP>LP |
| | Pre-pandemic: high paranoia subclinical (20); pre-pandemic: low paranoia subclinical (110) | Binary | Points | HGF (3-level) multi-armed bandit configuration | Kappa<br>Omega 2<br>Omega 3<br>Mu2<br>Mu3 | HP>LP<br>LP>HP<br>LP>HP<br>HP>LP<br>HP>LP |
| Hein et al., (2021) | ANX (high state) (21); ANX (low state) (21) | Binary | Money | HGF (3-level) | Omega 2<br><br>Sigma 2<br>Environmental uncertainty: Mu3 + w2 | STA<CTL<br><br>STA<CTL<br>STA<CTL |

| | | | |
|---|---|---|---|
| | | sigma3 | STA>CTL |

*ANX=anxiety; BPD=bipolar disorder; Borderline PD = borderline personality disorder; CHR=clinical high risk for psychosis; DEP=depression; HC=healthy controls; HGF = hierarchical gaussian filter; HP = High subclinical paranoia; LP = low subclinical paranoia; MDD=major depressive disorder; OCD=obsessive compulsive disorder, (+/- med) = medicated/non-medicated; SCZ=schizophrenia.*

# 5 Discussion

Given the interplay between symptoms of depression, anxiety and psychosis, this review systematically reviewed literature using computational modelling to capture belief updating in stable and volatile environments, across clinical and subclinical anxiety, depression, and psychosis disorders. The aim was to disentangle deficits in belief updating that may be shared or unique to these disorders. A range of modelling approaches were identified, and as they increase in complexity, offer varying explanatory contributions to any belief updating deficits. Overall, the distribution of disorders across the RL literature was relatively even (psychosis disorders: n=19 (including four transdiagnostic studies); depression disorders: n= 13 (including five transdiagnostic studies; anxiety disorders: n=9 (including two transdiagnostic studies)). However, BL modelling was applied to psychosis disorder research more than other disorder groups (psychosis disorder: n=6; depression disorders: n=1; anxiety disorders: n=1) and fulfilled a higher percentage of recommended modelling steps across studies (71%), than RL (41%) and CPD modelling (66%) (Wilson & Collins, 2019).

## *5.1 Learning rates and valenced feedback: a lack of overlap between depression and anxiety disorders*

To capture learning rates to feedback specifically, the review combined literature where models used separate learning rates for rewards and punishments, i.e., dedicated learning rates for valenced feedback. It was expected that individuals with anxiety and/or depression would display abnormal belief updating in response to positive and/or negative feedback, for example increased learning rates in response to punishments over rewards (Pike & Robinson, 2022).

However, when synthesising the literature by task type (sequential PLT-S/V) and modelling approach (error-based), this effect was predominantly found only in depression disorders (Cavanagh et al., 2019; Cooper et al., 2014). Specifically, in stable learning environments, depression groups displayed both a difficulty in learning from positive feedback, as well as increased learning from negative feedback (Cavanagh et al., 2019; Cooper et al., 2014). No studies using this modelling approach found this effect in anxiety disorder (Cavanagh et al., 2019; Myers et al., 2013).

It was surprising not to uncover a similar outcome for anxiety groups, given the high comorbidity rates between anxiety and depression disorders, and previous review findings (Kessler et al., 2005; Pike & Robinson, 2022). However, while the average modelling quality of the studies was similar across disorder type (MQ percentage rating: anxiety = 37.5%; depression 40%), there was a tendency in the RL literature using multiple valenced learning rates, towards i) research into depression disorders, and ii) research into stable learning environments (n=5; PLT-S: Cavanagh et al., 2019; Cooper et al., 2014; Kumar et al., 2018; PLT-V: Dombrovski et al., 2019; Takano et al., 2019), as compared with anxiety disorders (n=2; PLT-S: Cavanagh et al., 2019; Myers et al., 2013). Therefore, while these findings indicate that processing valenced feedback may be uniquely abnormal in depression disorders, further research would be needed to confirm this.

While this review focuses predominantly on extracted learning rates and decision noise parameters, additional evidence for a deficit in feedback responsiveness in depression was shown across behavioural findings, and other, associated modelling parameters. For example, Kumar et al., (2018), showed that individuals with MDD exhibited reduced learning from rewards, via poorer task performance (behavioural analysis). Similarly, Dombrovski et al., (2019) showed

that individuals with depression who had attempted suicide, were less sensitive to one-back reinforcement, as indicated by a reduced effect on both choices and decision times.

As a core symptom of depression, anhedonia i.e., a difficulty experiencing pleasure and motivation, has been shown to be associated with reduced learning from rewards (Eshel & Roiser, 2010; Pizzagalli et al., 2005, 2008). While findings stem from studies using different experimental designs, such as non-sequential probabilistic and non-probabilistic learning tasks, and those with no computational modelling, this dysfunctional reward learning may be related to an inability to assess, update, and/or maintain the value of rewards. This may potentially represent a pathway between reward learning and symptoms of depression. For example, individuals with high levels of anhedonia show a reduction in effective value for rewarding outcomes i.e., they treat rewarding outcomes as less rewarding (Huys et al., 2013; Lawlor et al., 2020; Webb et al., 2015). However, there is some variability in the literature on this point (Chase et al., 2010; Must et al., 2006; Pizzagalli et al., 2005, 2008), which may be in part due to variability in modelling approaches and task designs, given the differences across these studies.

While findings from this review indicate that feedback responsiveness may not be the central information processing issue for anxiety disorder, there was limited evidence for this effect when learning under a volatile social environment specifically (Beltzer et al., 2019). In relation to changing/volatile social information, presented to socially anxious groups and healthy controls, individuals were unable to successfully adapt their learning rates after a change in the valance of a social cue i.e., when the "rewarder" became a "punisher". This finding may suggest that any issue relating to feedback responsiveness in anxiety groups exists in relation to volatile environments particularly, and more specifically – in relation to the ability to dynamically respond to changes in rewarders. This could lead to, for example, difficulties in adapting pre-

existing beliefs about a socially punishing situation that has now improved, leading to an ongoing negative perception, despite an objective improvement. Further research is required to understand if this feedback responsiveness effect under volatility is related to the feedback valance of social information specifically, or – given findings discussed below – in fact more strongly related to difficulties in learning under increased environmental volatility generally.

### *5.2 Learning rates and valenced feedback: evidence of overlap between depression and psychosis disorders*

While we have seen that anxiety disorders do not appear to display a deficit relating to feedback responsivity specifically, overlap in this regard was identified between depression and psychosis disorders. Specifically, evidence revealed lower learning rates in response to rewards in both subclinical depression (Cavanagh et al., 2019) and schizophrenia disorders (Dowd et al., 2016; Waltz et al., 2018), during learning in a stable environment (MQ rating: depression studies: 25%; schizophrenia studies: 75%). Interestingly, while studies investigating depression showed deficits relating to learning rates in response to both rewards and punishments, individuals with psychosis symptoms appeared to display lower learning rates specifically when the feedback was positive. Given the high quality and consistent evidence (albeit in only two studies) showing reduced learning from rewards in psychosis disorders, this may be an interesting avenue to further pursuit.

One possible mechanism underlying this effect may relate to outcome sensitivity i.e., an insensitivity to types of feedback, such as rewarding stimuli. For example, Montagnese et al., (2020), found a difference between psychosis disorder and healthy groups in a parameter

designed to capture sensitivity to rewarding outcomes. In fact, these findings indicate that a deficit around sensitivity to feedback may be an early indicator of psychosis illness, as sensitivity to reward was found to be significantly reduced in at risk groups such as CHR and FEP, in comparison to controls (Montagnese et al., 2020). Albrecht et al., (2016) however, found that rather than reduced reward sensitivity, individuals with schizophrenia (plus high levels of negative symptomology) showed a reduction in punishment sensitivity. These findings were amplified in participants taking clozapine, leading the authors to suggest that these findings may link punishment sensitivity to the serotonergic antagonist profile of most antipsychotics. These findings may also highlight subtle learning differences within psychosis disorder subtypes, and the importance of fully recognising and profiling individuals symptomatically.

Further evidence is required to disentangle unique and dissociated deficits driving abnormalities associated with the processing of valenced feedback. Importantly, related processes may also be disrupted. For example, motivated behaviour requires an effort cost/benefit calculation, which has been shown to be abnormal in individuals with MDD and schizophrenia (Berwian et al., 2020; Patzelt et al., n.d.; Treadway et al., 2012). One example in a (remitted) MDD population went further, showing that model-based parameters indicating sensitivity to anticipated effort cost were in fact predictive of relapse after antidepressant discontinuation (Berwian et al., 2020). As such, a shared deficit for learning about positive feedback in MDD and schizophrenia may be related to a tendency to exert a reduced level of physical effort when confronted with increasing incentives (Berwian et al., 2020; Huys et al., 2013; Treadway et al., 2012).

### *5.3 Learning under volatility is affected in anxiety and psychosis disorders*

Higher learning rates do not necessarily mean "better" learning. In everyday life, we must dynamically adapt our learning rates in response to the environment. Research has developed experimental designs and modelling approaches that support i) measurement of learning in response to blocks of stable vs. volatile environments, and ii) the identification of learning rate adaptation to changes in our environment (Behrens et al., 2007; Browning et al., 2015; Nassar et al., 2012). A second key finding of this review indicates that psychosis and anxiety disorders show a degree of overlap in their inability to adapt appropriately to volatile environments. This is shown via RL, BL, and CPD modelling approaches.

Firstly, RL modelling studies measuring learning rate in PLT-V environments are able to be compared given the relatively even distribution of disorder types and study quality, albeit with a slight bias towards frequency and quality of studies with anxiety disorder populations (psychosis disorders: n=4 (MQ=31%) (Culbreth et al., 2016; Hernaus et al., 2018; Katthagen et al., 2020; Li et al., 2014); anxiety disorders: n=5; (Beltzer et al., 2019; Browning et al., 2015; Howlett et al., 2021; Howlett & Paulus, 2020; Huang et al., 2017) (including one transdiagnostic sample) (MQ=35%); depression disorders: n=3; (Dombrovski et al., 2019; Howlett & Paulus, 2020; Takano et al., 2019) (MQ=33%)). Findings in this category showed that anxiety and psychosis disorder groups displayed an insensitivity and/or difficulty adapting to changing underlying contingencies specifically (Beltzer et al., 2019; Browning et al., 2015; Hernaus et al., 2018; Huang et al., 2017; Li et al., 2014). In these examples, this insensitivity led to suboptimal decision-making strategies when learning under volatility (Browning et al., 2015; Hernaus et al., 2018; Huang et al., 2017). While these studies used a mixture of feedback type (aversive and rewarding), and different experimental designs (manipulating volatility either between or within blocks), RL findings showed some consistency: anxiety and psychosis disorder groups show a deficit in the adaptation or optimisation of learning rates to changing environments. While no

studies reported this effect for depression disorders, there were i) fewer overall studies into depression disorders, and ii) studies measuring learning in volatile environments in depression groups tended to have designed models specifically to capture learning in response to feedback i.e., measuring learning about rewards and punishments, rather than learning rates specifically designed to capture adaptation to changes in volatility (Dombrovski et al., 2019; Takano et al., 2019).

BL modelling approaches provide a novel lens with which to view these findings, offering i) a mechanistic explanation supportive of the disaggregation of observed behaviours, and ii) the ability to integrate and build on RL findings given similarities in their algorithmic formalisations. It is important to note that the MQ scores for BL modelling studies was notably higher than RL, and there was a skew in research towards psychosis disorders (psychosis groups n=6 (MQ=58%); anxiety groups n=1 (MQ=75%); depression groups n=1 (MQ=75%)). Nevertheless, findings from BL modelling to PLT-V data in psychosis groups suggested that individuals with high subclinical levels of paranoia, CHR and/or had a diagnosis of schizophrenia, perceive their environment to be higher in volatility than controls (Cole et al., 2020; Deserno et al., 2020; Reed et al., 2020; Suthaharan et al., 2021). Similarly, we see evidence that individuals with high levels of subclinical paranoia tend to react to changes in trials as though there has been a change in underlying contingency, even if there hasn't been – i.e., they showed decreased tonic volatility weightings, and increased phasic volatility weightings (see Box 1; see Table 2-4) (Reed et al., 2020; Suthaharan et al., 2021).

Taken together these findings may suggest that individuals with psychosis symptoms at differing severity levels have higher initial expectations of task volatility i.e., they anticipate more changes in stimulus-outcome associations, but also tend to switch choices excessively in anticipation of

reversal events. The occurrence of the same findings across severity levels indicates that elevated beliefs about environmental volatility may represent an important mechanism of impaired flexible decision making in individuals with psychosis symptoms, potentially causing (hyper)sensitivity to new input and impeding the detection of regularities in probabilistic environments. In turn this may lead to increased updating in response to irrelevant information.

Limited evidence using BL modelling in anxiety disorder indicated overlap with psychosis findings, specifically in terms of reduced tonic volatility weightings (anxiety: (Hein et al., 2021; Reed et al., 2020; Suthaharan et al., 2021). In other words, state anxiety was associated with less flexibility in their updating – because beliefs about reward contingencies were relatively more precise i.e., less uncertain. This could suggest an overlapping deficit between these disorders that relates to an issue estimating uncertainty, leading individuals to feel repeatedly surprised by predictable events. While more evidence is required to establish an effect, the overlap found here is specifically identified to be between state anxiety groups and high subclinical paranoia groups, while we see no similar effect for depression disorder groups. This is interesting given the relationship between paranoia and anxiety symptoms (Freeman et al., 2008; Huppert & Smith, 2005; Moorey & Soni, 2009). While clinically this link is already established via for example, the treatment of safety behaviours for both psychosis and anxiety disorders in cognitive behavioural therapy, anecdotally, it is also not hard to imagine – being paranoid about one's food being poisoned is likely to cause a level of anxiety, and being anxious that you may be speaking oddly, for example, could be considered to be somewhat paranoid. Future research is required to untangle these findings, specifically whether phasic volatility also presents abnormally in anxiety. Ignoring the important causality question here, it is at least possible to suggest that the use of computational modelling supports the idea that in fact, these disorders are unlikely to be entirely separate and need to be studied with this in mind.

Finally, CPD modelling in psychosis (schizophrenia) and anxiety (subclinical OCD) groups, demonstrated some distinction between disorders (Fradkin et al., 2020; Nassar et al., 2021). Again, studies looking into depression disorders using this modelling approach were not available. These models are conceptually similar to the HGF model but use a different mathematical approach (see Box 1). Both studies suggest a difficulty in integrating old and new information, but the mechanistic models once again offer us the opportunity to disentangle differences driving observed deficits in belief updating under volatility in anxiety and psychosis disorders. For example, whereas findings in anxiety groups suggest a reluctance to rely on previously learned contingencies, with no evidence of perseverating on previously learnt information - leading presumably to these individuals to feel continually surprised by new information; psychosis groups were prone to completely ignoring new information, or at least unable to integrate it into their decisions, showing increased perseverating on previous responses in comparison to controls. When the schizophrenia patients did update their belief, they did so completely, when in the large majority of cases, a moderate update would be more appropriate, and increase flexibility of decision making. While these findings show the potential for such modelling approaches to interrogate both highly specific functioning, as well as precise direction of effects, more evidence is needed to establish if this subtle difference truly exists within these groups.

One final point, currently not addressed fully in the literature, is to understand whether distinction between disorders can be made when considering the interplay *between* volatility and valenced feedback. While we see evidence of abnormalities in the ability to adapt learning rates to volatility (described above e.g., Browning et al., 2015), this research has primarily been carried out in tasks using either positive or negative feedback, rather than both. This leaves open the

question of whether learning rates in response to volatility are affected by the specific feedback type (positive/negative), or if the increase in learning rate to environmental volatility is agnostic to feedback type. One study independently manipulated the volatility of both positive and negative feedback in healthy participants, measuring whether this manipulation altered learning rates (Pulcu & Browning, 2017). The study found that firstly, learning rates for positive and negative feedback are adjusted independently and are therefore not accounted for by a general estimate of environmental volatility. And secondly, that learning rates in response to positive and negative outcomes are influenced by how informative the individual estimates the outcomes to be. In other words, higher learning rates will be used for feedback that is perceived to be most informative. This idea of separate, parallel, systems for processing positive and negative feedback is echoed in recent reviews, such as Pike & Robinson (2022), where individuals' with mood and anxiety disorders showed higher punishment learning rates, but did not find an effect for reward learning rates. However, a recent experiment did not find that poor learning rate adaptation to volatility was dependent on the valence of the feedback associated with it, in a group of individuals displaying high internalising symptomology (Gagne et al., 2020). Further research is required using tasks designed to capture the interaction between volatility and feedback type, to understand how this mechanism may be perturbed across disorders.

### *5.4 Noisiness in decision-making*

Reinforcement learning models provide one parameter (termed temperature, beta, noise belief etc.) to capture nosiness in decision making for each individual. The RL modelling literature was evenly distributed among disorder types, revealing a relatively strong and consistent effect that individuals with psychosis symptoms are noisier in their decision making, as compared with healthy individuals (via direct comparison), and individuals displaying

symptoms of anxiety and depression (predominantly via a lack of significant effects found for these disorder categories). This was the case in both volatile and stable learning environments.

BL modelling approaches, namely the HGF, use a mathematically related approach to determine noisiness of decision making, however, these models dynamically weight choices on a trial-by-trial basis using an interplay between values from both the perceptual/learning model and the response/decision-making models (see box 2). Specifically, the trial-by-trial belief about volatility (third-level beliefs from the perceptual model) is used as a "dynamic" softmax parameter for decision making. Thereby, a higher volatility belief ("something has changed") would lead to exploration by choosing the option with a previously lower value, and a lower volatility belief ("the environment is stable") would lead to exploitation by sticking with the "safer" option that has been previously rewarded more often. A common approach in the literature is to compare models that include variations within a response model, where the decisions for example, do and do not depend on volatility estimates from the perceptual model (Diaconescu et al., 2020).

A concrete example: Cole et al., (2021) compared BL models that included differences in how their response models interacted with the perceptual/learning model. This was to consider how beliefs are translated into response/decisions. In one response model, subjects' choices were affected by a fixed decision noise, and in another the decision noise varied as a function of the estimated volatility of the stimulus-outcome probability i.e., volatility. The latter decision model was found to be a significantly better fit and implies that decision noise might be directly related to how volatile they believe the environment to be. However, please note that this modelling choice also entangles the theoretically different concepts of decision noise and volatility (see Katthagen et al., 2022, for a discussion).

Within this review all studies using the HGF applied to data from psychosis disorder groups found that data was best fit by the described use of volatility beliefs as a dynamic softmax parameter (Cole et al., 2020; Deserno et al., 2020; Diaconescu et al., 2020; Henco et al., 2020; Reed et al., 2020; Suthaharan et al., 2021). While a directionality cannot be determined from these findings given their cross-sectional or correlational designs, these groups additionally display more stochastic observable behaviour, such as higher switch rates, and poorer overall performance, suggesting that a heightened representation of environment volatility may contribute towards generating noisier decision-making behaviour in psychosis. However, this is not always the case. For example, the opposite pattern, i.e., more reliance on prior information in patients with delusions, was revealed when using a different task design (beads-task) and controlling for general confounds as socio-economic findings. Thus, further research on the relationship between beliefs about volatility and decision noise is warranted, that captures independent neurophysiological measures of executive functioning as well as confounds such as socio-economic status.

The one exception to this finding was a study using BL modelling (HGF) in anxiety disorder (Hein et al., 2021), where a 3-level HGF model with a "normal" softmax explained the data best. Authors suggest that this may be due to task differences: the volatile environment did not alternate between high and low conditions (e.g., in Browning et al., 2015), but rather had a fixed value of true volatility i.e., a constant rate of change of contingency blocks. Further, the decision noise parameter did not differ between groups. Given this is a solitary study using the HGF in anxiety disorders, more research is required in this area. However, the lack of RL modelling findings for noisy decision making in anxiety disorder further supports this finding of no impact of volatility beliefs on decision noise. Taken together, this could indicate a subtle information

processing difference between anxiety and psychosis disorders that may be useful to disentangle for future diagnostic, prognostic, and general clinical applications.

Overall, higher decision noise as reflected by less optimal behaviour seems to be specific for psychosis patients compared to other diagnostic groups. BL studies imply that this is due to an overestimation of volatility that might be clinically reflected by symptoms of delusional mood (Heinz, 2002; Kapur, 2003; but see: Baker et al., 2019). More research is needed to disentangle whether noisy choices reflect (heightened) beliefs about systematic change (as suggested by the HGF findings) or a lack of understanding of the task and general cognitive deficits (see: Findling et al., 2019). Additionally, it is important to incorporate components of neurocognition that have shown strong links to reinforcement learning (Collins et al., 2017; Collins & Frank, 2012; Radulescu et al., 2019). For example, individual variation in working memory has been shown to affect the interpretation of valenced information (Collins et al., 2017; Collins & Frank, 2012; Radulescu et al., 2019). Findings showed that learning performance was sensitive to load and delays, hallmarks of working memory use during a task. Interestingly, this study finds that individuals with schizophrenia consistently show links between impaired working memory and poorer performance on the learning task. Overall, the studies highlight the importance for future research to incorporate (well hypothesised) drivers of information processing that contribute to decision making, into their experimental design and modelling approaches (Collins et al., 2017).

### *5.5 Social bias in decision making*

Two BL modelling studies using the HGF employed a PLT-V with a social element embedded both within the task and the response models. In one instance individuals were required to learn about non-social contingencies in the presence of social cues, using a response

model that included a decision parameter representing the degree to which social over non-social information was used (Henco et al., 2020). Whereas the second study focussed on the ability of individuals to infer the intention of an advisor under volatile and stable conditions, by manipulating the trial-wise prediction of a probabilistic lottery in the presence of social and non-social advice sources (Diaconescu et al., 2020). This experiment additionally manipulated the intentions of the social advisors, for instance, by emphasising the advisors as having hidden intentions. Again, a response model parameter representing how much the advice (social cue) was taken into account when making a decision was compared between groups. This study also compared groups using a decision noise parameter to account for increase response stochasticity.

With regard to social decision making specifically, evidence from these studies showed that individuals with schizophrenia over-weighted their social-domain predictions more strongly than healthy controls and individuals with MDD (this study also included a borderline personality disorder group not discussed here). Diaconescu et al., (2020), found that individuals with high levels of paranoia did not show increased noisiness in their decision making. However, they did find that highly paranoid individuals did make less use of social context when learning from advice. More evidence is required to fully understand the role of social context in decision making in psychosis disorder and wider psychopathology. However, a deficit in the domain may speak to a general hypersensitivity toward interpersonal information reflected in excessive and inaccurate assumptions about other peoples' mental states (hypermentalising) (Gunderson & Lyons-Ruth, 2008; Henco et al., 2020; Okruszek et al., 2015; Sharp et al., 2011).

### *5.6 Overview of non-error-based Bayesian learning literature*

To provide a systematic and maximally informative comparison of extracted parameters from tasks measuring the same types of learning processes, our review focussed on studies using error-based modelling. However, to provide further context, here we also give a brief overview over a variety of studies applying other computational frameworks and tasks, that also provide valuable insights into the question of dysfunctional learning in patients.

In psychosis disorder, evidence from Hidden Markov Models applied to reversal learning, points towards a difficulty for these groups in representing the hidden task structure itself (Schlagenhauf et al., 2014). Here, individuals with schizophrenia appear to apply a much simpler model of the task, as compared to healthy individuals. Additionally, findings from this study showed an increased tendency towards switching behaviours (Schlagenhauf et al., 2014). In accordance with this latter finding, schizophrenia groups also showed a tendency to update their beliefs more to unexpected information, and less to consistent information (Adams et al., 2018; Stuke et al., 2017).

Such effects can further be explained via differences in Bayesian inferencing, though results here are mixed. On the one hand, and in line with the previously mentioned findings of more updating and less stable choice behaviour, one study found that patients with schizophrenia weighted sensory evidence over prior beliefs within Bayesian updating. While this effect was related to delusional ideation specifically (Jardri et al., 2017), the opposite finding (more ascending loops, i.e., more prior weighting) was found to relate to increased presentation of negative symptoms (Jardri et al., 2017), On the other hand, a study using a similar (beads) task (Baker et al., 2019) showed that increased draws to decision making, specifically related to delusion severity, were underpinned by a stronger reliance on prior beliefs formed early in the inferential process i.e., a specific deficit in belief updating. Crucially, this was found when

controlling for socio-economic status which was related to less draws to decision and which might be a confound in other studies.

Evidence using alternative Bayesian models measuring dynamic belief updating is sparser across anxiety and depression disorder. However, some evidence suggests that depression may be characterised by prior beliefs that are biased towards hypotheses that make loss of punishments more likely (Stankevicius et al., 2014), and/or an impaired ability to update an initial belief when presented with disconfirming evidence (Rupprechter et al., 2018). Importantly, a mediating factor in learning related deficits in depression disorder may be stress. One recent study showed that healthcare workers with high levels of cortisol displayed higher levels of exploitation in their decision making, during a bandit task. While the healthcare workers showed worse task performance, and lower learning rates overall, the difference in exploratory/exploitation behaviour that predicted stress was amplified by self-reported (subclinical) depressive symptoms (Kaske et al., 2022).

Anxiety disorders, on the other hand, may present more as a negative bias during learning about ambiguous stimuli, resulting in pessimistic, risk-averting decisions (Aylward et al., 2020; Kim et al., 2020). For example, they may assume that an ambiguous stimulus is more likely to lead to the worse of two potential outcomes. Bayesian inferencing can also be used to understand how closely individuals with anxiety track changes in contingencies underlying an aversive learning task (Browning et al., 2015). Here, as trait level anxiety increased, participants diverged more from the optimal change in learning rate described by the Bayesian learner model, between stable and volatile blocks. Instead, individuals with increased trait anxiety showed decreased adaptation of learning rate to the changing environment, revealing a unique association between trait anxiety and the influence of volatility.

## *5.7 Treatment implications and methodological considerations*

There has been recent excitement regarding the possibility of using computational characterizations of behaviours to provide a unique and highly specific assessment of a patient's condition and ongoing treatment outcomes. The motivation for this is based on the advantages that computational modelling offers in terms of principled theoretical frameworks, offering a bridge between psychological constructs and neural circuitry, function, and behaviour. Therapeutic interventions, such as cognitive behavioural therapy, require learning i.e., the integration of new information into an existing schema or model (Moutoussis et al., 2018). Computational modelling techniques have been suggested as a route to understanding deficits in this process, using testable hypotheses and quantifiable parameters representing individual differences in belief updating, learning, and behaviour.

There are multiple tangible ways that model-based approaches could support therapeutic intervention e.g., in the stratification of patients for specific intervention, to inform the design of new interventions themselves, or to provide practitioners with a method to both adapt and tailor their therapeutic approach to the individual in question, via for example, the continued assessment of treatment outcomes, and improvement over the course of a therapeutic intervention (Moutoussis et al., 2018; Nair et al., 2020; Scholl & Klein-Flügge, 2018). One recent model-based intervention study into individuals with depression showed that symptom change following cognitive behavioural therapy was correlated with remediation of altered learning parameters, such as an increased reward learning rate and a more positive outcome shift during loss learning (Brown et al., 2021). This suggests that extracted model parameters may be sensitive to treatment-induced changes in observable symptoms, rather than simply describing

alterations at baseline. While this would support the monitoring of treatment, it could also encourage the development of personalised treatment plans constructed to target specific information processing deficits within the individual.

Research has also shown computational mechanisms identified via modelling to be predictive of treatment response in individuals with schizophrenia spectrum disorders (with delusions) (n=261), as compared with healthy controls (n=56) (Hauke et al., 2022). Here, the study found that patients displayed increased belief instability i.e., increased updating in response to disconformity evidence. Increased belief stability was then significantly associated with better treatment response (metacognitive training intervention), at the group and individual level. While the quality of this finding is high, more longitudinal studies are required to assess whether model parameters can reliably predict treatment outcomes (Hauke et al., 2022).

It should be noted that the field of computational psychiatry and neuroscience still faces several hurdles that currently limit a clinical translation of findings. For example, in order to appropriately apply this approach to a clinical setting, the field must first demonstrate reproducible findings and increasing test-retest reliability of task performance, parameter estimation, and parameter stability over time using longitudinal studies (Scholl & Klein-Flügge, 2018; Tavares et al., 2008; Thoma et al., 2015). Similarly, rules governing proper modelling application must be standardised and agreed upon for wide scale, clinical use, to ensure well validated and meaningful outcomes for patients. For this reason, this review has chosen to abstain from recommending any specific treatment applications for symptoms or disorders, based on the findings discussed.

While differences across task design hampers comparison between studies, and subsequently the

ability to use them in a clinical context due to a lack of e.g., replicability, the use of novel, bespoke, tasks does offer flexibility in the experimental questions that can be asked. In fact, the development of novel, ecologically valid tasks, could support researches' ability to understand learning and decision making in more realistic environments (Scholl & Klein-Flügge, 2018). Examples of these tasks use smartphone APPs or online formats, making them easily available and practical both for the patient, and researcher or clinician (Chekroud et al., 2017; Kumar et al., 2008; Msetfi et al., 2012). The application of such a convenient and more ecologically valid approach would also provide opportunities for longitudinal self-assessment, monitoring or treatment evaluation. The application of computational modelling to such tasks, could offer researchers and clinicians the possibility of capturing and integrating real-life phenomena in ecological settings, such as biometric data collected on smart phones. This would allow parameters derived from the task to be validated in concordance with real-life phenomena they are argued to capture (Gradin et al., 2011; Scholl & Klein-Flügge, 2018).

## *5.8 Limitations*

No learning model is a perfect representation of reality, but all models are attempting to capture the behaviour of an individual by partitioning the variance in learning outcomes into one or more parameters within a given model structure. Given the complexity of some of these models, the estimated parameters can appear highly distinct in mathematical formulation and interpretation. However, as all the models seek to explain very similar and low dimensional task inputs, and behavioural outputs. there are conceptual relationships between parameters from the different models. These relationships enable findings from different modelling frameworks to be considered together to seek to identify further implications. For example, RL modelling approaches often partition variance among relatively few parameters, and seek to capture core

learning constructs, such as learning rate. Whereas probabilistic modelling approaches are more complex in the structure and number of parameters included, in an attempt to offer a more mechanistic description of belief updating to disentangle the role of different learning constructs, such as volatility weightings.

The vast majority of reviews in the field, though excellent and insightful overviews, are not systematic (for examples, see: Barch et al., 2016; Deserno et al., 2017; Heinz, 2002; Huys et al., 2013; Huys et al., 2020; Katthagen et al., 2022; Lee, 2013; Maia & Frank, 2017; Stephan & Mathys, 2014; Sterzer et al., 2018; Voon et al., 2017; Yu & Dayan, 2005). The lack of systematic overviews in this field is likely a direct result of the heterogeneity that exists in i) the algorithmic differences in computational modelling approaches that obscure/complicate direct comparisons between studies, and ii) the subtle differences in task types, and specific features, affecting the type of learning being measured. As such, it was necessary to apply strict criteria to the synthesis of the literature, in order to provide a less noisy comparison of results, in a systematic fashion. However, this has meant that aspects of learning and decision making measured using slightly different tasks (e.g., tasks that require the acquisition of evidence before choice, like the beads task), and/or modelling approaches (e.g., the HMM), were beyond the scope of the review. A benefit of this approach is that as a field, we are more able to clearly see the overlap and distinction between research using the same task, and highly related modelling, which ultimately appears to have potentially uncovered some unexpected findings. However, while direct comparability may be harder when including a wider range of tasks and modelling approaches, learning and decision making involves many cognitive processes, and as such, we may not be reflecting the picture of deficits in their entirety. One solution to this problem could be to use a simulation-based approach, for example used in Pike and Robinson (2022). This review utilises an innovative, simulation based, meta-analytic approach to deal with complexities in the field,

showing that individuals with mood and anxiety disorders more meaningfully updated their learned values after a punishment, compared to controls; and less meaningfully after receiving a reward outcome. Conventionally, this could only be established by comparing studies that used a computational RL model with two (or more) learning rates (to represent learning from positive or negative feedback). The simulation approach used in this review allowed the authors to test for differences in the parameters across all studies, regardless of the specific mathematical formulation of the model in the given study (Pike & Robinson, 2022).

### *5.9 Future directions*

Task and modelling designs were often heterogeneous, utilising for example, different reward types, and task structures between disorder categories, as well as an array of modelling formalisations. Interestingly, within disorder categories, there was an additional issue that choice of task and model tended towards pre-existing theories in the field – for example, depression is commonly associated with a deficit in reward responsivity, and in line with this, we see a larger number of tasks and models designed specifically to measure learning in response to feedback, and fewer studies looking at for example, learning in response to changes in volatility. These problems lead to issues in the comparability of research, as well as difficulties specifying domain specificity, or generality. While this review attempted to deal with this issue by strict synthesisation of research, this issue must be addressed in future research by using more homogeneous methodological procedures across disorder categories and studies, and ensuring that experimental designs, while building on previous hypotheses, are not restricted.

In general, tasks must strike a balance between how applicable they are clinically, how ecologically valid they are practically, and how informative they are in relation to the modelling

approach used. While smartphone APPs and online tasks may be one route forward, test-retest reliability and replication of parameter estimates using these specified tasks, ideally in a longitudinal format, must be evidenced. Development of a set or battery of commonly used, well validated and ecologically valid tasks, would support this process. Specific operational improvements within tasks designs could include the development of tasks that use both primary (prediction error, performance error), and secondary outputs (derived via modelling e.g., learning rate). The use of directly measurable outputs, for example prediction error and confidence measures, would improve the accessibility of such approaches by minimising the need for complex modelling. Additionally, tasks could include other variables that affect the association between a stimulus, or action, and the subsequent outcome, for example – "expected uncertainty"- that may also lead to differences in how informative the outcome is (Yu & Dayan, 2005). Future studies should attempt to explore whether manipulations of expected uncertainty produce differences in learning rates, and whether these differences are mediated by a preference for positive or negative outcomes (Pulcu & Browning, 2017). Finally, choice of computational model to apply to task data must be carefully considered in relation to the question or hypotheses. These issues are compounded by the field's unmet gold standard target for behavioural computational modelling (Wilson & Collins, 2019) and exemplified via a lack of simulation and parameter recovery steps needed to show whether model parameters do in fact explain observable behaviour.

# 6 Conclusion

In conclusion, methodological heterogeneity exists across this field, making comparability a challenge. The review attempted to address this using a stringent categorisation

of tasks and models. The review found that psychosis disorders displayed overall lower learning rates in stable learning environments, both overall, and in relation to positive feedback. While this decreased responsivity to rewards overlapped with depression disorders, individuals with depression additionally showed increased learning from negative feedback, indicating a general deficit related to feedback responsivity. No overlap was found between anxiety and depression disorder in terms of responsivity to valenced feedback. Instead, anxiety and psychosis spectrum disorders showed a shared inability to adapt their learning rates to changes in volatility. Decision noise was consistently higher in psychosis disorders, whereas no differences were noted between depression or anxiety groups when compared with healthy controls. Though these effects were shown across both RL and BL modelling findings, the relative abundance of probabilistic modelling studies in psychosis disorders indicates specific mechanisms, such as abnormal initial expectations of volatility, and weightings of volatility estimates, as i) an explanation for observable symptoms in psychosis disorder and ii) as likely candidates for RL modelling findings.

These findings highlight the need for research to look beyond traditional diagnostic boundaries, towards the identification of fundamental biobehavioural mechanisms underlying symptoms. While computational approaches offer great promise, the field would benefit from a more homogeneous methodological framework, that would support the generation of reproducible findings, and increase reliability of task performance, parameter estimation, and parameter stability over time. In turn, this would support the use of model-based parameters as a route towards targeted and personalised clinical treatment options.

## 7 Author contributions

Author contributions are writing in accordance with CRediT author statement guidelines. **Kelly Diederen:** supervision, conceptualization, review, and editing. **Thomas Spencer:** supervision**,** conceptualization, review, and editing. **Teresa Katthagen:** conceptualization, review and editing, technical support. **Iveta Tsenkova:** data curation, review, and editing. **Rubbia Ali:** data curation, review, and editing. **Xinyi Liang:** data curation. **Toni Gibbs-Dean:** conceptualization, methodology, formal analysis, investigation, data curation, writing: all drafts and final manuscript, writing: review and editing, visualisation, project administration

## 8 Acknowledgement

Many thanks for the additional data curation work carried out by: Ashok Velineli, Carina Kuehne, Miao Liu, Ying Zhou, Yungen Cheah, Sambodhi Baiid, Seema Jasiwal, Lin-Yu Wu.

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# 10 Supplementary materials

*Table 2-5. Showing modelling procedures by study*

| Author/year | Models Fitted (n) | Model Type (RL/BL/CPM) | Was Data Simulated? | Were Parameters Recovered? | Model comparison criteria | Sample reduction due to poor model fit | Total |
|---|---|---|---|---|---|---|---|
| Browning et al., 2015 | 3 | RL | yes | yes | Negative log likelihood; AIC; Pseudo-R2; Adjusted Pseudo R2 | not reported | 3 |
| Haarsma et al., 2020 | 6 | RL | yes | not reported | Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) | not reported | 2 |
| Strauss et al., 2015 | 3 | RL | yes | not reported | Pseudo-r2 AIC | not reported | 2 |
| Katthagen et al., 2020 | 6 | RL | not reported | not reported | Random-effects Bayesian model selection, exceedance probability, protected exceedance probability, predictive probability | not reported | 1 |
| Ermakova et al., 2018 | 1 | RL | not reported | not reported | None | not reported | 0 |
| Dowd et al., 2016 | 2 | RL | yes | not reported | LLE, BIC, AIC | yes | 3 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Culbreth et al., 2016 | 2 | RL | not reported | not reported | Predictive probability, negative log likelihood, Pseudo-R2 | not reported | 1 |
| Geana et al., 2021 | 8 | RL | yes | yes | AIC | not reported | 3 |
| Gold et al., 2012 | 3 | RL | yes | not reported | mean (and standard error) pseudo-r2, AIC | not reported | 2 |
| Gradin et al., 2011 | 1 | RL | not reported | not reported | none | not reported | 0 |
| Hernaus et al., 2018 | 3 | RL | yes | not reported | AIC, Bayesian Model Selection | not reported | 2 |
| Hernaus et al., 2019 | 5 | RL | yes | not reported | AIC, Bayesian Model Selection | yes | 3 |
| Li et al., 2014 | 1 | RL | yes | not reported | none | not reported | 1 |
| Murray et al., 2018 | 1 | RL | not reported | not reported | none | not reported | 0 |
| Moutoussis et al., 2018 | 8 | RL | not reported | not reported | BIC | not reported | 1 |
| Reinen et al., 2016 | 3 | RL | yes | not reported | Bayesian Model Selection | not reported | 2 |
| Waltz et al., 2016 | 3 | RL | yes | not reported | AIC, BIC, Pseudo-R2 | yes | 3 |
| Howlett et al., 2020 | 6 | RL | not reported | not reported | WAIC | not reported | 1 |
| Murray et al., 2019 | 1 | RL | not reported | not reported | none | not reported | 0 |
| Myers et al., 2013 | 2 | RL | not reported | not reported | BIC | yes | 2 |
| White et al., 2017 | 1 | RL | yes | not reported | none | not reported | 1 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Howlett et al., 2021 | 1 | RL | not reported | not reported | none | not reported | 0 |
| Huang et al., 2017 | 2 | RL | yes | not reported | AIC | not reported | 2 |
| Beltzer et al., 2019 | 2 | RL | not reported | not reported | BIC, −2 log likelihood | not reported | 1 |
| Cavanagh et al., 2019 | 2 | RL | not reported | not reported | AIC, pseudo-R2, LLE | not reported | 1 |
| Takano et al., 2019 | 1 | RL | not reported | not reported | none | not reported | 0 |
| Bakic et al., 2017 | 4 | RL | not reported | not reported | BIC | not reported | 1 |
| Rupprechter et al., 2020 | 5 | RL | yes | yes | integrated BIC | not reported | 3 |
| Kumar et al., 2018 | 2 | RL | not reported | not reported | LLE, pseudoR2 | yes | 2 |
| Rothkirch et al., 2017 | 1 | RL | not reported | not reported | none | not reported | 0 |
| Dombrovski et al., 2019 | 6 | RL | yes | yes | random effects Bayesian model comparison | not reported | 3 |
| Cooper et al., 2014 | 4 | RL | yes | not reported | AIC | not reported | 2 |
| Liu et al., 2017 | 3 | RL | not reported | yes | BIC | not reported | 2 |
| Albrecht et al., 2016 | 6 | RL | not reported | yes | widely applicable information criteria, BIC | not reported | 2 |
| Montagnese et al., 2020 | 4 | RL | yes | not reported | lowest LOOIC | not reported | 2 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Nassar et al., 2021 | 5 | CPD | yes | yes | Bayesian model selection, AIC | not reported | 3 |
| Reed et al., 2020 | 1 | BL | yes | yes | none | not reported | 2 |
| Suthaharan et al., 2021 | 1 | BL | not reported | not reported | none | not reported | 0 |
| Fradkin et al., 2020 | 3 | CPD | yes | not reported | WAIC | yes | 3 |
| Hein et al., 2021 | 5 | BL | yes | yes | Bayesian model selection | not reported | 3 |
| Diaconescu et al., 2020 | 6 | BL | yes | yes | Bayesian model selection | not reported | 3 |
| Henco et al., 2020 | 8 | BL | yes | yes | random- effects Bayesian Model Selection, Posterior model probabilities, Exceedance Probabilities and Protected Exceedance Probabilities | not reported | 3 |
| Deserno et al., 2020 | 10 | BL | yes | yes | random-effects Bayesian Model Selection, posterior model probability, exceedance probability | yes | 4 |
| Cole et al., 2020 | 6 | BL | not reported | yes | Bayesian model selection | not reported | 2 |

*AIC = Akaike information criterion; BL =Bayesian learning model; BIC = Bayesian information criterion; CPD = change point detection model; LOOIC = leave-one-out cross validation (LOO) information criterion; LLE = log likelihood estimate; RL = reinforcement learning model; WAIC = widely applicable information criterion*

# Chapter 3. Methods: *development of a novel learning task*

## 1 Abstract

*Background:* Learning involves adapting our behaviours in response to feedback. Uncertainty within information about feedback can affect our ability to optimize decision-making and may be perturbed in mental illness. However, existing experimental paradigms are oversimplified e.g., binary choices, and fail to consider the full problem facing the learner: simultaneous estimation of volatility *and* noise. The aim of this research was to assess the validity and reliability of a novel learning task that addresses these limitations.

*Methods:* A novel task was developed that sampled inputs from "ground truth" probability distributions (in a continuous space). Distributions were manipulated in terms of their noisiness, via changes to the standard deviation, and volatility, via changes to the mean. Participants could

provide trial wise, parallel estimates of the noise (beam width) and mean (rover positioning) of the distribution. In two online samples (n=555; n=169), analysis was conducted to assess whether metrics were used to reflect the underlying distribution as expected, to test the consistency of metrics across individuals, and via replication of previous findings (Berniker 2010).

*Results:* Version 1 of the task failed to show construct validity and had high exclusion rates in an online context. Version 2 of the task, with modifications to the input presentation and task design, successfully improved exclusion rates and demonstrated integration of information across trials. However, calculating trial-wise learning rates led to erroneous results, and alternative approaches such as averaged learning rates and computational modelling could be considered for future research.

*Conclusion:* This study validated a novel online learning task by showing evidence of its consistency with prior research (Berniker et al., 2010), and construct validity and reliability of key metrics. Additionally, Version 2 of the task was found to perform well in an online environment, shown via substantially increased attention and engagement with the task.

## 2 Introduction

Learning involves adapting our behaviour in response to feedback. This type of learning is referred to an instrumental learning. In a simple learning scenario, learning refers to the formation of an association between a stimulus e.g., a red or blue square, and an outcome e.g.,

a reward or punishment (Akpan, 2020; education & 1971, n.d.; Williams et al., 2017). By integrating and adapting our expectations and/ or behaviour (e.g., choices) to the outcome received, we can seek to optimise gains and minimise losses associated with our decision. Complexity arises however, when we consider the fact that the outcome or feedback presented to us as a consequence of our behaviour, response or action, is often not deterministic – either correct or incorrect – but is in fact probabilistic e.g., can be associated with a reward some proportion of the time, and a lack of reward or a punishment otherwise. In fact, this uncertainty runs much deeper. Take for instance, how we receive feedback – via our senses. This information is inherently uncertain, as our senses can be tricked and manipulated, we only perceive the world intermittently, and there is no way to fully know the content of another entity's inner worlds (Pulcu & Browning, 2019). As such, to effectively formulate our stimulus-response associations (or anything more complex), this uncertainty must also be accounted for, and ideally, minimised. The uncertainty inherent in our lives impacts the stimulus-response association in multiple ways. For example, the noisiness of the association across a proportion of events - termed expected uncertainty, or noise. Or the volatility of the association, where a previously learnt response suddenly switches or changes to become associated with a different outcome – termed unexpected uncertainty (Behrens et al., 2007; Pulcu & Browning, 2019).

There are different experimental paradigms in which feedback guided learning and the role of uncertainty processing, can be assessed. Most experimental paradigms in this field manipulate uncertainty within an environment using probabilistic learning tasks (PLT). PLTs often involve a binary probabilistic choice framework with abstract stimuli. Participants are presented with these stimuli and required to select the square that they believe will yield a better outcome. Subsequently, the participant will receive probabilistic feedback regarding their choice, which

could be a reward, neutral outcome, or punishment. Because the relationship between the choice and feedback is probabilistic, this introduces a sense of expected uncertainty (De Berker et al., 2016; Feeney, 2017; Katthagen et al., 2022; Pulcu & Browning, 2019; Sandhu et al., 2023). Probabilistic reversal learning tasks (PRLT) involve an environment where the reward for selection varies probabilistically, but switches unexpectedly (Behrens et al., 2007; Soltani & Izquierdo, 2019; Yu & Dayan, 2005). For instance, the initially disadvantageous choice becomes less likely, while the advantageous choice becomes more likely. This creates a volatile learning environment and induces the subjective experience of unexpected uncertainty in an individual, requiring participants to adapt their decision-making strategies to maintain favourable outcomes (Behrens et al., 2007; Pulcu & Browning, 2019).

There are several critiques to PLT and PRLT design format, which may limit researchers' ability to access important aspects of learning, or compare across research (Karvelis et al., 2023). Firstly, the way in which volatility is manipulated can vary significantly between studies, inhibiting direct comparison. For example, studies can use direct reversals (80:20; 20:80), or a change to a non-mirrored reversal (80:20; 90:10) (Katthagen et al., 2022a). The timing of the reversals can also differ, with some studies adhering to a predetermined schedule, and others reversing once the agent has learnt the association for example, made ten correct estimates (Reed et al., 2020). While the timing of the switch can differ, common to these paradigms is that they often do not use a block design, i.e., blocks of volatility vs. blocks of stability. This precludes the ability to perform some types of analysis, such as looking at how individuals adapt to changes in uncertainty between blocks (Browning et al., 2015; Gagne et al., 2020). This is important because rather than looking at overall learning rates or average learning rates, it captures the ability to update learning rates in response to changes in uncertainty, which may represent an important way in which learning

can be altered in psychopathology (Browning et al., 2015). Secondly, in both PLT and PRLT frameworks, task designs often use binary inputs and choices. However, real-life situations are often more complex and less straightforward. Incoming information in real-life scenarios is uncertain and weighted based on its likelihood and given certain parameters. Consequently, the probabilistic relationships underlying our estimates of hidden processes are unlikely to be binary, but rather continuous and multidimensional (Katthagen et al., 2022a).

The use of continuous inputs and responses in experimental learning task design offers several advantages. Firstly, it enables participants to dynamically infer the underlying statistics of the task. This has been suggested to improve the ability to disaggregate between noisy decision making i.e., more “random responding”, and changes in choice that are due to the perception of increased volatility, on a trial-by-trial basis (Katthagen et al., 2022a). This is particularly important in assessing participants' ability to adjust their learning rates according to the presence of unexpected uncertainty (volatility). Finally, continuous measures can provide directly observable prediction errors and learning rates, eliminating the need to infer hidden states as required in computational models such as reinforcement learning and Bayesian learning. This approach facilitates a more direct and accessible assessment of learning processes under uncertainty. To better capture the complexity of the real world, recent novel tasks have been developed using continuous inputs that sample from underlying Gaussian probability distributions (Fromm et al., 2023; Haarsma et al., 2020; Nassar et al., 2010, 2012, 2021a; Vaghi et al., 2017). These tasks aim to replicate uncertainty by manipulating the statistics that govern the shape of the distribution i.e., the standard deviation (SD) and the mean. As such, expected uncertainty is manipulated through variations in the standard deviation (SD) of the probability distribution, while unexpected uncertainty or volatility is simulated by sampling from distributions with different means, and switching between them without prior indication. For example, the

helicopter task (McGuire et al., 2014; Nassar et al., 2010, 2012, 2021a) – where continuous inputs were sampled from Gaussian distribution whose means changed discretely at predetermined "change points". To succeed at the task, participants had to dynamically infer the underlying hidden means, which involved differentiating random noise from meaningful change points.

Trial wise data from learning tasks are typically used in conjunction with computational modelling approaches to parameterise aspects of learning. For example, the speed at which an individual learns the association of interest – or learning rate – is a key measure of interest usually estimated within the modelling process (Pearce & Pearce, 1980; Rescorla and Wagner, 1972). The majority of computational models algorithmically describe learning, or the update of a belief, as how unexpected the outcome is in relation to what was predicted – termed prediction error (PE). The degree to which the PE is used to update their belief is determined by the free parameter: learning rate (Behrens et al., 2007; Mathys et al., 2011; Nassar et al., 2010). According to a normative account of learning, learning rates will increase in response to volatility. This is because, all else being equal, high volatility leads to an increase in uncertainty about the cue's value, due to the increased fluctuations, and so the reliance of each new outcome i.e., learning rate, is found to be higher (Behrens et al., 2007, 2008; Nassar et al., 2012, 2021a); punishing: (Browning et al., 2015; Pulcu & Browning, 2017). Noise, on the other hand, has the opposite effect. Here, all else equal, more noise leads to less informative outcomes in relation to the cue's true value – leading to lower learning rates (Diederen & Schultz, 2015; Diederen et al., 2016; Krishnamurthy et al., 2017; Nassar et al., 2010, 2012).

While there is a strong argument that this process represents a crucial mechanism underlying learning, aberrant uncertainty estimation, or an inability to accurately track this uncertainty, may underpin poor learning effects seen across mental illness (Browning et al., 2023; Huys et al., 2020; Katthagen et al., 2022b). Importantly, the vast majority of research in this area has preferentially investigated how learning rate is impacted when individuals are confronted with volatility (Beltzer et al., 2019; Cole et al., 2020; Deserno et al., 2020; Gagne et al., 2020; Hein et al., 2021a, 2021b; Katthagen et al., 2020; Lawson et al., 2017; Piray & Daw, 2021; Pulcu & Browning, 2019; Walsh et al., n.d.), with fewer studies looking specifically at learning under noise (Haarsma et al., 2020; Nassar et al., 2021b; Vaghi et al., 2017). However, despite the fact that learning rates are jointly determined by a comparison between estimates of *both* the volatility and the noise, there are no examples of studies investigating how individuals jointly estimate the volatility and the noise, on a trial wise basis, and under conditions that simulate a noisy and volatile environment (Piray & Daw, 2021). This may be important for further understanding and disaggregation of learning related deficits that appear to play in important role in metal health disorders (Katthagen et al., 2022a).

A primary aim of this study was to develop and test a novel learning task that addressed these issues. The novel task included continuous input measures sampled from underlying Gaussian probability distributions, that simulated different uncertainty environments by varying their statistical configurations (mean, standard deviation) i.e., a large SD and non-changing mean tested learning in high noise, whereas a block consisting of many signalled mean changes, but a stable and small SD, tested learning under volatility. These contingencies were displayed in a block format, with both isolated volatility and noise blocks, as well as combined volatility and noise conditions. Participants were able to

make trial wise and parallel estimates of both the noise and the volatility, also in a continuous space. The task was gamified with a view to increasing engagement.

To achieve this overall goal, a previously validated task, that included several highly relevant features for testing learning under uncertainty, was adapted for this purpose (Berniker et al., 2010). The experiment tested the temporal acquisition of underlying statistics of an environment i.e., the mean and variance of the underlying probability distribution. Berniker et al., (2010), and found that the mean of a probability distribution could be acquired rapidly, while the variance was acquired more slowly. As such, this study aimed to replicate these findings in the novel task, as well as provide evidence for the feasibility of the task in an online context, and for the construct validity of the task metrics. This was achieved using two large-scale online studies (version 1: n=555; version 2: n=164). Given the need for validation, and therefore large populations, the novel task was tested using an online platform. This enabled large scale testing at the level required for robust exploration and replication (Wise et al., 2023).

### *2.1 Aims, hypotheses, and outline*

A broad aim of this experiment was to understand whether the acquisition of statistical learning could be replicated using a novel learning task. While aims and hypotheses around specific metrics in the task are described in the methods sections (after a description of the task has been provided), in general the study aimed to:

1. Develop effective exclusion criteria suitable for an online context.
2. Provide evidence on construct validity in relation to the metrics used in the task.
3. Provide validation in line with the adapted task (Berniker et al., 2010).

To achieve this, multiple versions of the task were compared. Specifically, two versions of the task were applied to two separate large-scale online samples (n=555; n=164). Two separate experiments were carried out (part A and part B). Part B was conducted after changes to version 1 had been made, in response to findings from part A. As such the methods and results are presented separately for each version. A discussion and conclusion are provided in response to the overall process. The following sections detail the development of the task in line with the above hypotheses, making explicit the development process.

# 3 Part A. validation of a novel learning task - Version 1

## *3.1 Methods*

### *3.1.1 Participants*

Participants were recruited and assessed over a seven-day period via the online recruitment platform "Prolific", which enabled participant anonymity (see: prolific.co) (N=555, mean age = 27.82, SD= 6.31). Requirements for participant inclusion included: age 16-40yrs and residence in the UK. Participants were compensated for their time at a rate of £5.00 per hour.

### *3.1.2 Procedure*

This was a cross-sectional population study. Participants were provided a webpage link through Prolific to an online testing platform "Gorilla" (gorilla.sc). Participants could use their own internet-accessible devices including smartphones, tablets, or computers. Participants were required to complete several symptom and demographic questionnaires; however, these are not discussed here. They then went on to complete three tasks: the novel task (the Space Task), another learning task (the Two-Tone task; see Teufel et al., 2015, as well as a speech task (see: Olah et al., 2023).

### *3.1.3 Materials*

#### *3.1.3.1 Novel task: Space Task - Version 1*

Participants performed a game-based learning task where the overall aim was to collect enough space junk to build a rocket and escape a planet (see Figure 3.1). Participants were told that the space junk was falling from unseen passing spacecrafts, that varied in size,

location, and frequency (full details given in Appendix: Table 3-4). To catch the space junk, participants were given a rover, that they could move along the *x* axis, and a beam attached to the rover, whose power could be adjusted on the *y* axis. Participants were instructed to use the previous falling space junk locations to predict the location that the next piece would fall. Participants were instructed to indicate their estimate by moving the rover to catch the falling space junk, and increase or decrease the beam size to where they felt appropriate, while conserving as much power as possible i.e., using the smallest beam size they felt safe to do so, while still catching the space junk. Version 1 of the space task provides the player with two pieces of information per trial, sampled from the same distribution. As such the individuals experience of each trial includes input A: a piece of falling space to be used to inform the prediction (from a Bayesian point of view, this information is novel sensory information used to update a prior); and input B: a second piece of space junk that provides explicit feedback as to the prediction (see Figure 3.1). Limited information about the size, location and frequency of the incoming unseen space craft was given at the start of every block (exact description found in Appendix, Table 3-4)).

Underlying the task are probability distributions that differ in their means and standard deviations, to simulate uncertainty environments. For example, a condition of high noise would consist of a stable mean, but a wide standard deviation. The exact means and SDs used, alongside the rules by which the distributions change, are displayed in

Table ***3-1***. The task inputs (space junk positions) were sampled from these distributions. The sampled inputs were then themselves subject to simulation (iterated over 100,000 replications). From the simulated inputs, the most normally distributed distribution was chosen. This was to ensure that the sampled inputs were not non-normally distributed by chance, i.e., include outliers that would confuse the participants. These distributions can be seen in the App, Figs 1:3.

The task included 219 trials (ITI: 1000-5000ms) overall, split into six blocks that differed in their configurations of volatility and noise, via manipulations to the underlying probability distribution that the junk was sampled from. The rules by which the distributions changed throughout the task mirrored Berniker et al., (2010). Block one was a practice round that included three practice trials and required successful completion i.e., to catch every piece of junk, before the participant could continue. If the participant did not pass the practice round, they would be directed back to the start of the instructions to begin again. Block two (n=10 trials) was a stable learning environment i.e., no mean changes, and a small SD (0.03). All participants were exposed to low noise and volatility during block two. In block three, the noise was manipulated in isolation i.e., there were no mean changes (Mean=0.01), but the variance increased after 20 trials (SD=0.03 to 0.12) (total trial n=40). Block four (n=40 trials) tested learning under isolated volatility. Volatility was manipulated by the inclusion of un-cued changes to the mean of the underlying distribution from which the junk was drawn (see

Table ***3-1***.), alongside a stable variance (SD=0.01). Here, the probability distribution switched between two previously unseen means. The switch rate for mean change was computed at a 0.25 chance every 5 trials, resulting in 5 overall mean switches across the block (see Figure 3.1; as seen in (Berniker et al., 2010)). Blocks five (n=84 trials) and six (n=40 trials) updated the mean and SD of inputs every ten trials (plus jitter), resulting in continuously high volatility, and periods of high and low noise (Figure 3.1). In each case, two previously seen means were used alongside two new means i.e., block five used the two means from block four, plus two new means etc. While learning requirements were the same across blocks five and six, blocks differed in terms of its reward policy, described below.

Feedback was presented in terms of points per individual trial and an ongoing cumulative score in the top right of the screen. Written confirmation e.g. “Well done, you caught it!”, “missed”, or “timed out!” was also provided on a trial-wise basis. Each trial could score a maximum of ten points. The score was shown after each trial and between each block. During blocks one to five participants could win points if they caught the junk, or they would receive no winnings if they missed the junk, on each trial. In block 6 participants could win and lose points, leaving open the possibility that they could lose their bonus points, and as such, the additional points they had earned. Scores were generated for each trial as a function of accuracy (successful catch/unsuccessful catch) and the width of the beam used. Scoring in block 6 differed in that participants could lose the points they had gained, as well as win double the points. Just as participants were incentivised to use the smallest beam possible in blocks one-five i.e., a higher score given for catching with a narrower beam, in block six, participants would lose more points if they missed using a large beam, compared to missing using a small beam. Participants were informed of this change during the instructions screen preceding the start of block 6.

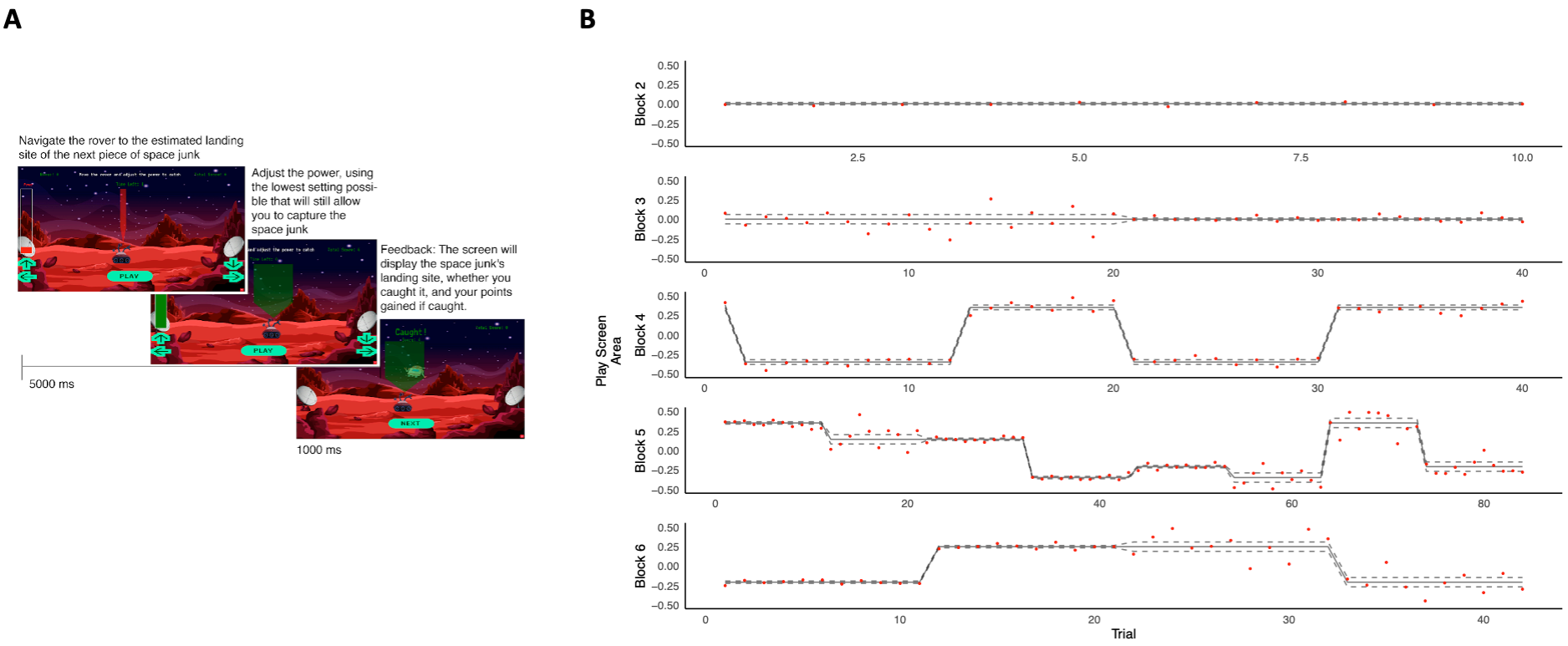


**Figure 3.1A**. *Showing trial structure. Here, once the participant is exposed to the cue for a maximum of 5000m/s, participants are then instructed to make an estimate of the mean, using rover positioning; and variance using manipulation of the beam width. Feedback i.e., another piece of space junk drawn from the same distribution, is then presented to the participant (1000m/s).* **3.1B.** *The black solid line shows the mean(s) used for each block (see Table 3.1 for further details), indicating both the stability of the mean over trials (x axis), and the location of the mean on the play screen area. The standard deviation used to simulate noise in the space junk locations is shown using the black dashed*

*line (see Table 3.1 for further details). Here, the width of the dashed line around the mean indicates both the width of the SD used, and the area of the play screen available for space junk locations to be drawn from. The red dots show the actual space junk positions that the participants were exposed to, in accordance with the underlying probability distributions.*

**Table 3-1** *Showing the details of the contingencies underlying the task for each block.*

| Screen | | Contingency Information | | | |
|---|---|---|---|---|---|
| **Name** | **Description** | **Trials (n)** | **Mean** | **SD** | **Rules** |
| **Block 1** | Practice round | 3 | -0.07 | 0.045 | Option to repeat |
| **Block 2** | Stable learning environment | 10 | 0 | 0.12 or 0.03 | 50% participants SD=0.12; 50% participants SD=0.03 |
| **Block 3** | Learning when the SD changes (high and low noise) | 40 | 0 | 0.12 or 0.03 | SD changes halfway through. Fixed mean. Counterbalanced condition is reversed. |
| **Block 4** | Learning when the mean changes (high volatility) | 40 | 0.35, -0.35 | 0.06 | A 25% chance of changing to the distribution with the second mean, every four turns. |
| **Block 5** | Learning with combined SD and mean changes | 84 | 0.35, -0.35, 0.14, -0.21 | 0.12 or 0.03 | Each SD/mean combination changes every 10trial+/-jitter of around 3 trials. |
| **Block 6** | Learning with combined SD and mean changes. Block includes loses. | 42 | 0.35, -0.21 | 0.12 or 0.03 | Each SD/mean combination changes every 10+/-jitter of around 3 trials. Randomly ordered. Extra points for catching. Loose points for missing/using a larger beam. |

#### *3.1.3.2 Outcome measures*

Overall performance was measured by score. Score was calculated as a function of both catch success i.e. whether they caught the junk on that trial, and the size of the beam used to capture it (i.e., screen size), and was presented to participants as a score out of ten on each trial. Participants were incentivised to use the smallest possible beam to catch the space junk (by giving them more points when catching the junk with a smaller beam) to motivate them to reveal their true prediction/ belief of the variance, and hence make the task incentive compatible. In block six, participants could receive double points for a catch, or could lose points if they were unsuccessful at catching the space junk. Losses were calculated in the same way as rewards, but

reversed, so missing the space junk with a wider beam led to a loss of more points than missing the space junk with a small beam. Beam width (size of the screen taken by the beam) could also be taken as a separate measure, intended to provide additional information about the ability of participants to acquire the underlying variance of the distribution.

Derived metrics included performance error and/or prediction error, that could be calculated by subtracting the participants estimate of the mean of the distribution i.e., rover position, from the either the actual observed location of the falling junk on the next trial, in the case of prediction error, or the mean of the underlying distribution in the case of the performance error. While prediction error provided insight their trial-wise estimate, performance error, as related to the mean of the underlying distribution, provided insight into whether the individual was successfully learning/acquiring the underlying mean. This is because the optimal strategy for the task would be to place each estimate as close to the unseen mean as possible.

### *3.1.4 Analysis*

#### *3.1.4.1 Aims and hypotheses (related to specific outcome measures)*

1. Development of a set of exclusion criteria for an online context.
2. Validation of metrics included in the Space task:
    a. The rover positioning represents a trial-wise ongoing estimate of the underlying mean of the distribution the space junk is drawn from.
    b. The variance of the underlying distribution will be tracked by participants, shown via use of the metric: beam width. Specifically, we will see larger beam widths used during periods of high variance.

c. Prediction errors and performance errors will increase at mean change points and decrease rapidly.

3. Task validation in line with a previously published task (Berniker et al., 2010):
    a. Individuals will display a stronger relationship between their positioning of the rover and the cue input during periods of high noise. Whereas positioning of the rover will be closer to the mean during periods of low noise.
    b. Individuals acquire the mean of the underlying distribution rapidly (within around 3-5 trials), shown via strong relationship between the estimate (rover position) and the underlying mean.
    c. Error between the mean of the underlying distribution and the participants estimate (performance error) will be larger under conditions of high variance, compared to low.

#### *3.1.4.2 Development of exclusion criteria*

While online experimental paradigms provide researchers with many benefits to data collection, including access to large-scale populations, several disadvantages do exist. One important factor to consider is the lack of control that experimenters have over the environment in which the participant completes the experiment. This can lead to poor performances on tasks due to a lack of attention, a poor understanding of the task requirements, and/or differences in mental states for example, inebriation during testing (Dandurand et al., 2008). As such, it was imperative that this study spent time on the development of a set of exclusion criteria that properly represented individuals who were not partaking in the experiment as needed, but that did not exclude individuals who were participating properly, but perhaps had chosen a poor strategy to complete the task.

As such, built into the task are a set of metrics that can be used to identify individuals this category. The exclusion metrics centre around response time for example, regularly completing trials in under 1000m/s, as well as how the participant was interacting with the stimuli available to them i.e., the rover, and the beam attached to the rover. For example, it was possible to infer that the individual may not have been properly paying attention if their data displayed a distinct lack of movement across many trials. Intial metrics used to assess spamming behaviour were:

1. The time taken to complete the trial i.e., less than 1000ms
2. Lack of movement for the rover
3. Lack of movement for the beam
4. Lack of movement for the beam and rover combined

Given our interest in behavioural strategies for game play, and the fact that for example, non-movement could indeed be a strategy for some individuals, a trial-wise percentage was taken for each criterion. Trial-wise percentage cut off points were tested against performance outcomes in the task. Investigation was carried out to assess whether individuals displaying these behaviours regularly were also performing poorly on the task in terms of overall score.

#### *3.1.4.3 Analysis of basic metrics*

Analysis was carried out to determine whether the metrics used in the space task in fact captured intended aspects of behaviour (full scripts, please see here). To achieve this, the positioning of the rover on a trial wise basis was mapped onto the underlying contingencies, with the expectation that the rover positioning would mirror them. Similarly, the beam metrics were

assessed in relation to the underlying contingencies, and specifically the standard deviation of the underlying probability distribution. It was expected that the beam width would track the underlying variance i.e., when exposed to a wide distribution, a wide beam would be used on average. This was tested using a linear mixed effects model with random effects of participant and counterbalancing condition nested in block, and fixed effects of noise condition (high or low) and starting standard deviation (high or low). The relationship between the rover positioning and the cue, i.e., input A, for each trial was also assessed given the presence of two pieces of information per trial.

To assess whether this task was able to replicate the original task it was adapted from, several hypotheses were tested. Firstly, to understand whether the noise impacted the relationship between the cue and the estimate of the mean, a correlation analysis was completed. Secondly, the speed with which individuals appeared to acquire the mean was tested by investigating the size and trajectories of performance errors at mean change point trials and beyond. To understand whether the noise impacts the individuals estimate of the mean in the way we would expect i.e., it should be harder to estimate the mean in conditions of high noise, the relationship between noise (high and low), and participants average performance errors across those conditions was compared. Relatedly, as found in Berniker et al., (2010), participants were also expected to rely more heavily on the cue information during high noise conditions. This was tested by plotting the relationship between participant rover position and the cue, under conditions on high and low noise.

### *3.2 Results*

### *3.2.1 Exclusions*

Figure 3.1 shows the difference in overall performance in the task (score), when participants displayed all four exclusion criteria, in at least 50% of their trials. Here we can see that aside from attention checks (indicating failed attention check status for at least 2 checks across the experiment as a whole), all other criteria at this threshold appear to capture some difference in overall scores, with those committing the behaviours in over 50% of trials peaking around a score of zero. Specifically, we see that for example, a lack of rover and beam movement in at least 50% of trials least to a higher proportion of low scores for these individuals. This contrasts with participants that did not fall into this category, where we see a wider distribution of overall scores.

The differences between individuals paying attention, but still performing poorly as indicated by score, and those performing poorly due to poor attention, is a challenge to accurately measure. One route to understanding these differences was to set the thresholds for these behaviours at different intensities (see Figure 3.2 A-C). Shows an example of this using movement versus a lack of movement in both the rover and beam on any given trial. Plots illustrate the differences in scores between movers and non-movers when thresholds are set at strict (10% of trials), medium (50% of trials), and lose (90% of trials).

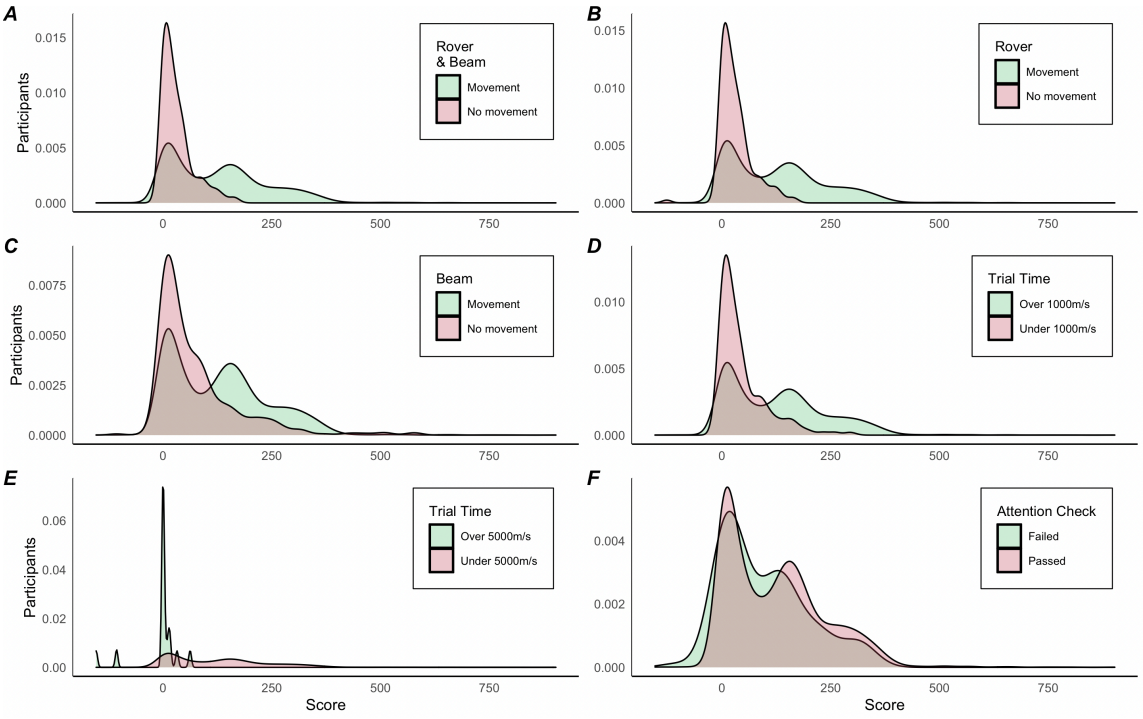


**Figure 3.1** *A-F: Figures showing scores between groups of people that displayed specific behaviours in at least 50% of trials, and those that did not. Plot A: density of participants that did and did not display movement of the beam and rover in at least 50% of trials; Plot B: density of participants that did and did not display movement of the rover in at least 50% of trials; Plot C: density of participants that did and did not display movement of beam the in at least 50% of trials; Plot D: density of participants that did and did not complete at least 50% of trials in less than 1000 m/s in at least 50% of trials; Plot E: density of participants that did and did not complete at least 50% of trials in over 5000 m/s in at least 50% of trials; Plot F: showing the density of scores of those who failed attention checks, and those that did not.*

We see that a strict (10%) threshold increases the amount of overlap between movers and non-movers, with non-movers also showing a wider distribution of overall scores. This indicates that this threshold may be at risk of misidentifying individuals who are not moving for strategic reasons, rather than due to poor attention. One the other hand, we can also see that non-movers

in 50% of trials show a large peak at zero, over and above the expected bimodal peak. This indicates that this threshold may be more appropriate for identifying individuals spamming the task intentionally and/or who are not paying attention.

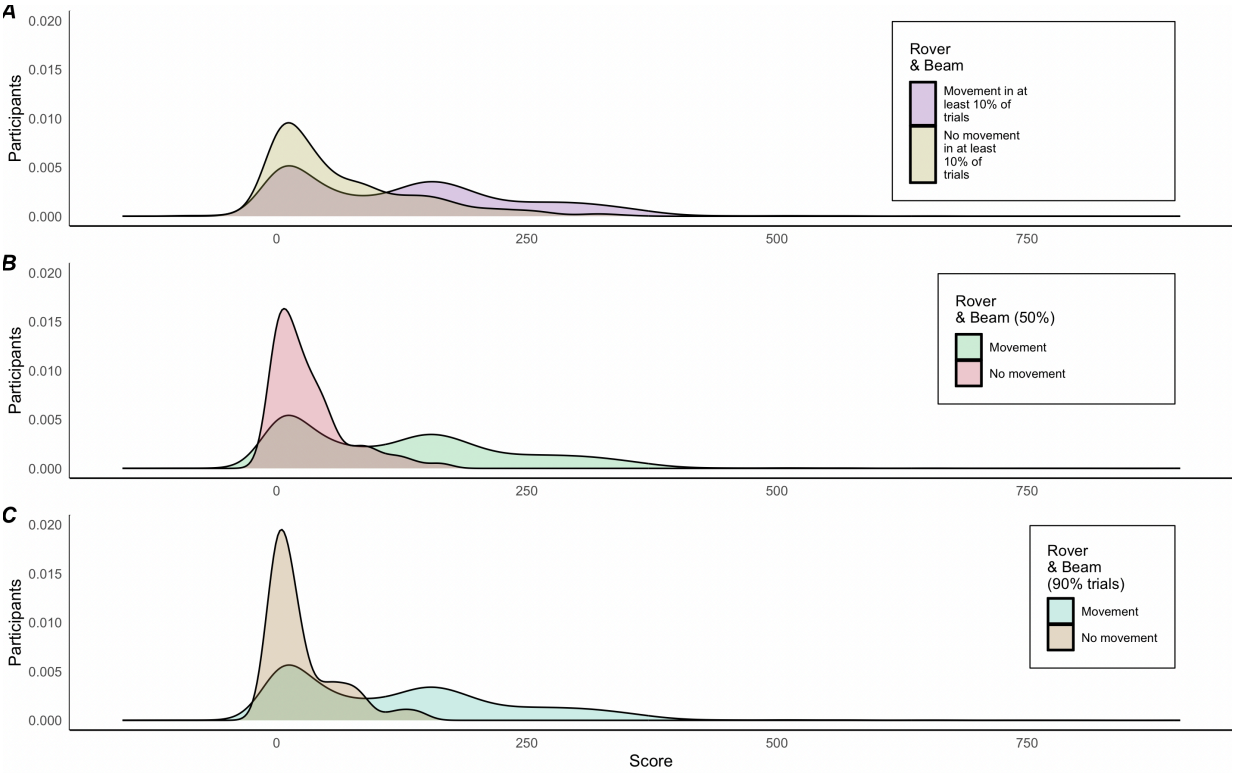


**Figure 3.2** *Showing density of participants that fulfilled exclusion criteria relating to a lack of movement for the beam and rover stimuli, and those that did not, set at different thresholds (10%, 50%, 90%), against score from the space task. Plot A. showing participants that did not meet exclusion criteria for a lack of movement on the rover and beam in 10% of trials (beige) and those that did not (purple). This is repeated in plot B, but the threshold is set at 90% of trials. Here, those that would be excluded at this threshold are in pink, and those that would not are in green. Finally, Plot C has set the threshold at 90%. Here, those that would be excluded are in brown, whereas those that would not are in turquoise.*

The cumulative number of exclusions based on the different exclusion criteria thresholds is shown in Table 3-2. Criteria can be judged on how well they cumulatively represented the individuals potentially not paying attention. For example, if the majority of the individuals not moving the rover or the beam in 50% of their trials also completed the 50% of their trials in less than 1000ms, then it is more likely that this group is displaying poor levels of attention, rather than adopting behaviours as a strategy for the task. In other words, it is sensible to predict a relationship between those with a lack of movement and those that complete many trials in under 1000ms, as it can be hypothesised that a strategy to not move either the beam or the rover would require at least some degree of thought, and therefore time.

Table 3-2 shows that while the "lose" and "medium" exclusion conditions appear to capture the majority of "undertimers" i.e., those that complete trials in under 1000m/s, within the non-movers for the beam and the rover criteria, the "strict" exclusion criteria identifies many more "undertimers" (n=96) additional to the non-movers for the beam and rover. This may suggest that the strict criteria threshold is not only capturing all of the incidents of individuals playing quickly and not moving the beam and rover, but also incidents of trials where individuals are moving the apparatus of the task but are playing quickly. Given these findings, a threshold of 50% was set for this dataset. Given the large number of participants excluded using these criteria, several changes were made to version 2 of the Space Task, outlined in the document below.

**Table 3-2** *Showing exclusions given differing exclusion criteria and thresholds.*

| Exclusion Condition | Criteria | Threshold | Cumulative n reduction |
|---|---|---|---|
| **Lose (90%)** | Repeats/incomplete | 1% | 22 |
| | Beam & rover | 90% | +4 |
| | Undertime | 90% | +1 |
| | Attention check fail | 2 | +16 |

| | | | |
|---|---|---|---|
| | Overtime | 90% | +0 |
| | **total** | na | **43 (8%)** |
| **Medium (50%)** | Repeats/incomplete | 1% | 22 |
| | Beam & rover | 50% | +23 |
| | Undertime | 50% | +5 |
| | Attention check fail | 2 | +15 |
| | Overtime | 50% | +2 |
| | **total** | na | **67 (13%)** |
| **Strict (10%)** | Repeats/incomplete | 1% | 22 |
| | Beam & rover | 10% | +69 |
| | Undertime | 10% | +96 |
| | Attention check fail | 2 | +9 |
| | Overtime | 10% | +24 |
| | **total** | na | **220 (43%)** |

### *3.2.2 Use of task stimuli: rover and beam*

Firstly, it appears that players' rover positions are a good reflection of the underlying mean, when calculated as a cumulative mean across a coarseness of three trials (Figure 3.3 plot A). Figure 3.3 Plot A shows that participant rover position (grey line) closely mimics the cumulative means at a coarseness of as little as three trials (orange line). Beam widths were also shown to mimic the underlying noise of the distributions (in this case either high or low), albeit less closely than the rover/mean relationship. Figure 3.3 Plot B shows the average beam width across the whole task alongside cumulative noise estimation across a coarseness of 5 (yellow), and 15 (red) trials. The plot background is shaded in green and purple to represent conditions of high and low noise and it is possible to see average beam widths rising and falling in line with these noise conditions. Additionally, using a linear mixed effects model with random effects of participant and counterbalancing condition nested in block, and fixed effects of noise condition (high or low) and starting standard deviation (high or low), beam widths averaged across noise conditions are significantly higher in the high noise conditions compared to the low ($\beta$(SE) = -0.01(0.01), p = .001; Figure 3.3; plot C).

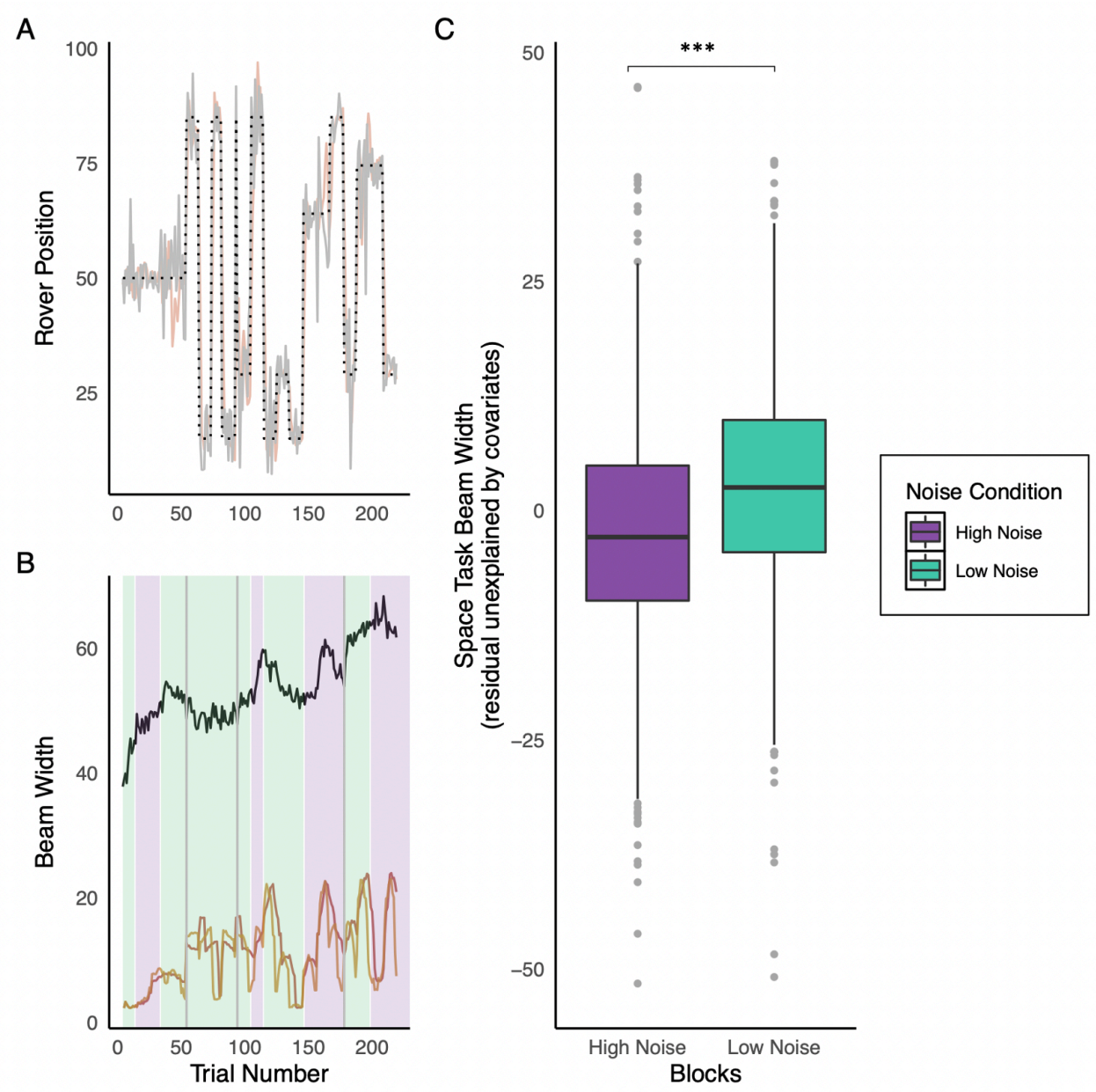


**Figure 3.3** *Plot A. shows the average rover position for each trial, across all participants in grey; the cumulative mean, using a rolling calculation across three inputs is shown in orange. The dotted line is the actual mean of the underlying distribution.* **Figure 3.3B.** *shows the average beam width for each trial, across all participants (black). The background is shaded in purple and green to represent high and low noise conditions respectively. The yellow and red lines depict the cumulative standard deviation estimate given differing levels of coarseness, specifically over5 trials (yellow), and 15 trials (red).* **Figure 3.3C.** *shows the residual beam width variance,*

*unexplained by covariates, compared between high and low noise conditions across the whole game.*

### *3.2.3 Comparison on input A (cue) and input B (outcome)*

Given the presence of multiple inputs (input A and input B) per trial, it was also important to investigate whether players were preferentially attending to one input over the other, on any given trial. Figure 3.4 shows that while both inputs show a strong correlation to players rover positions, input A (cue) (gold line) i.e., the first piece of junk they see on a given trial, is a near perfect correlation ($r(97408) = .94, p < .001$), and is a stronger relationship than input B (in red) ($r(96975) = .75, p < .001$) from the previous trial. This indicates an issue for intended functionality in gameplay as it may suggest that players overly rely on the novel information (input A) when the intention is for players to integrate information across inputs. A focus on input A on every trial changes task behaviour towards more of a matching style, i.e., rather than attempt to estimate to unseen mean, participants instead they place the rover in a similar position to input

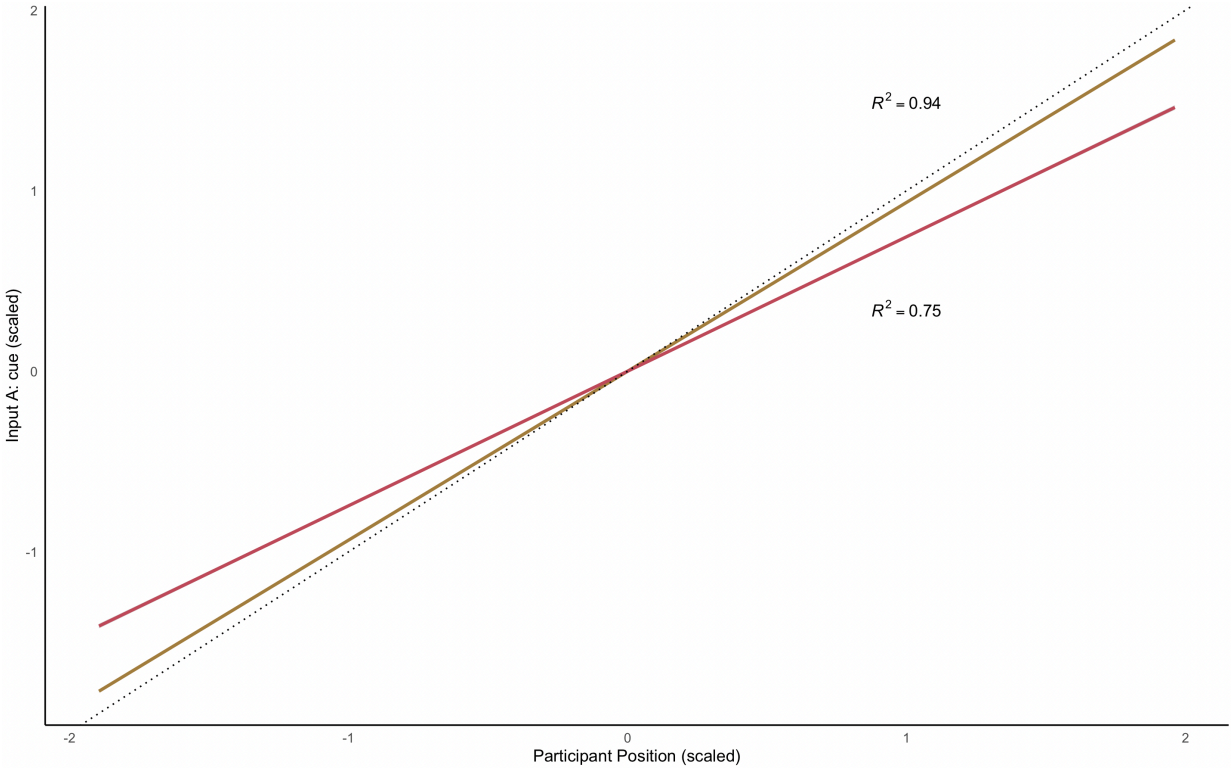


**Figure 3.4** *shows the relationship between the participants rover positions and the inputs (input A i.e., the cue – in gold, input B in red. The dotted line represents perfect matching of the input A (the cue) The correlation between the participants rover positions and input A i.e., the cue (r=0.94), and input B i.e., the result (r=0.75).*

### *3.2.4 Validation of task in line with original task (Berniker et al., 2010)*

Version 1 of the space task was able to partially replicate the finding that individuals acquire the mean. This was shown via rover positioning reflecting the underlying mean (Figure 3.3 plot A). However, since participants tended more towards the input A (cue), leading to less clear performance error metrics i.e., distance between the estimate and the mean, we were unable to show that the performance error i.e., the participants estimate of the mean reduces rapidly (Fig 3.6). Figure 3.5 shows that there does not appear to be a spike in PE at or after a mean change point, as expected. Authors suggest that the structure of inputs in the task i.e., input A - make

estimate - input B – input A – make estimate etc., may be encouraging participants to preferentially use the novel information (input A).

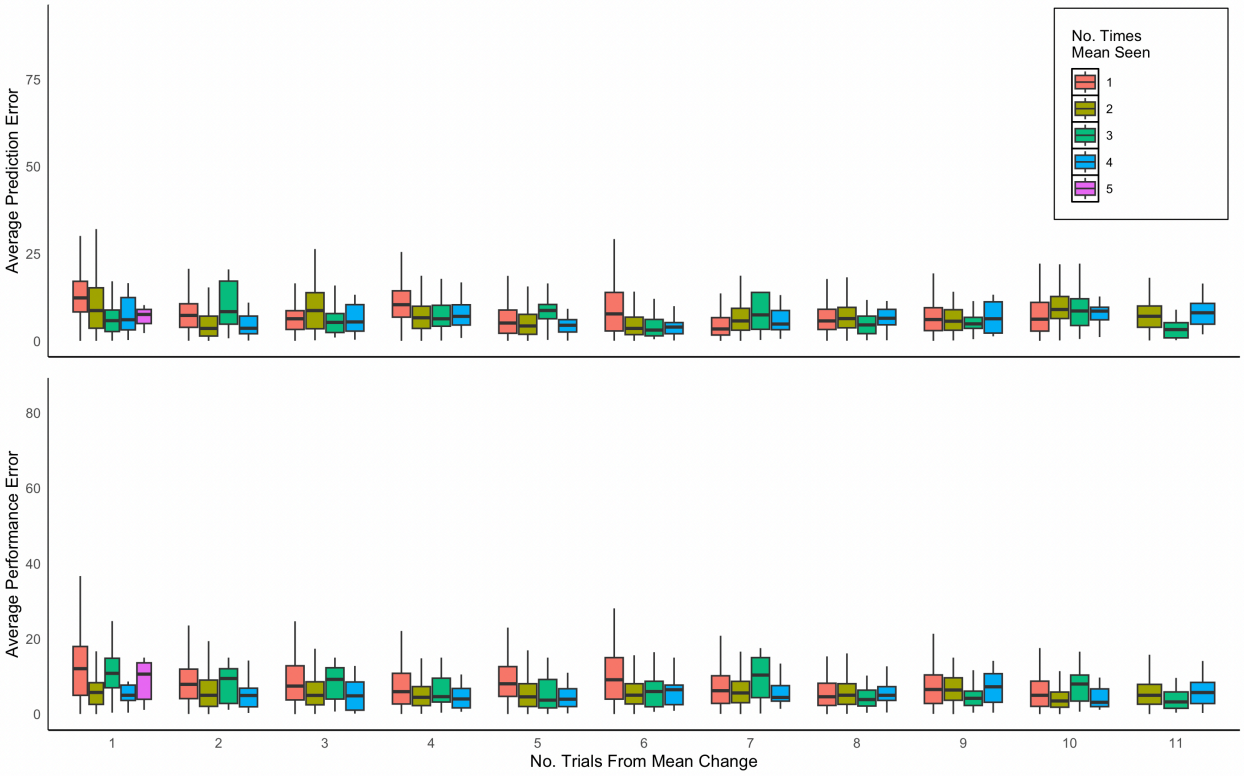


**Figure 3.5** *shows the average prediction error (Fig A) or performance error (Fig B) during block four (volatility only), at trials 1:11 after a mean change point. Colours depict the number of times that the mean has been seen - for example the same mean may have been seen twice, and therefore may have a different impact on the errors.*

Version 1 of the space task was able to replicate the Berniker et al., (2010) finding that as hypothesised, reliance on a cue i.e., input A, is increased during periods of high variance (or noise), ($r(9018) = .63$, $p < .001$) shown using the purple line in Figure 3.6 Plot A. Whereas participants' estimates (rover positions) are closer to the mean of the distribution when the variance is smaller (turquoise) ($r(9018) = .28$, $p < .001$). Secondly, the distance between the mean

of the underlying distribution and the individuals' estimate (i.e., the performance error) was found show a higher degree of error during conditions of larger variance, compared to smaller variances, indicating that uncertainty in the estimate of the mean increases when the variance is increased. A linear mixed effects model was used to test this relationship. The model included random effects of participant and counterbalancing condition nested in block, and fixed effects of noise condition (high or low) and starting standard deviation (high or low). Performance error was averaged across noise conditions and was found to be significantly higher in the high noise conditions compared to the low ($\beta(SE) = 4.91(0.10)$, $p < .001$; Figure 3.6B).

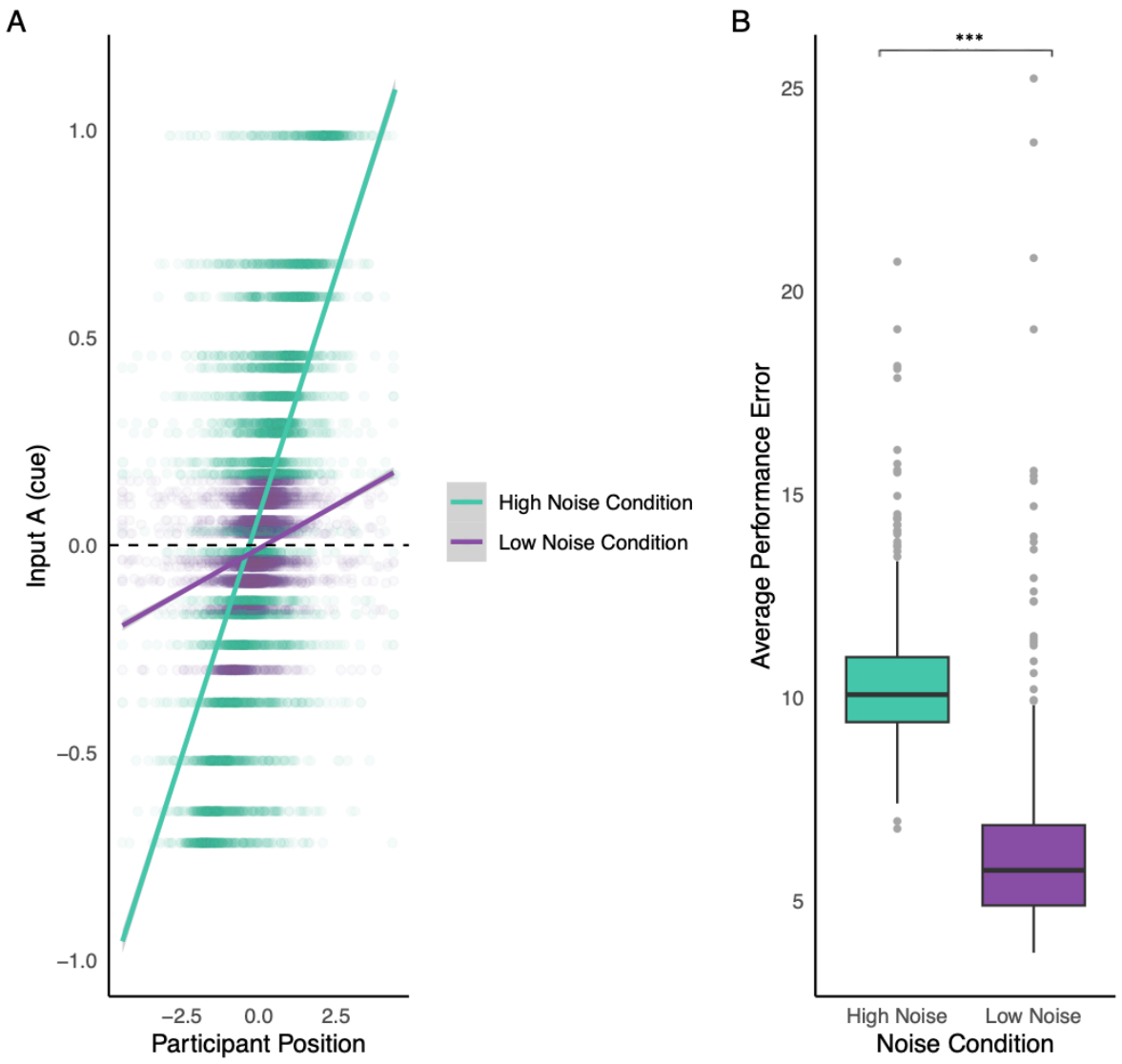


**Figure 3.6 Plot A.** *Showing the relationship between the cue (input A) and the location that participants placed their rover i.e., participant position, during conditions of high (green line) and low noise (purple line). Data is from block 3 only, where noise is manipulated in isolation, and the mean is stable across. A black dashed line indicates the position of the mean.* ***Plot B****. Showing performance errors averaged across noise conditions (high: green; and low: purple) across the entire task. As expected average performance error is significantly higher in conditions of high noise, as compared to low noise (β(SE) = 4.91(0.10), p < .001).*

## *3.3 Discussion of findings: Version 1*

The aim of this experiment was to test a novel learning task against several predetermined hypotheses relating to feasibility, functionality and sensitivity. Findings suggest that while the task could be improved in terms of its' suitability for an online format, it was able to show that participants displayed evidence of learning the underlying statistics of the task. Importantly, this finding is in the context of a shorter, and gamified version of the task (Berniker et al., 2010). The findings also showed that the task was able to replicate results from the original task, suggesting changes made to the novel task did not affect the sensitivity with which the task metrics could capture learning.

An important consideration to explore is the large number of individuals that were excluded from the study. While we were able to successfully identify useful and coherent exclusion criteria, this finding may indicate that the novel task may not be feasible in an online context. Primary reasons participants were excluded were i) a lack of engagement with the task stimuli (rover and beam), and ii) speed of responding (<1000m/s), over 50% of trials. Using a combination of anecdotal feedback from the participants, and behavioural attention strategies, several changes were made to the task in an attempt to reduce these behaviours. Firstly, the instructions for the task were simplified and the overall amount of explanation was reduced (see Appendix Table 3-4). Secondly, the trial structure was altered in several ways i) trials had to be completed in 5000m/s or less, otherwise participants were redirected back to the start of the trial, without receiving the information again – to avoid repeated exposure; and ii) for each trial participants would have to turn the beam "on", shown visually as a change from red to green, before they were able to submit their estimate (please Figure 3.7 for an illustration). This prevented participants being able to simply click through the trials. A bonus payment structure was also introduced as a means to

encourage engagement, and in line with the reinforcement learning paradigm. As such, participants could win an additional payment for every 250 points that they achieved. This was displayed in the corner of the screen and in the inter-block screens. As points could be lost in the final block, participants were at risk of losing any bonuses they may have made.

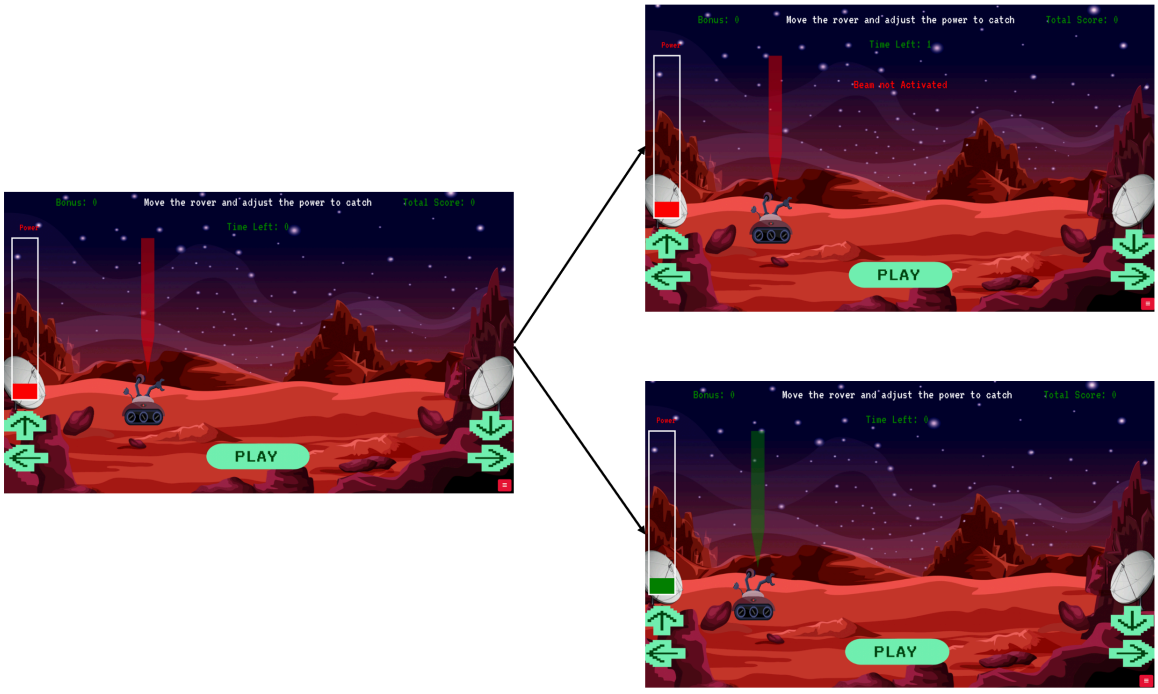


**Figure 3.7** *Showing that in version 2 of the task, the beam now has to be turned "on" to play the trial. Here we see the instruction slide informing participant to move the rover and adjust the power/beam to play. If the participant attempted to play the trial without turning the beam on, then a message would appear that reminded participants to turn the beam on. This would change the beam colour from red to green, as illustrated.*

Another issue raised via these findings related to the presentation of the inputs. Version 1 of the task includes two pieces of information per trial (Input A/the cue; and input B). Participants were instructed to make their estimate in between inputs A and B. They would then receive input A for

the next trial, and so on (see Figure 3.8). While this structure was in line with the original task, and also a Bayesian task structure (Diaconescu et al., 2014; Jacobs & Kruschke, 2011; Payzan-Lenestour & Bossaerts, 2011), it was found that this presentation impacted both how participants were playing the game, and as a result, how some metrics could be calculated. Specifically, participants were found to be overly guided by the input A/the cue, i.e., the last piece of information they saw, rather than predicting the location of the next piece of junk by placing their estimate as close to the unknown mean of the distribution as possible – as would be most sensible strategically. The secondary impact of this finding was that prediction errors – an important metric used to capture trial wise learning, was potentially compromised. This was because the calculation for prediction error is the *rover position – input B position* i.e., how far their estimate was from the actual observation. The fact that participants tended to under rely on input B in their ongoing estimates was therefore somewhat problematic. To resolve this issue, the presentation of inputs was altered so that individuals only received one piece of information per trial before making their prediction. While participants would still go on to then receive input B i.e., information to confirm or disconfirm the accuracy of their estimate, this input would also represent the cue for the preceding trial (see Figure 3.8). All of these changes were made within Version 2 of the space task and tested in a separate large online study, described in detail below.

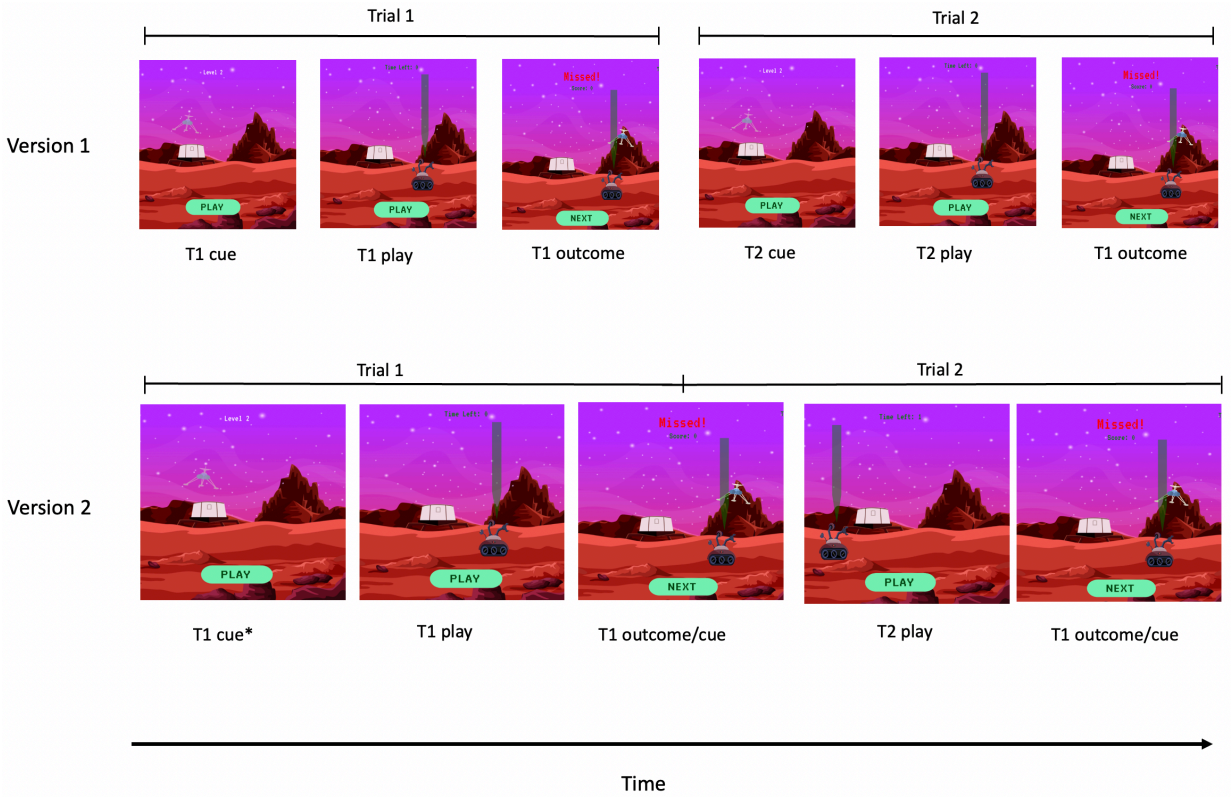


**Figure 3.8** *Showing the structure of trial inputs between versions 1 and 2 of the task. In version 2, the outcome was also made to be the cue/novel information for the next trial. *for version 2, the "cue" was only presented at the start of every block.*

# 4 Part B: validation of a novel learning task -Version 2

## *4.1 Methods*

### *4.1.1 Participants*

Participants for this study were selected from the general population for high and low traits of schizotypy. While this is irrelevant for this analysis, the process is outlined below for clarity. One thousand participants were collected using an online platform Qualtrics (*see* qualtrics.com). Participants completed the Schizotypal Personality Questionnaire (SPQ)

questionnaire and provided demographic information. The top and bottom 10% of scorers (n=164; top: n=82; bottom: n=82) were selected and asked to take part in further cognitive testing on the online platform Gorilla (*see* gorilla.ac). Participants were eligible to take part in the study if they resided in the UK currently, spoke English as their first language, were aged between 18 and 40yrs, and had no history of serious head injury or neurological disorder. Data was additionally subject to quality control screening, where a participant is deemed to not be attending to the task in the expected or necessary way.

Task based exclusion criteria remain the same as part A and are list below:

1. The time taken to complete the trial i.e., less than 1000ms
2. Lack of movement for the rover
3. Lack of movement for the beam
4. Lack of movement for the beam and rover combined

### *4.1.2 Procedure*

Participants were provided a webpage link to an online testing platform "Gorilla" (*see* gorilla.sc). Participants could use their own internet-accessible devices including smartphones, or computers. Before proceeding with the study, participants provided informed consent and completed a baseline demographic survey. On completion of the study, participants were paid £5 for their time and could earn additional payments of up to £1.50 during the task in performance-based bonuses.

### *4.1.3 Materials*

#### *4.1.3.1 Space Task-Version 2*

Participants performed the same basic game-based prediction task as described in part 1, where the overall aim was to collect enough space junk to build a rocket and escape a planet (see Figure 3.9). To play the task, please click here. Changes to this version of the task included:

- Simplification and shortening of the instructions (see Appendix Table 3-4 for full details of the differences in instructions between version 1 and 2).
- Participants were now required to turn the beam on before submitting their estimate.
- Bonus rewards were introduced. Every 250 points participants received an extra payment.
- The input schedule of the task was changed (see Fig. 9).
- Trials would terminate at the 5000m/s mark. If participants went over time a message would pop up on screen informing them of this. Participants would then have to make an estimate without any new information

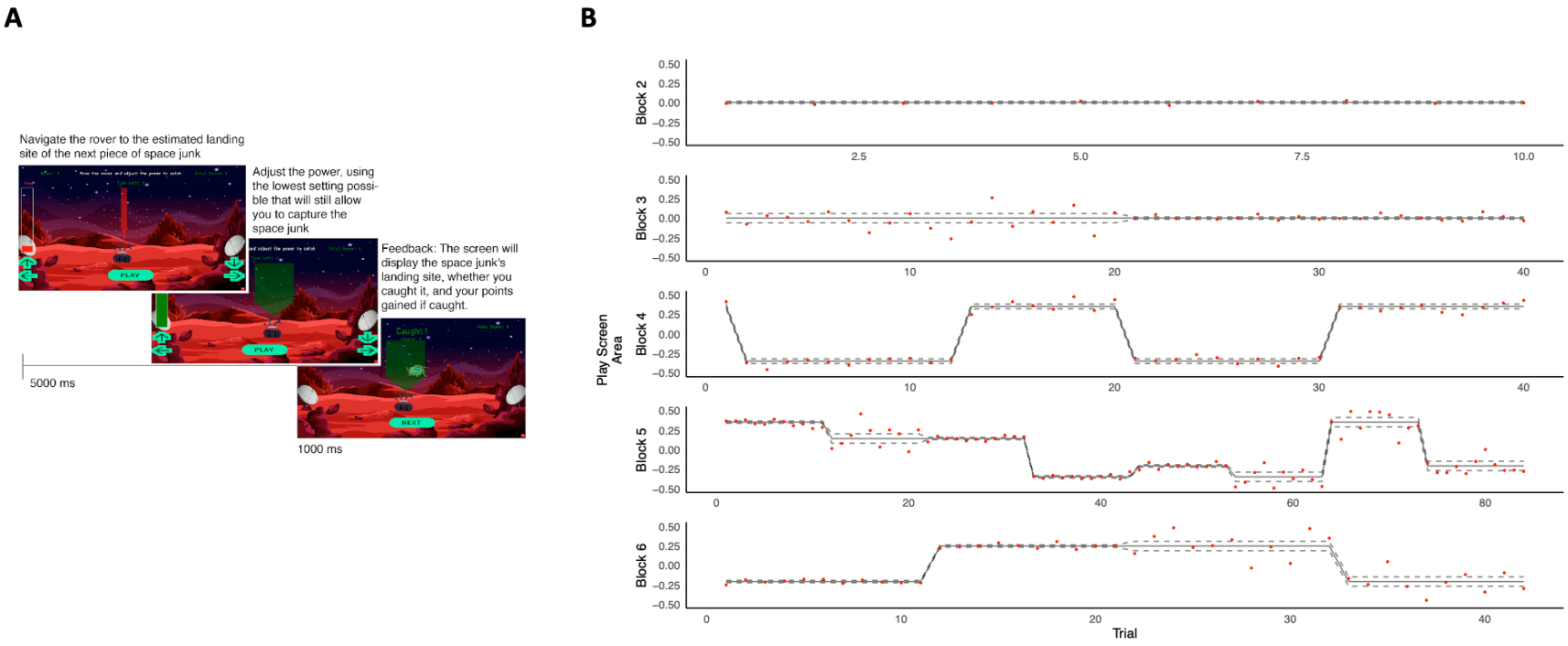


**Figure 3.9A**. *Showing trial structure. Here, once the participant is exposed to the cue for a maximum of 5000m/s, participants are then instructed to make an estimate of the mean, using rover positioning; and variance using manipulation of the beam width. Feedback i.e., another piece of space junk drawn from the same distribution, is then presented to the participant (1000m/s).* **Figure 3.9B.** *The black solid line shows the mean(s) used for each block (see Table 3.1 for further details), indicating both the stability of the mean over trials (x axis), and the location of the mean on the play screen area. The standard deviation used to simulate noise in the space junk locations is shown using the black dashed line (see Table 3.1 for further details). Here, the width of the dashed line around the mean indicates both the width*

*of the SD used, and the area of the play screen available for space junk locations to be drawn from. The red dots show the actual space junk positions that the participants were exposed to, in accordance with the underlying probability distributions.*

### *4.1.3 Analysis*

#### *4.1.3.1 Aims and hypotheses (related to specific outcome measures)*

1. Repeated analysis of the selected exclusion criteria developed in part A of this chapter. Specifically, to understand whether the criteria continue to identify the relevant people the exclusion criteria will be reapplied.
2. Validation of metrics included in the Space task:
    a. Testing the reliability of the finding that the rover positioning represents a trial-wise ongoing estimate of the underlying mean of the distribution the space junk it is drawn from.
    b. Testing the reliability of the finding that the variance of the underlying distribution will be tracked by participants, shown via use of the metric: beam width. Specifically, whether we again see larger beam widths used during periods of high variance.
    c. Given the new structure of the task, we will test whether prediction errors and performance errors will now increase at mean change points and decrease rapidly, as expected.
    d. In version one of the task, participants appeared to show a preference to match their estimate to the cue position they had just seen, rather than seek the unknown underlying mean. To understand whether Version 2 rectifies this, we will also directly compare the versions on the relationship between i) the distance between the cue and the mean, and ii) the distance between the rover position and the mean. We hypothesise that version two will show a weaker relationship between these two variables than version one.

3. Task validation in line with a previously published task (Berniker et al., 2010):
    a. Repeat of the analysis regarding rover positioning. It is expected that individuals will display a stronger relationship between their positioning of the rover and the cue input during periods of high noise.
    b. As with version 1, it is expected that version 2 will also show that individuals acquire the mean of the underlying distribution rapidly (within around 3-5 trials), shown via strong relationship between the estimate (rover position) and the underlying mean.
    c. As with version 1, it is expected that the error between the mean of the underlying distribution and the participants estimate (performance error) will be larger under conditions of high variance, compared to low.
4. Learning rates
    a. Additional exploratory analysis will be carried out into the calculation of learning rates and their relationship to change points and noise conditions.

#### *4.1.3.2 Exclusion criteria*

The exclusion criteria developed in part A will be re-applied to this dataset, using the same approach.

#### *4.1.3.3 Analysis of basic metrics*

Analysis into the construct validity of the primary metrics in the task was replicated. To achieve this, the positioning of the rover on a trial wise basis was mapped onto the underlying contingencies, with the expectation that the rover positioning would follow the underlying

contingencies. Similarly, the beam metrics was assessed in relation to the underlying contingencies, and specifically the standard deviation of the underlying probability distribution. It was expected that the beam width would track the underlying variance i.e., when exposed to a wide distribution, a wide beam would be used on average. This was tested using a linear mixed effects model with random effects of participant and counterbalancing condition nested in block, and fixed effects of noise condition (high or low) and starting standard deviation (high or low). The relationship between the rover positioning and the cue, i.e., input A, for each trial was also assessed given the presence of two pieces of information per trial.

To assess whether the participants might be over relying on the novel information received in the form of the cue, version 1 and version 2 were compared. Here, the relationship between i) the distance between the cue and the mean, and ii) the distance between the rover position and the mean on each trial was compared. It was expected that the new structure of the task would encourage participants to integrate learning across trials, and as such, participants would have a less strong relationship between these two variables. Analysis will then be carried out into the prediction and performance errors, specifically looking at whether increases are seen at change points.

Analysis was repeated, to establish whether Version 2 of the Space Task was also able to recapitulate findings from Berniker et al., (2010). Firstly, to understand whether the noise impacted the relationship between the cue and the estimate of the mean, a correlation analysis was completed. Secondly, the speed with which individuals appeared to acquire the mean was tested by investigating the size and trajectories of performance errors at mean change point trials and beyond. To understand whether the noise impacts the individuals estimate of the mean in the way we would expect i.e., it should be harder to estimate the mean in conditions of high noise,

the relationship between noise (high and low), and participants average performance errors across those conditions will be compared. This was tested using a linear mixed effects model with random effects of participant and counterbalancing condition nested in block, and fixed effects of noise condition (high or low) and starting standard deviation (high or low). The relationship between the rover positioning and the cue, i.e., input A, for each trial was also assessed given the presence of two pieces of information per trial. Relatedly, as found in Berniker et al., (2010), participants will also be expected to rely more heavily of the cue (input A) information during high noise conditions. This will be tested by plotting the relationship between participant rover position and the cue, under conditions on high and low noise.

Analysis into learning rates was also carried out in version 2 of the space task. Learning rates (LRs) can be calculated in a variety of ways depending on the which theory and associated modelling framework is used. For example, reinforcement learning models such as the Rescorla Wagner model have a constant learning rate where the reward value is updated iteratively as a function of the size of the PE, in response to a reward (Rescorla and Wagner, 1972). Or modelling approaches that use a dynamic learning rate, such as the Pearce Hall model that is design so LRs are highest when a stimulus is novel (Pearce and Pearce, 1980). While application of more sophisticated modelling approaches can be academically useful, it does increase the risks of incorrect applications/lack of procedures being followed (Katthagen et al., 2022a). As such, this task used directly measurable metrics to calculate trial wise LRs, replicating the equation for trial-wise learning rates used in a previously validated prediction task (Nassar et al., 2010; Nassar et al., 2020). Here trial-wise learning rates are calculated by dividing the rover update – i.e., the signed change in rover position from $trial_1$:$trial_2$ by the signed prediction error observed prior to that update.

## *4.2 Results*

### *4.2.1 Exclusions*

A total of eight individuals were excluded from Version 2 of the task, equating to 5% of the sample, when using the "strict" criteria. This is in comparison to Version 2 of the space task where 43% would have been removed, when using the same criteria. Version 2 appears to be more effective at sustaining the attention of players. For example, every participant moved the beam and rover, and completed their trial between 1000-5000m/s, in at least 50% of their trials, making this threshold redundant. Once the threshold for the movement and timing criteria's i.e., under 1000m/s, were set to a stricter level, at 10% of overall trials, we started to see some grouping of these individuals around the lower score (see Table 3-3).

**Table 3-3** *Showing cumulative exclusions of participants in SPQ data using strict criterion (n=164)*

| Exclusion Condition | Criteria | Threshold | Cumulative n reduction (%) |
|---|---|---|---|
| **Medium (50%)** | Repeats/incomplete | 1% | 4 |
| | Beam & rover | 10% | 0 |
| | Undertime | 10% | 0 |
| | Overtime | 10% | 0 |
| | **total** | na | **4 (2%)** |
| **Strict (10%)** | Repeats/incomplete | 1% | 4 |
| | Beam & rover | 10% | +2 |
| | Undertime | 10% | +2 |
| | Overtime | 10% | +0 |
| | **total** | na | **8 (5%)** |

*4.1.3.3 Construct validity*

Rover and beam metrics were again used appropriately. For example, **Figure *3.10***A. Shows that participants were successfully able to track the underlying mean of the task. Similarly, **Figure *3.10***B and Figure 3.10C shows that the beam width use increased during high noise ($\beta(SE) = 8.36(0.78)$, $p < .001$), and the average beam width corresponded with the underlying noise conditions. Figure Figure 3.10D and Figure 3.10E provides evidence that, compared to version 1, the altered structure for the task inputs in Version 2 reduced matching behaviour i.e., participant position was less strongly related to the cue (input A) in Version 2, compared to Version 1. This effect is also seen when looking by block. Here we continue to see a weaker relationship between the distance between the cue and mean, and the distance between the rover position and the mean. This reorganised structure of the task meant that PEs could be extracted. As expected, results here show larger PEs and performance errors at the mean change points. These increases then decay over the subsequent trials (Figure 3.11A and Figure 3.11B).

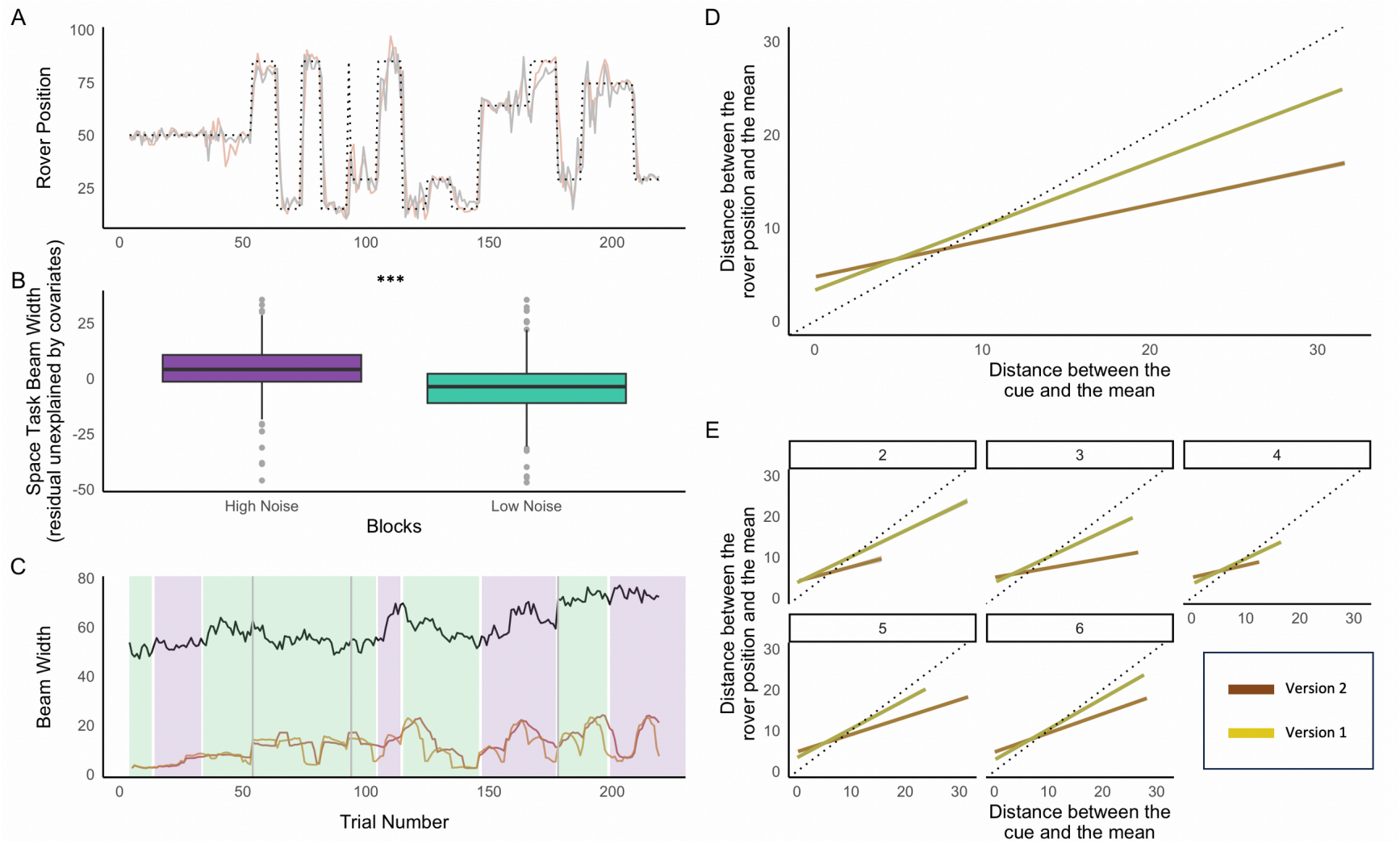


**Figure 3.10** *Plot A. shows the average rover position for each trial (n=219), across all participants (grey line); and the cumulative mean (using a rolling calculation across three inputs) is shown in orange. The dotted line is the actual mean of the underlying distribution.* ***Figure***

**3.10B.** *shows the residual beam width variance (beam width averaged across noise conditions), unexplained by covariates, compared between high and low noise conditions across the whole game.* **3.10 C.** *shows the average beam width for each trial, across all participants (black). The background is shaded in purple and green to represent high and low noise conditions respectively. The yellow and* orange *lines depict the cumulative standard deviation estimate given differing levels of coarseness, specifically over 5 trials (yellow), and 15 trials (red).* **3.10D.** *showing rover positioning from the mean, in response to cue inputs at varying distances from the mean. This is shown across version 1 (gold line), and version 2 (brown line) of the Space Task. The dotted line indicates total updating in line with the cue****;*** **3.10E.** *splits this plot into the different testing blocks, where we can see the effect remains the same.*

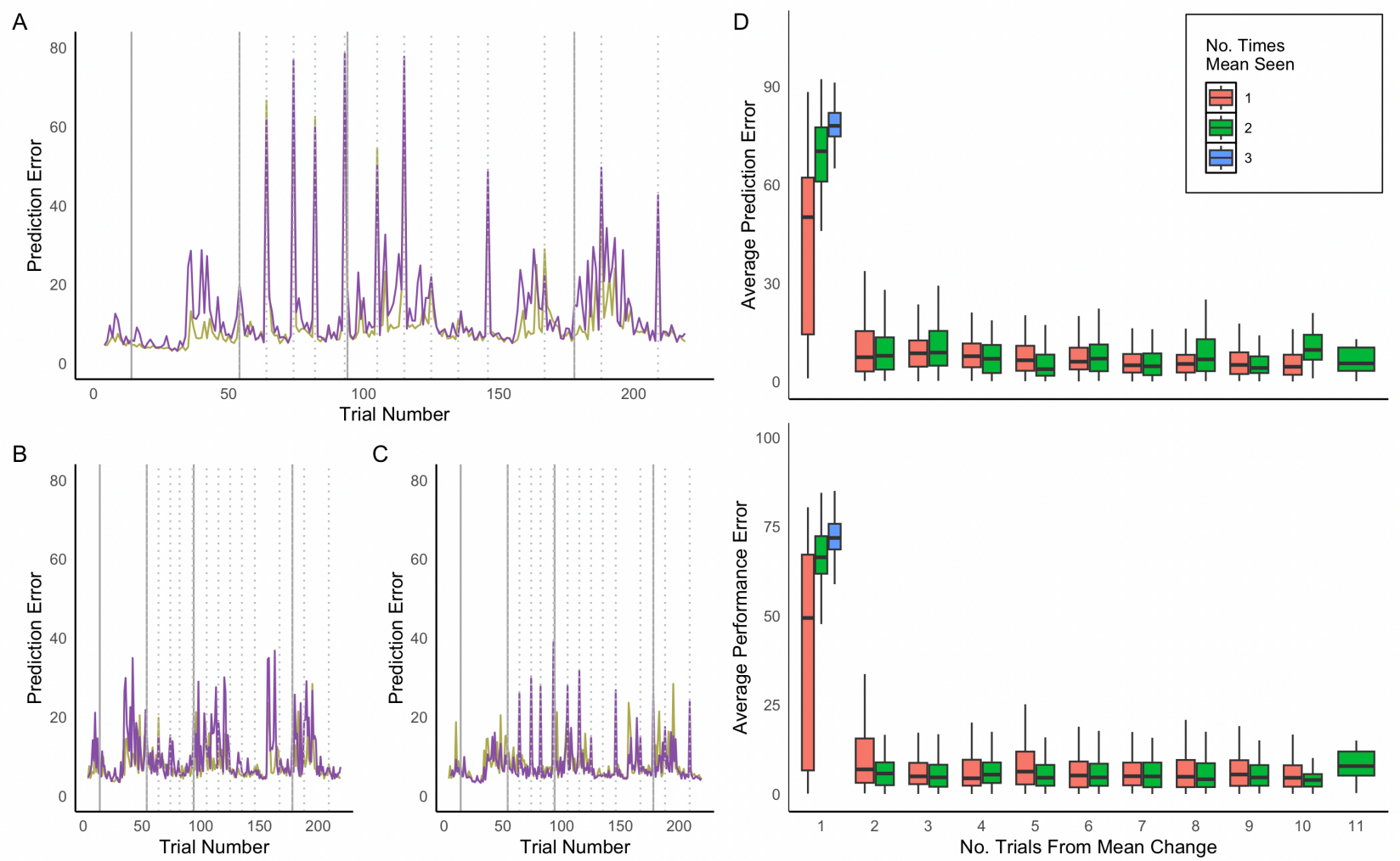


**Figure 3.11** *Plots showing prediction errors (purple), and performance errors (gold), at mean change points (dotted vertical lines). Grey vertical lines indicate blocks. The x axis shows trial numbers.* **3.12A** *uses data from Version 2 of the space task, where the prediction error is*

*calculated as the difference between the rover position and the following piece of junk seen by the participant. In version 2 of the task, the second observed junk input also acts as the cue for t+1.* **3.13B and C** *show the same plots for the Version 1 space task data.* **3.14B** *shows prediction error calculated using input B (Version 1 of the task used two pieces of information per trial).* **3.15C** *calculates the prediction error using a median value between input A (the cue) and input B.* **3.16D** *showing the PE and performance error averaged across mean change point trials (1) and post-mean change trials (2:11), in block four (high volatility, low noise) – indicated on the x axis. Colours indicate the number of times that the participant has been exposed to that mean.*

### *4.2.4 Validation of task in line with original task (Berniker et al., 2010)*

Version 2 of the space task was able to successfully replicate findings from the Berniker et al., (2010) task. Specifically, the mean appeared to be learnt in around three trials, shown via rapidly decreasing performance errors post mean change (Figure 3.11 plots A, D). As hypothesised, input A was more strongly related to participant position due increased during periods of high variance (or noise), shown using the purple line in Figure 3.17 Plot A ($r(2998) = .30$, $p < .001$). Whereas participants' estimates are closer to the mean of the distribution when the variance is smaller (turquoise) ($r(2998) = .09$, $p < .001$). Secondly, the error between the mean of the underlying distribution and the individuals' estimate (i.e., the performance error) showed a higher degree of error during conditions of larger variance, compared to smaller variances, indicating that uncertainty in the estimate of the mean increases when the variance is increased. Plot Figure 3.17B shows performance error across conditions of high and low variance and confirms that higher performance errors are noted during periods of high variance, compared to low noise ($\beta(SE) = 4.07(0.21)$, $p < .001$; Fig Figure 3.17B).

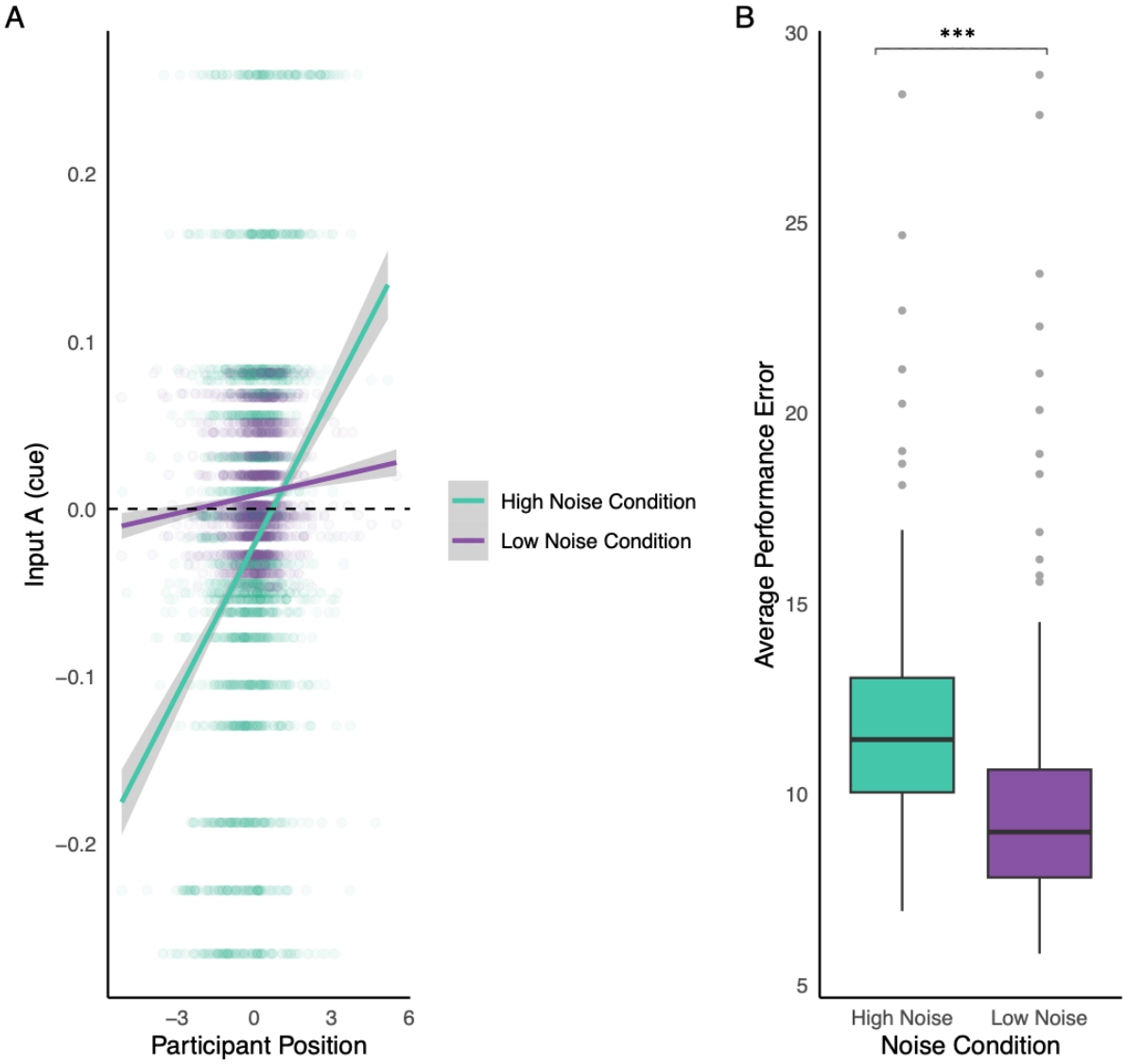


**Figure 3.17** **Plot A.** *Showing the relationship between the cue (input A) and the location that participants placed their rover i.e., participant position, during conditions of high (green line) and low noise (purple line). Data is from block 3 only, where noise is manipulated in isolation, and the mean is stable across. A black dashed line indicates the position of the mean.* ***Plot B****. Showing performance errors averaged across noise conditions (high: green; and low: purple) across the entire task. As expected average performance error is significantly higher in conditions of high noise, as compared to low noise( β(SE) = 4.07(0.21), p < .001).*

### *4.2.5 Learning rates*

Trial-wise learning rates are calculated by dividing the rover update – i.e., the signed change in rover position from $trial_1$:$trial_2$ , by the signed prediction error observed prior to that update. The downside to this approach was that the equation introduced erroneous learning rates due to the presence of very small prediction errors (Figure 3.18A). Several methods were used to overcome this issue. These included i) correcting the LRs i.e., forcing all erroneous learning rates over one to be categorised as one i.e., total updating, and all LRs under 0 to be categorised as zero – a method used by Nassar et al., (2010, 2021); and ii) excluding all LRs over and above zero and one. Figure 3.18 Plot A:C show results for LRs calculated using these two approaches, averaged across trials. From Figure 3.18 plot A-C, we can see that the extreme outliers are produced using the Nassar LR calculation. This occurs on trials where the PE is very small. The expected pattern of effects is more obvious when the corrected and excluded LRs are used, such as increases at mean change points.

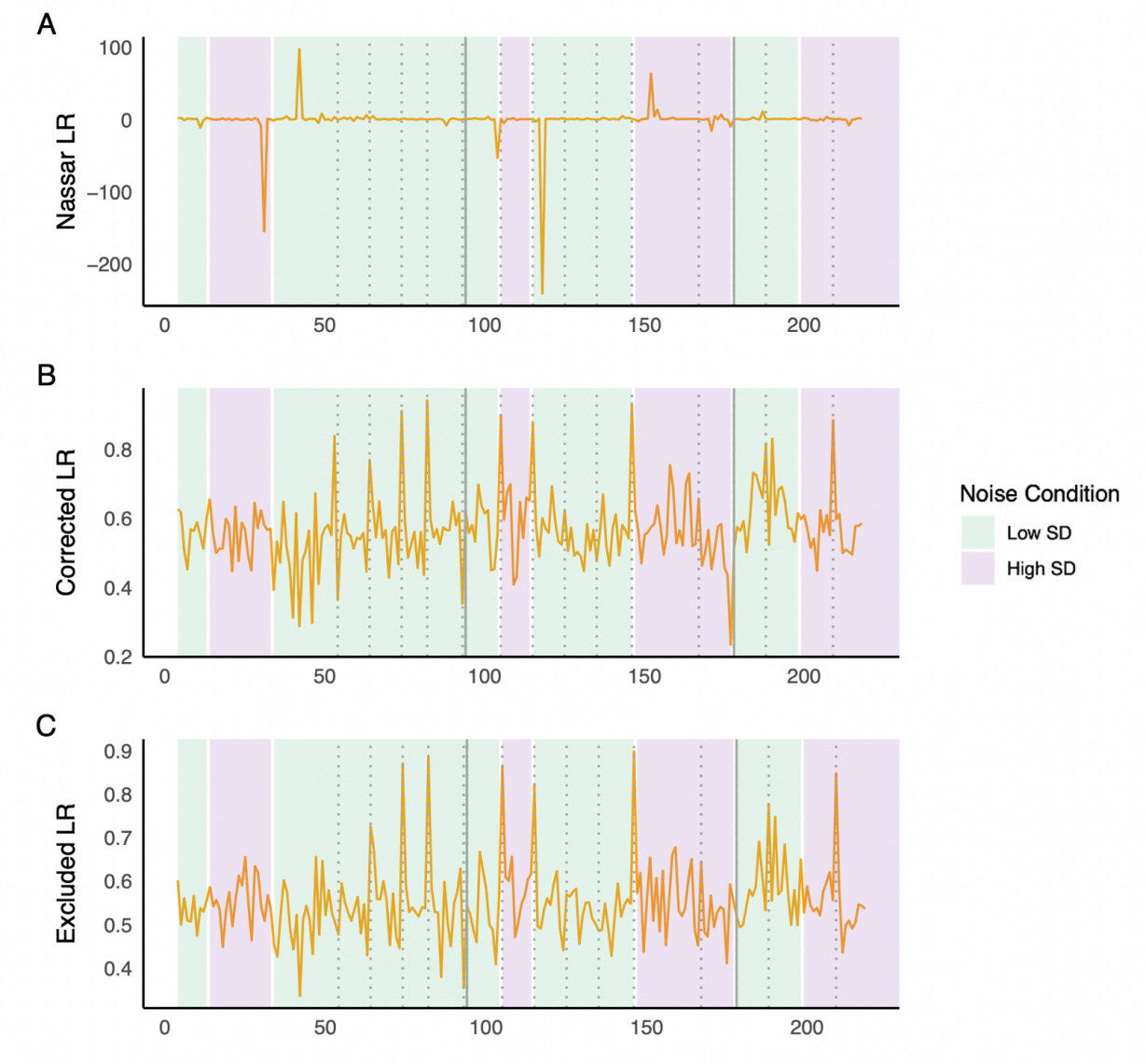


**Figure 3.18** *Showing LR averages for each trial across all participants. Dotted lines depict mean change points, solid grey lines indicate block* changes. **3.19*A*** *shows Nassar learning rates, which are calculated as the rover position change divided by the previous PE.* **3.20*B*** *shows corrected LRs, which are the Nassar LRs but with any LRs over 1 or under 0 groups at 1 or 0 accordingly.* **3.21*C*** *shows excluded LRs, which are the Nassar LRs but excluding the LRs over 1 and under 0. The background shading shows the noise conditions (high=purple; low=green).*

However, while we do see increases in learning rates at mean change points, as expected, we have lost some information during this process. For example, as the equation uses signed PE and position change, those "over updating" i.e., those over 1, are in fact trials where participants have placed their rover beyond the input (B), albeit in the correct direction. Whereas total updating i.e., a LR of 1 usually indicates exact placement of the rover onto the following input (B), in this case it is also capturing trials where people have "over updated". Additionally, constricting the data in such a way causes peaks to arise at no updating and total updating (0 and 1 LRs), obscuring effects and making further analysis difficult.

To further assess whether LRs increase at mean change points and decrease rapidly, as we would expect, and in line with PE and performance errors, Figure 3.22 Plots A and C show mean LRs at trials post-mean change. Here we see that when using corrected LRs, we are unable to see this pattern of effect. When looking at the distribution of LRs we (Figure 3.22B), we see that the distribution is highly skewed toward total and no updating. This is because we have constrained the erroneous LRs to 0 or 1 artificially changing the distribution. For excluded learning rates, although result in a loss of data, we do see a weak trend towards decreasing LRs after a mean change (Figure 3.22C) and looking at the distribution of LRs after a mean change, we see that the bias towards all or no updating is no longer apparent (fig. Figure 3.22D).

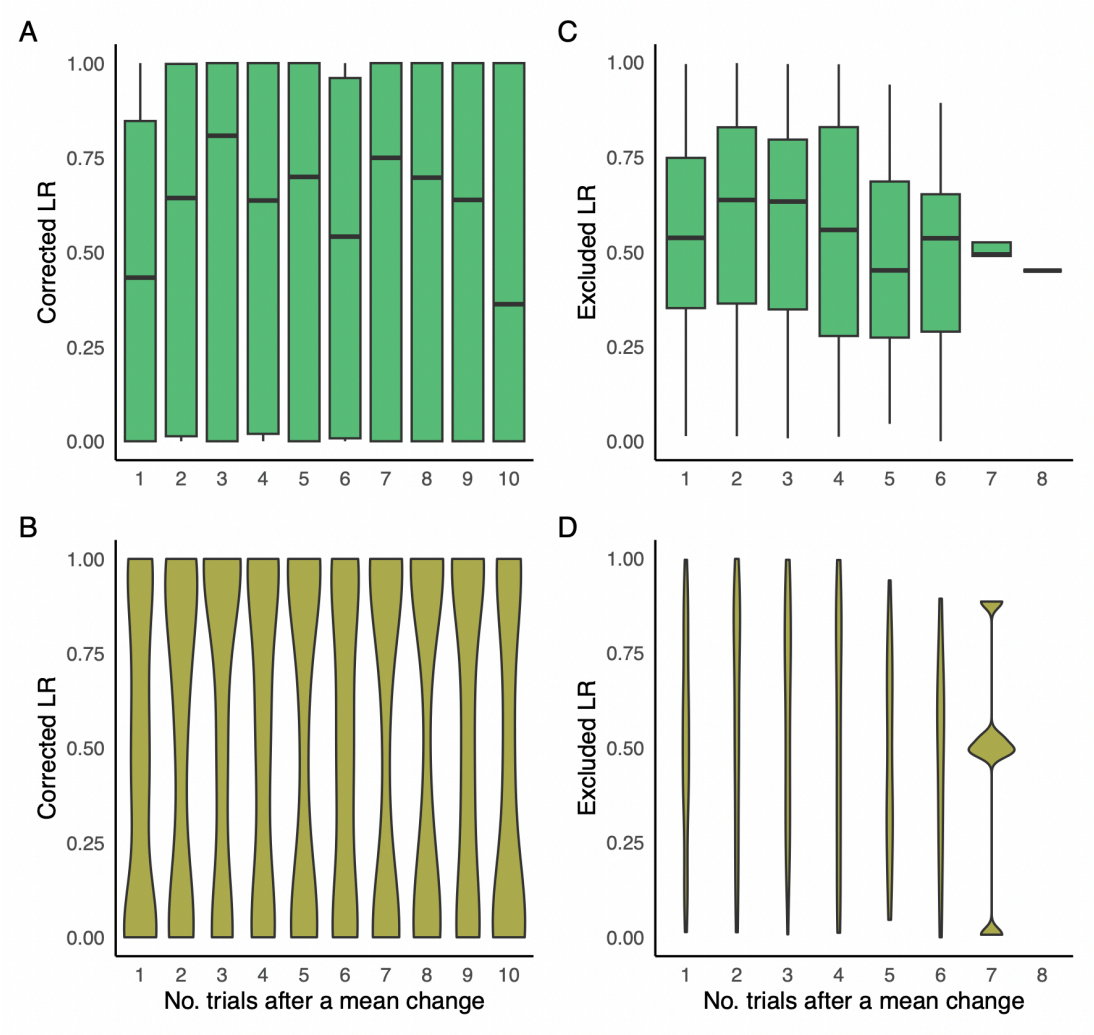


**Figure 3.22** *Plots A and C shows the corrected (i.e., Nassar et al., () learning rates, with all LRs outside of 0 and 1 grouped at 0 and 1 (plot A), and excluded LRs (i.e., as above but with LRs outside of 0 and 1 removed from the analysis), averaged over trials after at a mean change (1) and in the subsequent trials (2 onwards). Data from block four where volatility is manipulated in isolation.* ***3.23B and D*** *shows the distribution of LRs for these two types of LRs, using a violin plot, across trials where the mean changes (1), and in the subsequent trials after a mean change.*

# 5 Discussion

This study aimed to test and validate a novel learning task. As such the novel task was assessed in its' feasibility for online testing, its' construct validity and sensitivity to aspects of learning, and in its' ability to replicate previous findings (Berniker et al., 2010). To achieve this, two experiments were carried out. While Version 1 of the task was able to replicate findings from the original task, it failed at clearly showing construct validity in metrics such as prediction error. Authors suggest this was because of the structure in which inputs were presented on a trial-wise basis. Version 1 also failed to successfully show that the task was useful in an online context, shown via high exclusion rates. Changes made to Version 2 of the task included an alteration to the presentation structure of the inputs, as well as alterations to the design of the task to improve engagement and attention. According to our predetermined criteria, Version 2 of the task was successful in achieving the aims of the study. Namely, changes to the task drastically improved exclusion rates, and led to behaviours that indicated an integration information across trials, as opposed to matching the novel information. Both versions of the task were able to replicate findings from the original task.

While it was hoped that we would be able to establish trial wise learning rates from the data, the equation that was used for calculation led to erroneous learning rates (extreme outliers), that were problematic for data. This has been found across other studies analysis (Nassar et al., 2010, 2021a). Several methods were used to try to overcome this, however none were completely satisfactory for reasons such as loss of data, or data skew. One way to overcome this issue would be to use averaged learning rates. While this would lose information about trial-wise learning, it would be possible to, for example, use the averaged standardised beta coefficients from a model predicting the signed prediction error (participant rover position – space junk position at $t_{+1}$), from the signed rover position change indicated (participant rover position $t_1$ – participant rover position $t_{+1}$), as an index of learning rate across participants. Future research could consider using

this approach in conjunction with the Space Task. Additionally, computational modelling approaches, including Bayesian modelling approaches, would support a trial wise analysis of learning (Katthagen et al., 2022a; Mathys et al., 2014). However, it is important to keep in mind that in this case, it would also be important to complete all required methodological staps, such as simulation and parameter recovery, to make extract model parameters a valid measure (Wilson & Collins, 2019).

Computerised tasks are a common tool to assess aspects of cognition and are commonly used across cognitive sciences. However, recent work has shown a lack of correlation between learning tasks on similar cognitive measures (Eckstein et al., 2021). To sufficiently show a task is able to capture and measure aspects of cognition intended, several criteria must be confirmed. Firstly, the task must show a degree of reliability. Reliability refers to the ability of a task to yield similar results when repeated under equivalent conditions (Cook & Beckman, 2006; Mokkink et al., 2010). Test-retest reliability evaluates the agreement of measures gathered over repeated testing of the task. Similarly, internal consistency relates to consistency among different parts of the instrument itself, i.e., whether different metrics relate in the way researchers would expect. Although different versions of the task were tested that differed in aspects of design, and so was unable to concretely demonstrate re-test reliability, this study did show a degree of reliability via consistency of findings between both versions of the task. For example, in terms of the tasks ability to replicate previous findings (Berniker et al., 2010). The task also showed coherence across metrics, for example, performance error (distance between the estimate and the mean) and beam width were higher in conditions of high noise, compared to low noise. However, further analysis is required to re-test Version 2 of the task. Use of the intraclass correlation coefficient (ICC) would support this analysis by providing the ratio of between-individual variance to total variance.

Within the field of cognitive science, there may also be lower reliability in group level testing due to the common practice of altering task designs prior to testing, usually with a view to matching specific research questions (Karvelis et al., 2023). While this offers a level of flexibility and specificity in testing, if aspects like the number of trials, the duration of inter-stimulus intervals, the number of practice trial, time constraints, task difficulty etc., are changed between experiments, the tasks can have different reliabilities (Nair et al., 2020). For example, the Go-NoGo task, which is often referred to by the same name but with subtle differences, may actually be varied in its level of reliability due to these design changes (Karvelis et al., 2023). One advantage of this novel task is that the task code is available and accessible to other researchers. This is to ensure that decisions made in the task design are completely transparent, but also so that when comparison is made between other cognitive tasks, it can be done so with much more detailed comparison (Karvelis et al., 2023). Derivation of task measures can also impact reliability, for example, averaging across trials can reduce reliability, due to information loss – masking a proportion of between subject variance (Cronbach & Meehl, 1955; Draheim et al., 2019; Hedge et al., 2018). Use of a continuous framework for sampling from inputs and for participant estimates, meant that the task was able directly access derived metrics such as prediction error on a trial wise basis. Use of linear mixed effect models would support this process, by including, for example, random effects of participant and block, to account for variance across multiple levels (Chen et al., 2021; Rouder & Haaf, 2019). Inclusion of a large number of trials per participant also improve reliability of estimates.

Tasks also need to display a level of construct validity. For example, criterion validity – i.e., statistical associations with other measures, including measures of the same construct (convergent validity), and measures of other constructs taken around the same time (concurrent

validity), or a future time (predictive validity) (Borsboom et al., 2004; Karvelis et al., 2023). While validity can be specific to these different types, in general construct validity is established by demonstrating that a measure is associated with some other measure in a sensible way. In this study, the task displays this internal coherence by the fact that participants are using the metrics in the predicted way. For example, beam widths are wider during high noise and vice versa, and estimates of the inputs (falling space junk) broadly mimic the actual inputs. Similarly, at a mean change point, participant prediction errors increase, and then decrease over time, suggesting that they are reacting to the change, and then adapting their estimate. In Version 2 of the experiment, participants are also integrating the information received and using that information to place their estimate close to the unseen mean. This is strategically the most sensible option, that would garner the most point and therefore money. These findings add to evidence that the task is able to show a level of confidence in the construct validity of the metric used.

Ecological validity is another form of validity which refers to how well a measure captures real world processes. The ecological validity of tasks measuring learning is also of the utmost importance, given the complexities of learning in every-day life. Simplification of the learning processes can be useful, and isolate specific aspects of learning. However, use of binary and abstract stimuli means that some tasks fall short of providing a framing that delivers an intuition of uncertainty, and as such fails to capture cognitions relevant for our everyday learning and decision making (Soltani & Izquierdo, 2019). This study sought to overcome this issue by providing a narrative (albeit fictional!), of uncertainty around and in the context of, an ongoing task/mission. While Version 1 of the task was thought to be too complicated in the narrative and instruction, Version 2, using a simplified version, was able to overcome this (evidence shown via reduced exclusion rates).

## *5.1 Limitations and future directions*

A parallel form of reliability refers to the consistency between two interchangeable versions of the task, something which this study partially shows via comparison of two versions of the task. However, this type of reliability can also refer to the administration of the task in different settings (laboratory vs. online). As such, while the task has been tested and validated online, and evidence shown that it is sensitive to capture aspects of learning under uncertainty, it is important to test these findings in a laboratory setting. This is because of the lack of control that researchers have over the participants state of mind, attention, and focus during the experiment. Providing an in-person replication of findings from this study to provide further evidence that the task is able to capture important aspects of learning. Similarly, one disadvantage of the task was that no other cognitive task was tested alongside the Space Task. This means we were unable to verify whether the task found similar learning effects across tasks. Replicating the experiment with a well validated task, such as a binary PLRT, would help to show whether the Space Task reliably finds similar aspects of learning.

## *5.2 Conclusions*

In conclusion, a novel learning task measuring learning under isolated and combined conditions of uncertainty was developed and tested in two large scale online studies. Changes were made to Version 2 of the task that reduced exclusion rates, increased engagement, and improved researchers' ability to extract important metrics such as prediction error. The task was successfully validated against previous findings (Berniker et al., 2010), and was found to be suitable for an online setting in terms of maintaining attention, and in the functionality and construct validity of the included metrics. While further testing is required, authors suggest that

this task could be useful in disaggregating deficits in learning and decision making and may be useful disaggregating aberrant cognitive processing seen across psychopathology, particularly given its novel ability to test the join estimation of uncertainty in learning.

## 6 Acknowledgements

This task is based on a concept originally conceived by Berniker et al., (2010), who I would like to acknowledge here. I would also like to thank my supervisor Dr Kelly Diederen for the initial conceptualisation of the "coin task", which provided the inspiration and theoretical underpinnings of the space task. Finally, I would also like to acknowledge the inputs from Adam Wallis, senior solutions architect, for the programming of the space task and ongoing technical support.

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# 8 Appendix

**Table 3-4** *Showing instructions given to participants in both versions 1 and 2 of the novel task.*

| Screen | | Text | |
|---|---|---|---|
| **Name** | **description** | **Text prompt – version 1** | **Text prompt – version 2** |
| **Introduction** | Intro screen 1 | `It is your first mission with the Intergalactic Space Defenders. However, a near miss has left you marooned on a strange planet in the treacherous Zammer region of sector 13…`, | `It is your first mission with the Intergalactic Space Defenders. However, a near miss has left you marooned on a planet that deals with all the waste and rubbish from the surrounding planets!' |
| | Intro screen 2 | `Luckily, abandoned spacecraft often drift by the planet dropping bits of space junk from them. You can use this space junk to power your machinery and build a rocket to escape the planet… `, | "Old spacecraft of all shapes and sizes are flown into orbit above you, one at a time. As they disintegrate, useful parts fall off them. Your job is to catch the parts so you can build a rocket and escape." |
| | Intro screen 3 | `The passing spacecrafts will be different sizes. When a passing spacecraft is large, the junk may fall off of it over a larger area. Information at the beginning of each level will give clues about the size of the spacecraft or spacecrafts passing by. `, | "Each spacecraft will be too high for you to see. To successfully capture the falling parts you will have to estimate two things:<br><br>1. The location of the passing spacecraft. This will help you estimate where the parts will be falling from. ii) The size of the passing spacecraft. For example, if the parts are falling from a large space craft, they are likely to be more spread out.<br><br>You will be given information about the incoming spacecraft at the start of each level that will help you to figure out the sizes and locations of the spacecraft." |
| | Intro screen 4 | `The spacecraft themselves are too high up for you to see them. But you can see the junk that falls off them. Each round you will see a piece fall off. Use this information to move your rover's electromagnet to try and catch the next piece that falls.`, | "You have an electromagnetic ray to capture the falling parts and bring them in, so you can build the rocket. IMPORTANT: You only have a small amount of fuel, so you must use the least amount of power possible to bring the parts in (the smallest ray possible)." |

| | | | |
|---|---|---|---|
| | Intro screen 5 | `You can increase the width of your beam from your electromagnetic (pictured below) by using more power. However, as we are trying to gather enough power for our rocket, you will get LESS points for using MORE power. Remember you will get ZERO points for missing the space junk! Try and catch space junk in the narrowest beam you can to get the best score.`, | You will get a HIGHER SCORE for catching the falling parts with a SMALLER ray - but remember you will get zero points if you miss it! |
| | Intro screen 6 | `Use the right and left arrows to position the rovers' electromagnet underneath where you think the space junk will fall off. Then use the up and down arrows to increase and decrease its power. Give it a try now!`, | After seeing where the last spacecraft piece fell, turn the ray ON by pressing UP and then press the RIGHT and LEFT arrows to position the electromagnet. Use the UP and DOWN arrows to increase and decrease its power.<br><br>Give it a try now!' |
| | Intro screen 7 | `On a computer left and right can be controlled with the left and right keys and up and down with the up and down keys. Use space to advance or click the play button.` | On a computer you can use the LEFT and RIGHT keyboard keys. Press enter, space or click to continue.' |
| **Block 1** | Practice round screen 1 | PRACTICE ROUND: Move the rover and adjust the electromagnet power using the arrows. Press continue or space when you have positioned the rover and adjusted the power. Press continue to start the next trial.`, | PRACTICE ROUND: You have 5 seconds to complete each turn. You must pass all 3 turns in the practice round to continue.<br><br>Turn the electromagnetic ray ON (red to green) by pressing UP, and then press the RIGHT and LEFT arrows to position the electromagnet. Use the UP and DOWN arrows to increase and decrease its power.<br><br>PRACTICE ROUND INFORMATION:<br><br>Number of incoming spacecraft: 1<br><br>Size of incoming spacecraft: Small<br><br>Location of incoming spacecraft: ONE location likely |

| | | | |
|---|---|---|---|
| | Practice round screen 2 | `The game can be tricky - if a spacecraft is large junk may fall off over a large area, making it unlikely you'll catch all the junk. But use your experience of where junk has fallen before and this will improve your chances!`, | Good job! A quick reminder:<br><br>The Spacecraft will pass overhead one at a time - but may be different sizes, and in different locations. Information at the start of each level will help you to figure this out. |
| | Practice round screen 3 | REMINDER: The aim of the game is to catch space junk that is falling from different spacecrafts that pass by - using the smallest amount of power possible! Do you want to repeat the tutorial? | "'Catch the parts that fall off the passing spacecraft using the smallest ray you feel is possible. This will earn you the most points. Every time you earn 500 points you get a bonus payment!. Do you want to repeat the tutorial? " |
| **Block 2** | Stable learning environment | There is one spacecraft overhead now, and it's dropping loads of junk. Better get to it!", | Level 1 INFORMATION:<br><br>Number of incoming spacecraft: 1<br><br>Size of incoming spacecraft: No information<br><br>Location of incoming spacecraft: One location likely |
| **Block 3** | Learning when the SD changes | Good job! You passed that level! Now there are two old space cruisers over head, one small and one large - but its not clear which order they will come in… Careful - when the large one passes by the space junk could fall over a wider area…', | Level 2 INFORMATION:<br><br>Number of incoming spacecraft: 2<br><br>Size of incoming spacecraft: One large, one small. No information on the order they will pass.<br><br>Location of spacecraft: One location likely |
| **Block 4** | Learning when the mean changes | Well done! Looks like your lucky day! You have gotten a report that lots of spacecrafts are about to pass by, all of about the same size. Each spacecraft will pass one at a time.', | Level 3 INFORMATION:<br><br>Number of incoming spacecraft: Multiple<br><br>Size of incoming spacecraft: All around the same size<br><br>Location of incoming spacecraft: Multiple locations likely |

| | | | |
|---|---|---|---|
| **Block 5** | Learning with combined SD and mean changes | Incoming! There are now many discarded spacecraft of all sizes passing by, one after another. Now's your chance - collect all the junk you can falling from each ship as it passes. Only one ship will go by at a time.', | Level 4 INFORMATION<br><br>Number of incoming spacecraft: A large amount<br><br>Size of incoming spacecraft: All different sizes<br><br>Location of incoming spacecraft: Multiple locations likely |
| **Block 6** | Learning with combined SD and mean changes Round includes loses. | There are still many discarded spaceships passing by of all different sizes - but now some of the falling junk is heading straight for us! If you don't catch the junk now, it will damage our equipment and loose us points! But if you do catch it then you will get extra points and get us off this planet as quickly as possible! , | Level 5 INFORMATION:<br><br>Number of incoming spacecraft: A large amount<br><br>Size of incoming spacecraft: All different sizes<br><br>Location of incoming spacecraft: Multiple locations likely<br><br>IMPORTANT: If the falling spacecraft parts are not caught in this round you will LOOSE points, and potentially LOOSE the money you have earnt. BUT if you do catch the falling parts you will earn DOUBLE POINTS! Catch the parts in the smallest ray possible and earn 20 points each time! |

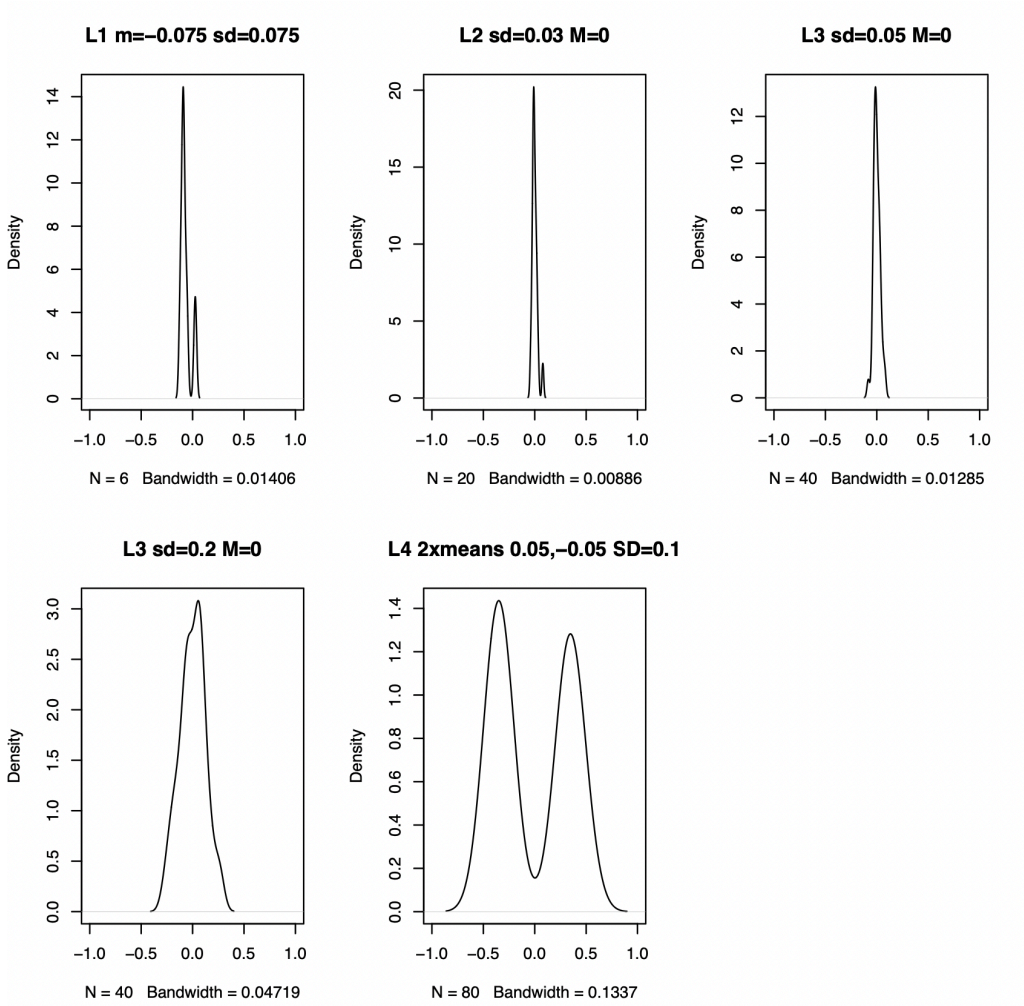


**Figure 3.24** *Showing the distributions of space junk inputs, for each combination of predetermined probability distributions (mean, and SDs). Exact statistical description of the distribution are written above each plot. This figure shows distributions of sampled inputs for blocks 1-4.*

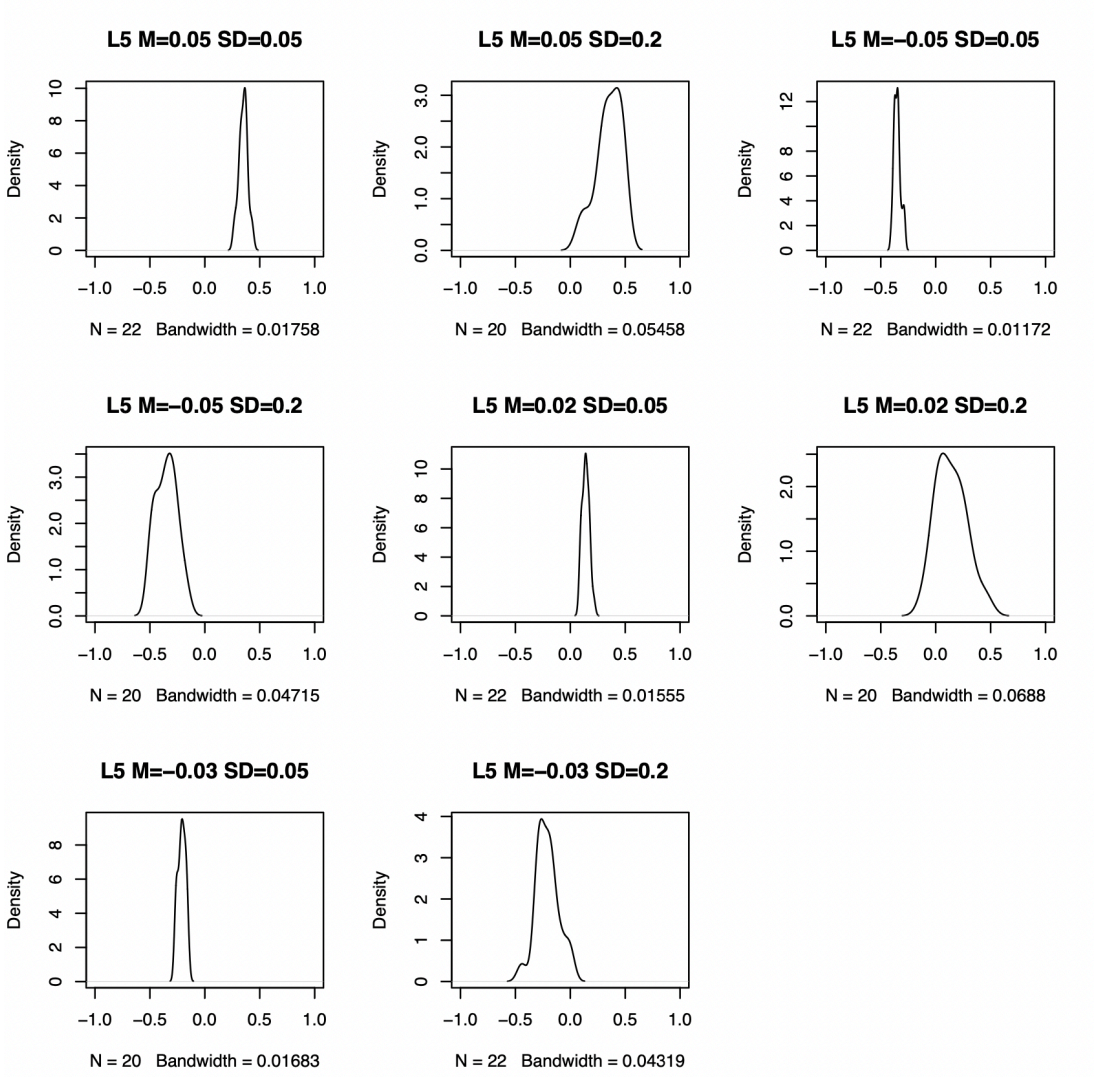


**Figure 3.25** *Showing the distributions of space junk inputs, for each combination of predetermined probability distributions (mean, and SDs). Exact statistical description of the distribution are written above each plot. This figure shows distributions of sampled inputs for block 5, where every 10 trials (+/-) jitter, the mean and/or the SD are updated.*

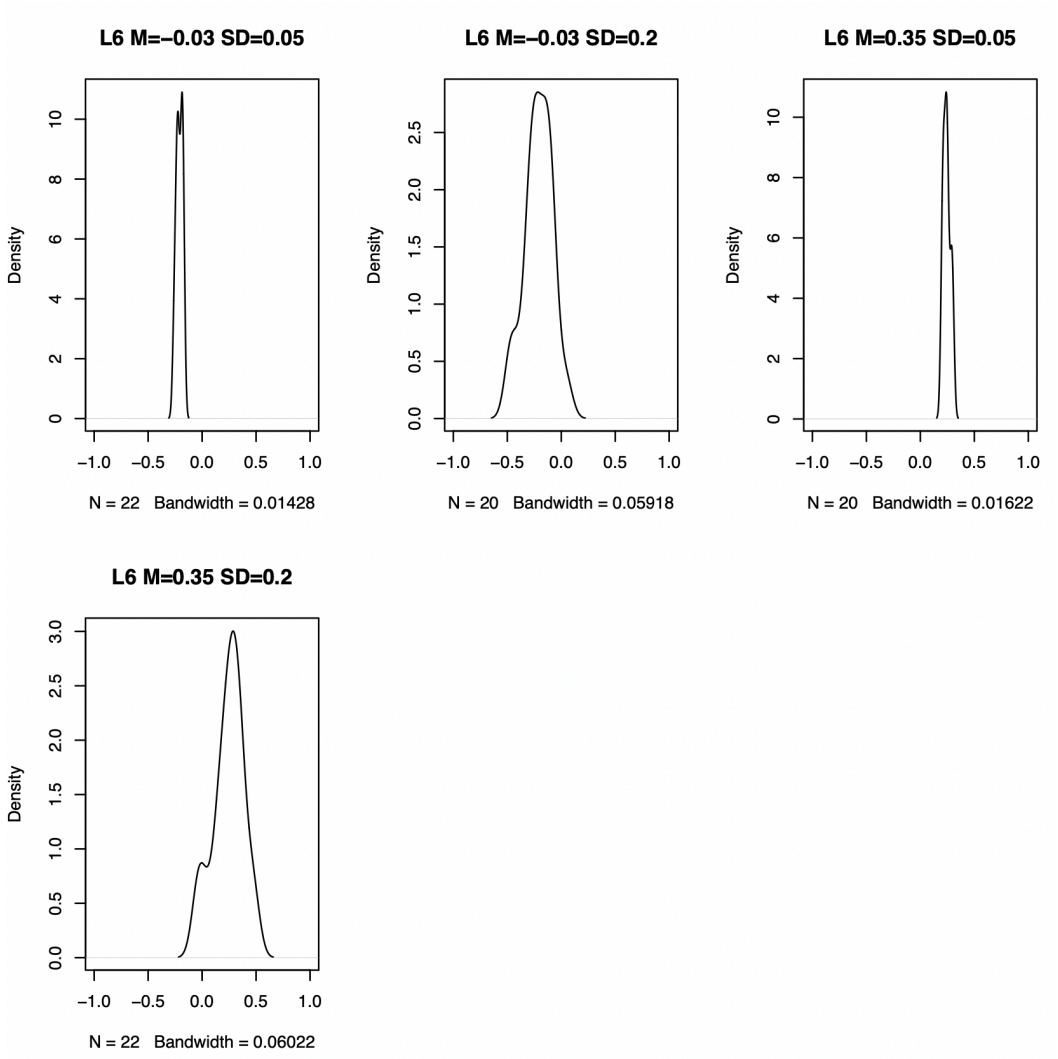


*Figure 3.26 Showing the distributions of space junk inputs, for each combination of predetermined probability distributions (mean, and SDs). Exact statistical description of the distribution are written above each plot. This figure shows distributions of sampled inputs for block 6, where every 10 trials (+/-) jitter, the mean and/or the SD are updated.*

# Chapter 4. Learning under uncertainty in eating disorders

## 1 Abstract

*Background:* Eating disorders (ED) are severe and debilitating conditions associated with high mortality and low rates of treatment response. Understanding the cognitive processes underlying EDs is considered crucial for developing effective interventions. One cognitive process that has been implicated in ED shows inflexible learning strategies in the face of uncertainty. However, to date, there is limited work investigating the adaptation of learning to changes in uncertainty. This study aimed to investigate the flexibility with which individuals with ED adapt their learning in response to increases in the changeability of information (volatility), and the noisiness of information (noise).

*Methods:* Using a novel experimental task, this study examined how individuals with EDs (n=116) and healthy controls (n=67) adapted their beliefs in response to changes in volatility and noise. Task performance was analysed using linear mixed-effects modelling to estimate the effect of task block and group on performance metrics, including total score, total catches, beam width, and (a proxy for) learning rate. Overall learning rates were compared between blocks, and

adaptation of learning to changes in uncertainty was measured using the learning rate difference between blocks.

*Results:* ED groups showed a small but significant effect suggesting less updating in response to increases in volatility, compared to healthy controls. Lower performance scores in ED groups were also observed in noise-manipulated blocks only. No other group effect was observed.

*Conclusions:* These findings add to evidence that ED groups display a degree of inflexibility in their learning. The findings provide additional evidence that this inflexibility occurs between high noise and high volatility conditions, and may relate to a difficulty in learning under noise itself. Future research should investigate the potential of a downstream effect between poorer processing of noisy information, and the decrease in flexibility between noisy and volatile learning conditions. Findings highlight the importance of considering the impact of uncertainty on belief updating in individuals with EDs.

# 2 Introduction

The term eating disorder (ED) is an umbrella term for multiple, highly debilitating disorders, such as Anorexia nervosa (AN), bulimia nervosa (BN) and binge eating disorder (BED) (Hudson et al., 2007). While clinical definitions differ between these subcategories, common to the group are symptoms such as body dissatisfaction (including a drive towards thinness), anxious psychological traits, and a sensitivity to salient stimuli (Frank et al., 2021). EDs are often severely disabling (Fichter et al., 2017; Steinhausen, 2002; Winkler et al., 2014) with increased risks of mortality (Arcelus et al., 2011; Fichter & Quadflieg, 2016; Smink et al.,

2012). While psychological and limited pharmacological treatments can provide relief, EDs show a relatively low rate of remission or treatment response (Bergh et al., 2013; Helverskov et al., 2010; Keel & Brown, 2010; Mallorquí-Bagué et al., 2018). To improve treatment success, it is vital that research provides a more mechanistic insight into the cognitive differences that precipitate and maintain symptoms (Godier et al., 2014). As such, more targeted and personalised treatments and interventions can be developed.

EDs and addiction disorders have been argued to share aberrant cognitive processing, namely, abnormal cue conditioning, and specifically, differences in the formation of stimulus-response (S-R) relationships during reinforcement learning (Janssen et al., 2022; Schaefer et al., 2021). For example, a sensory association to a food cue (stimuli) produces an increased craving impulse (response) in ED groups, compared to controls (Meule et al., 2018). Over time, this initially impulsive behaviour can evolve into a compulsion, where individuals are conditioned to perform this behaviour in response to the paired stimuli (Pearson et al., 2015). Using probabilistic reinforcement learning tasks, studies have shown that ED groups show patterns of aberrant learning such as blunted responses in relation to positive stimuli (Grob et al., 2012), higher rates of win-switch behaviour (Reiter et al., 2016), and an inability to flexibly update previously held beliefs when attempting to withhold previously learned responses to cues (Berner et al., 2023).

Importantly, the degree to which a S-R rule is formed or maintained is impacted by various types of uncertainty in the information being processed. For example, if the information is highly changeable (volatile), it is important for the agent to learn from each data point received as it may indicate important information about a change to the environment. In contrast, when the information is noisy and as such likely not to indicate a meaningful change to the environment, the agent must learn to disambiguate this from meaningful change points and not learn from this

information (Behrens et al., 2007; Pulcu & Browning, 2019). Using this normative account of learning, it is possible to assess whether aberrant learning is occurring in response to the type of uncertainty inherent in the environment, and thus provide insight into important, but subtle, aspects of cognition in ED groups. This understanding, in turn, could support improved treatment development.

Assessment of learning under uncertainty in ED has been researched in relation to learning under volatility specifically (Pike et al., n.d. *pre-print*). Here, authors showed a belief updating deficit in recovered anorexic groups that indicated an over-adaptation response to increases in volatility. While no behavioural group differences were noted, computational modelling revealed that ED groups responded appropriately to volatility by increasing their learning, but that updates were over and above heathy controls and other sub-types of EDs. This implied a level of over-updating in ED groups. However, Bayesian modelling analysis has also shown an opposing belief updating deficit i.e., a slower pace of behavioural adjustment and overall reduced flexibility, in bulimic patients (Berner et al., 2023). This finding is also in alignment with other research in the field showing cognitive inflexibility, perseverative behaviours, and set-shifting deficits in BN (Berner et al., 2023; Hirst et al., 2017; Wu et al., 2014). While sample and experimental design differences may explain contradictory findings, neither study included an experimental task that was able to concretely test for the joint estimation of noise and volatility. Given that simultaneous estimation of these variables is necessary to control the speed of learning, previous findings may be lacking the full picture (Piray & Daw, 2021; Pulcu & Browning, 2019). As such it is currently unclear how ED groups may differ to healthy controls in terms of their flexibility in adapting their learning styles to changing (volatile) environments.

Given these gaps in the literature, this study sought to provide further insight into the flexibility of learning in ED. To achieve this, a novel task was developed to test flexibility of learning under multiple types of uncertainty in eating disorder patients (n=86) and healthy controls (n=100). The novel task drew from "ground truth" probability distributions that varied in the configurations to simulate volatility (mean changes), and noise (increased standard deviation). Participants were able to make trial-wise parallel estimates of both the noise (beam) and volatility (rover position) of the environment. Groups were compared on their overall performance and learning between conditions of uncertainty (noisy, volatile), and on their ability to flexibly update from one condition to another i.e., the learning rate differences between conditions (Browning et al., 2015). It was hypothesised that ED groups would show a deficit specifically relating to the over-adaptation of learning rates to increases in volatility (Pike et al., n.d.).

# 3 Methods

## *3.1 Participants*

We recruited 302 participants through posted advertisements on social media, university mailing lists, ED charities, and adult ED NHS services in the East of England into two groups: ED (n=198 M(SD) = 24.14(6.07) years) and healthy controls (n=102 M(SD) = 24.6(5.64) years). Participants were recruited from July to October 2020. Eligible volunteers were 18–60 years old, currently living in the United Kingdom, and for the ED group, currently diagnosed with any ED as defined by the Diagnostic and Statistical Manual of Mental Disorders, 5th Edition (DSM-*5* (Nuckols & Nuckols, n.d.), including anorexia nervosa, bulimia nervosa, binge-eating disorder, or otherwise specified feeding or eating disorder. Participants were considered to have a current

ED diagnosis if they met one of two criteria: 1) they received an ED diagnosis within the last 12 months or 2) they were diagnosed with an ED >12 months ago and experienced ED symptoms within the past 12 months. Participants who normally resided in the United Kingdom but were temporarily displaced due to the COVID-19 pandemic were also eligible to participate. Patient participants who were non-English speakers, had not received an ED diagnosis from a licensed mental healthcare professional, did not suffer with current ED symptoms despite a lifetime diagnosis, or did not report clinically significant ED symptoms on the Eating Disorder Examination Questionnaire (EDE-Q; (Prnjak et al., 2020) were ineligible. We defined clinically significant ED symptoms using a validated cut-off score, corresponding to an EDE-Q global score >= 2.5, which previously demonstrated high specificity (0.86) and sensitivity (0.86) in a large sample of women with and without EDs (Prnjak et al., 2020). Exclusion criteria for healthy controls included diagnosis of a serious medical condition (e.g., cancer, neurological disease), lifetime diagnosis of any major DSM-*5* mental health condition or indicating clinically significant psychopathology symptoms on the DSM-5 Level 1 Cross-Cutting Screener (Mahoney et al., 2020), excluding depression, anger, and anxiety domains. All participants provided electronic informed consent prior to completing the study screening and again at the time of the experiment. Participants were matched on age, sex, and educational attainment (see Table 4.3).

### *3.2 Study procedure*

Interested volunteers completed an online screening to determine if they met the inclusion criteria for either participant group. Eligible volunteers were automatically emailed instructions and a hyperlink to the experiment, which was hosted on the Gorilla Experiment Builder platform (see *gorilla.sc*). Participants were instructed to limit distractions (e.g., music, television) as much as possible while completing the experiment on either a computer, smartphone, or tablet. They

were informed that the study would last 1.5 - 2 hours, and they were encouraged to take breaks as needed. Participants were compensated £24 pounds for completing the study.

### *3.3 Experimental task*

Participants performed a game-based learning task where the overall aim was to collect enough space junk to build a rocket and escape a planet (see Figure 4.1). Participants were told that the space junk was falling from unseen passing spacecrafts, that varied in size, location, and frequency (full details given in Appendix Table 4-4). To catch the space junk, participants were given a rover, that they could move along the *x* axis, and a beam attached to the rover, whose power could be adjusted on the *y* axis. Participants were instructed to use the previous falling space junk locations to predict the location that the next piece would fall. Participants were instructed to indicate their estimate by moving the rover to catch the falling space junk and increase or decrease the beam size to where they felt appropriate, while conserving as much power as possible i.e., using the smallest beam size they felt safe to do so, while still catching the space junk. Version 1 of the space task provides the player with two pieces of information per trial, sampled from the same distribution. As such the individuals experience of each trial includes input A: a piece of falling space to be used to inform the prediction (from a Bayesian point of view, this information is novel sensory information used to update a prior); and input B: a second piece of space junk that provides explicit feedback as to the prediction (see Figure 4.1). Limited information about the size, location and frequency of the incoming unseen space craft was given at the start of every block (exact description found in Appendix, Table 4-4).

Underlying the task are probability distributions that differ in their means and standard deviations, to simulate uncertainty environments. For example, a condition of high noise would

consist of a stable mean, but a wide standard deviation. The exact means and SDs used, alongside the rules by which the distributions change, are displayed in Table 4-1. The task inputs (space junk positions) were sampled from these distributions. The sampled inputs were then themselves subject to simulation (iterated over 100,000 replications). From the simulated inputs, the most normally distributed distribution was chosen. This was to ensure that the sampled inputs were not non-normally distributed by chance, i.e., include outliers that would confuse the participants. These distributions can be seen in the Appendix, Figs 4.5:4.7.

The task included 219 trials (ITI: 1000-5000ms) overall, split into six blocks that differed in their configurations of volatility and noise, via manipulations to the underlying probability distribution that the junk was sampled from. The rules by which the distributions changed throughout the task mirrored Berniker et al., (2010). Block one was a practice round that included three practice trials and required successful completion i.e., to catch every piece of junk, before the participant could continue. If the participant did not pass the practice round, they would be directed back to the start of the instructions to begin again. Block two (n=10 trials) was a stable learning environment i.e., no mean changes, and a small SD (0.03). All participants were exposed to low noise and volatility during block two. In block three, the noise was manipulated in isolation i.e., there were no mean changes (Mean=0.01), but the variance increased after 20 trials (SD=0.03 to 0.12) (total trial n=40). Block four (n=40 trials) tested learning under isolated volatility. Volatility was manipulated by the inclusion of un-cued changes to the mean of the underlying distribution from which the junk was drawn (see Table 4-1), alongside a stable variance (SD=0.01). Here, the probability distribution switched between two previously unseen means. The switch rate for mean change was computed at a 0.25 chance every 5 trials, resulting in 5 overall mean switches across the block (see Figure 4.1; as seen in (Berniker et al., 2010)). Blocks five (n=84 trials) and six (n=40 trials) updated the

mean and SD of inputs every ten trials (plus jitter), resulting in continuously high volatility, and periods of high and low noise (see Figure 4.1). In each case, two previously seen means were used alongside two new means i.e., block five used the two means from block four, plus two new means etc. While learning requirements were the same across blocks five and six, blocks differed in terms of its reward policy, described below.

Feedback was presented in terms of points per individual trial and an ongoing cumulative score in the top right of the screen. Written confirmation e.g. “Well done, you caught it!”, “missed”, or “timed out!” was also provided on a trial-wise basis. Each trial could score a maximum of ten points. The score was shown after each trial and between each block. During blocks one to five participants could win points if they caught the junk, or they would receive no winnings if they missed the junk, on each trial. In block 6 participants could win and lose points, leaving open the possibility that they could lose their bonus points, and as such, the additional points they had earned. Scores were generated for each trial as a function of accuracy (successful catch/unsuccessful catch) and the width of the beam used. Scoring in block 6 differed in that participants could lose the points they had gained, as well as win double the points. Just as participants were incentivised to use the smallest beam possible in blocks one-five i.e., a higher score given for catching with a narrower beam, in block six, participants would lose more points if they missed using a large beam, compared to missing using a small beam. Participants were informed of this change during the instructions screen preceding the start of block 6.

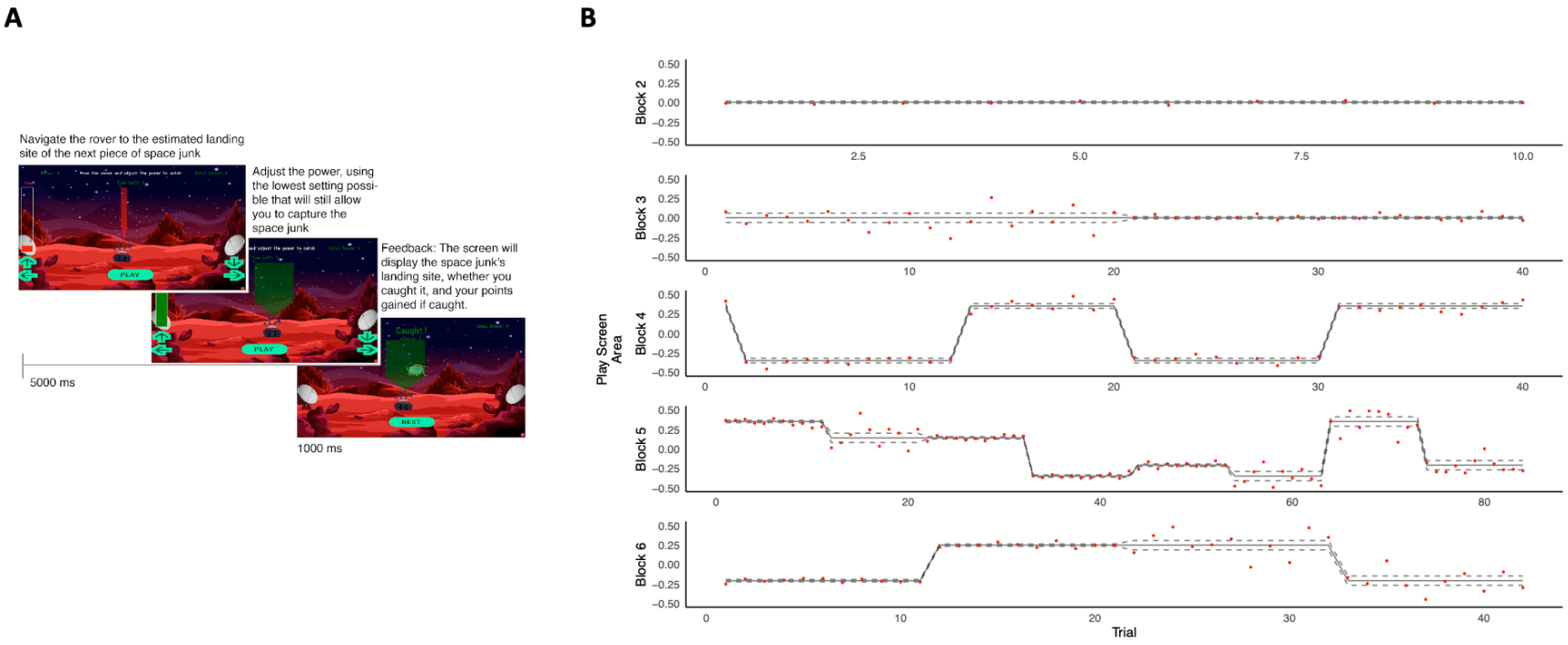


**Figure 4.1 A.** *Showing trial structure. Here, once the participant is exposed to the cue for a maximum of 5000m/s, participants are then instructed to make an estimate of the mean, using rover positioning; and variance using manipulation of the beam width. Feedback i.e., another piece of space junk drawn from the same distribution, is then presented to the participant (1000m/s).* ***B.*** *The black solid line shows the mean(s) used for each block (see Table 3.1 for further details), indicating both the stability of the mean over trials (x axis), and the location of the mean on the play screen area. The standard deviation used to simulate noise in the space junk locations is shown using the black dashed line (see Table 3.1 for further details). Here, the width of the dashed line around the mean indicates both the width of the SD*

*used, and the area of the play screen available for space junk locations to be drawn from. The red dots show the actual space junk positions that the participants were exposed to, in accordance with the underlying probability distributions.*

**Table 4-***1 Showing the details of the contingencies underlying the task for each block.*

| Screen | | Contingency Information | | | |
|---|---|---|---|---|---|
| **Name** | **Description** | **Trials (n)** | **Mean** | **SD** | **Rules** |
| **Block 1** | Practice round | 3 | -0.07 | 0.045 | Option to repeat |
| **Block 2** | Stable learning environment | 10 | 0 | 0.12 or 0.03 | 50% participants SD=0.12; 50% participants SD=0.03 |
| **Block 3** | Learning when the SD changes (high and low noise) | 40 | 0 | 0.12 or 0.03 | SD changes halfway through. Fixed mean. Counterbalanced condition is reversed. |
| **Block 4** | Learning when the mean changes (high volatility) | 40 | 0.35, -0.35 | 0.06 | A 25% chance of changing to the distribution with the second mean, every four turns. |
| **Block 5** | Learning with combined SD and mean changes | 84 | 0.35, -0.35, 0.14, -0.21 | 0.12 or 0.03 | Each SD/mean combination changes every 10trial+/-jitter of around 3 trials. |
| **Block 6** | Learning with combined SD and mean changes. Block includes loses. | 42 | 0.35, -0.21 | 0.12 or 0.03 | Each SD/mean combination changes every 10+/-jitter of around 3 trials. Randomly ordered. Extra points for catching. Loose points for missing/using a larger beam. |

### *3.3.1 Task outcomes*

The primary performance metric was score and was provided on a trial-wise basis out of a possible 10 points. Score was calculated for each trial as a function of accuracy of the prediction (successful catch/unsuccessful catch), and the width of the beam used. As such, catching the junk with a smaller beam size would get the player more points on that trial. In block six, participant could receive double points for a catch, or could lose points if they were unsuccessful at catching the space junk. Losses were calculated in the same way as rewards, but reversed, so missing the

space junk with a wider beam led to a loss of more points than missing the space junk with a small beam. Metrics that were used in the calculation of the score could also be taken separately. Beam width indicated a proxy for participants on how well they had acquired the variance in the underlying distribution i.e., whether the variance was wide or narrow should be reflected in use of a wide or narrow beam as use of a wide beam during high noise would be a more optimal strategy. Learning rate could also be calculated using the prediction error (participant rover position – the junk at $t_{+1}$), and position change between $t_1$ and t+1 (Nassar et al., 2021). The averaged standardised beta coefficients from a model predicting the signed prediction error (participant rover position – space junk position at $t_{+1}$), from the signed rover position change indicated (participant rover position $t_1$ – participant rover position $t_2$), was used as an index of learning rate across participants.

## *3.4 Analysis*

### *3.4.1 Quality control*

Several predetermined quality control steps were implemented to exclude participants whose task behaviour indicated poor attention or understanding of the task instructions. The process by which these criteria were decided is fully detailed in Appendix 8.3 and 8.4. Specifically, individuals were excluded if they 1) failed to move either the rover or the beam on more than 10% of trials, and/or 2) completed over 50% of trials in under 1000ms. Participants were excluded if they met both criteria.

### *3.4.2 Task performance*

We implemented linear mixed-effects modelling (LMMs; R package 'nlme' ("Linear Mixed-Effects Models: Basic Concepts and Examples," 2000) to estimate the effect of task block and participant group on three performance metrics: total score, total catches, beam width, and learning rate (by block, and between block). For access to the relevant scripts for analysis, please see here. To generate summary measures, total score and catch success were summed across each block and normalised by the number of trials per block. Trial-wise beam width was averaged across each block for each participant. Each LMM included fixed effects of group (ED vs HC) and task block, where the random intercepts for task block were nested within the random effect of participant, as well as three covariates, age, sex, and current medication use. Performance differences across each task block were evaluated using backward difference contrast coding, which compared the mean of, e.g., total score on a given block with the total score mean on the previous adjacent block (e.g., Block 3 vs Block 2, Block 4 vs Block 3, etc.) (see Table 4-2). Using this method, average learning rates were compared between blocks. Observations with extreme values (values >3 SD from the mean) were excluded from analyses, and a rank-based inverse normal transformation was applied when necessary to minimise negative skew (R package 'RNOmni' (McCaw et al., 2020). To control for multiple comparisons, we applied a Bonferroni correction for three tests ($p = 0.05/3 = 0.017$).

**Table 4-2** *Showing planned backwards contrasts.*

| Planned Contrasts | Description of comparison |
|---|---|
| Block 4 vs block 3 | High volatility vs. high noise |
| Block 5 vs block 4 | High volatility + noise vs. high volatility |
| Block 6 vs block 5 | High volatility + noise + losses + increased gains vs. High volatility + noise |

Learning rate differences between blocks were also compared. Here learning rate difference referred to the difference in learning rate (beta coefficients) between blocks e.g., learning rate block 4 (volatility) – learning rate block 3 (noise). In a similar analysis to task performance, LMMs were conducted for each comparison (block 3 – block 2; block 4 – block 3; block 5 – block 4; and block 6 – block 5). As block three consisted of both high and low noise, these analyses focussed on block 3: high noise only. As such, comparisons including block 3 always refer to high noise trials. The averaged learning rate difference was predicted by a linear mixed effects model that included age, sex, and current medication use. For each model group, an interaction term was tested between block and group.

# 4 Results

## *4.1 Quality control*

Participants were removed from subsequent analysis for failing to meet criteria (n=93; n = 73 ED group, n = 21 HC group) (Table 4-3. for sample characteristics). All participants that fell into one category of exclusion, also fell into the other category i.e., if a participant completed 50% of trials in under 1000ms, they also did not move their rover or adjust their beam estimate in over 10% of their trials. This provided additional support that the metrics used were capturing a form of inattention or poor understanding of the task instructions. Additionally, nine participants were excluded due to technical errors (e.g., incompatible web browser), which prevented completion of the task (ED = 7; HC = 3).

**Table 4-3** *Sample characteristics*

| **Characteristic** | **ED (n = 116)**<br>**M (SD)** | **Control (n = 67)**<br>**M (SD)** |
|---|---|---|
| Age | 24.14 (6.07) | 24.6 (5.64) |
| Gender (F/M) | 113/3 | 62/5 |
| Lifetime medication use | 84 (72.4%) | 1 (1.5%) |
| Current medication use | 52 (44.8%) | 0 (0%) |
| *Lifetime ED Diagnoses* | | |
| AN-R | 73 (62.9%) | - |
| AN-BP | 28 (24.1%) | - |
| BN | 30 (25.9%) | - |
| BED | 6 (5.2%) | - |
| OSFED | 20 (17.2%) | - |

## *4.2 Total score*

The ED group had similar overall total scores to the control group (p=.130). However, there was a significant effect of task block in several instances. Firstly, total score significantly differed from baseline to the first experimental block indicating a learning effect (Block 3 vs Block 2; $\beta(SE) = 1.37(0.07)$, $p < 0.001$). In line with a normative account of learning, total score was significantly reduced in conditions of high volatility compared with high noise (Block 4 vs Block 3; ($\beta(SE) = -0.47(0.07)$, $p < 0.001$). The same effect was noted as the game increase in difficulty, i.e., when losses were introduced in the final block (Block 6 vs Block 5; $\beta(SE) =$ -

1.32(0.07), p < 0.001). A nominally significant group-by-block interaction indicated that the ED group had lower total scores than controls between baseline (block 2) and block 3 (noise) scores (β(SE) = -0.06(0.14), p = 0.025). The inclusion of the interaction term significantly improved model fit (X2(df) = 9.65(4), p = 0.047).

### *4.3. Beam width*

Beam width did not differ significantly between the groups (p=0.96), but a significant main effect of block indicated that beam width significantly increased from baseline (block 2) to Block 3 (high noise) (β(SE) = 4.72(1.47), p = 0.001), indicating that participants were responding to higher levels of noise in the underlying distribution by using a wider beam to reflect the wider variance. Relative to Block 3, participants used a nominally lower beam width under conditions of high volatility and low noise (Block 4 vs Block 3; β(SE) = 3.21(1.47), p = 0.030). Moreover, bivalent outcomes in the context of high noise and volatility led to significantly higher beam width compared to the prior reward block (Block 6 vs Block 5; β(SE) = -6.67(1.48), p < .001). Age was nominally negatively related to beam width (β(SE) = -0.49(0.22), p = 0.027), and all other main and interaction effects were nonsignificant (all p>0.1).

### *4.4 Total catch success*

The ED group had nominally higher total catch success than the control group (β(SE) = 0.04(0.02), p = 0.033; see Figure 4.2). Aligning with total score findings, a significant main effect of block showed that total catch success increased between baseline and the first experimental block, indicating that participants were improving at the task (Block 3 vs Block 2; (β(SE) = 0.33(0.33), p < 0.001). Success rates decreased with the introduction of a highly changeable

(volatile) learning environment (Block 4 vs Block 3; β(SE) = –0.03(0.01), p = 0.009). In line with decreased total score, total catch success increased in the final block, during which participants lost points on missed trials. This indicated that participants were behaving in a risk averse manner - using a wider beam to catch more junk, but simultaneously getting fewer point for this strategy (β(SE) = 0.06(0.01), p < 0.001). All other main and interaction effects were not significant (all p > 0.1).

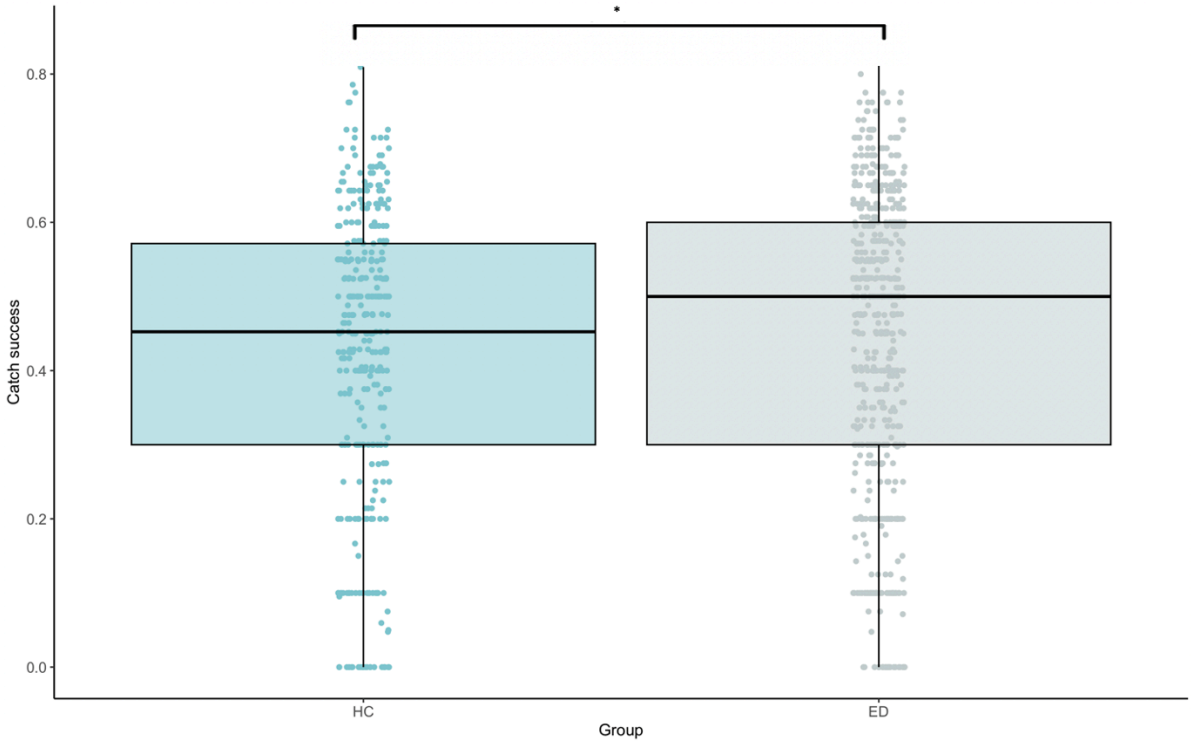


**Figure 4.2** *Showing boxplots depicting the mean and interquartile ranges (IQR) of catch success across the entire task, for healthy controls (blue) and eating disorder groups (grey). Catch success is an indication of how often the participant successfully caught the falling space junk, without reference to the beam size used. Catch success is calculated using the sum of successful catches divided by the total number of trials in the block. A small but significant difference was detected between the eating disorder groups (ED) depicted in grey (M=0.45, SD=0.21), and the*

*healthy controls (HC) shown in light blue (M=0.43, SD=0.19), independent of block (β(SE) = 0.04(0.02), p = 0.033). Dots reflect average catch success by block, for each individual.*

### *4.5 Learning rate*

Although learning rate did not differ significantly between groups (p = .660), the main effect of block was significant (see Figure 4.3). In line with a normative account of learning, learning rate decreased as the level of noise in the environment increased (Block 3 vs. Block 2; β(SE) = -0.23(0.01), p < 0.001). Similarly, learning rates increased in conditions of volatility relative to noise (Block 4 vs Block 3; β(SE) = 0.06(0.01), p < 0.001). The combination of noise and volatility in Block 5 was associated with a nominally lower learning rate than in Block 4, where only volatility was increased (Block 5 vs Block 4; β(SE) = -0.03(0.01), p = .040). Learning rate was again significantly reduced in the final task block, which suggests that participants have reduced learning with bivalent relative to positive outcomes in conditions of high uncertainty (Block 6 vs Block 5; β(SE) = -0.08(0.01), p < 0.001). Differences in learning rates between blocks were compared. A nominal group effect was found for the learning rate difference between blocks 4 (high volatility) and block 3 (high noise) (β(SE) = 0.03(0.02), p = .041; Figure 4.3. No other significant differences between groups were found (all p > 0.1) (see Figure 4.4).

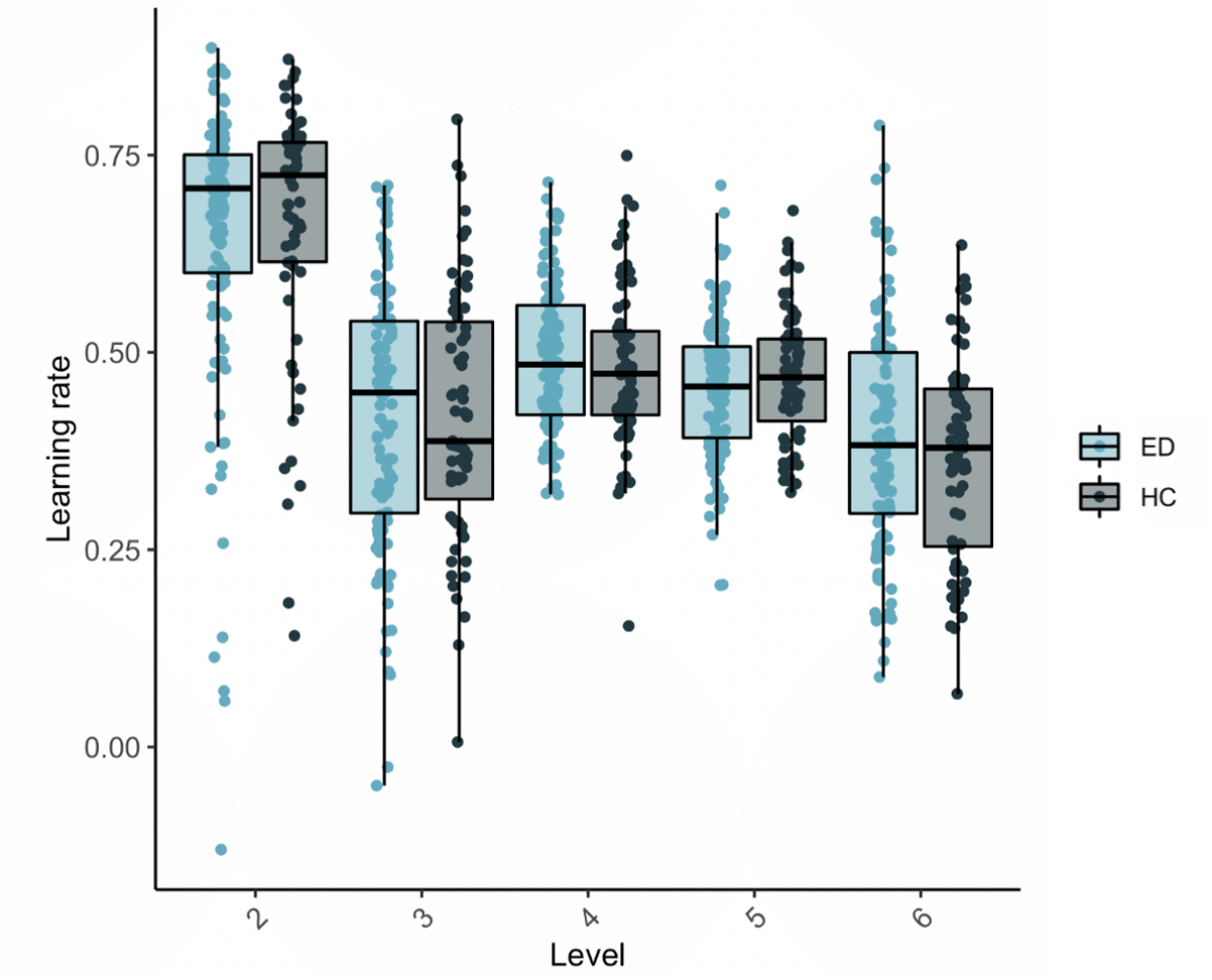


**Figure 4.3** *Showing boxplots depicting the mean and IQR of learning rates for each block (2-6), and for each group (healthy controls in grey, and eating disorder groups in blue). Individual dots reflect average learning rates for each individual, for each block. No significant differences between groups were found for any of the blocks (2:6).*

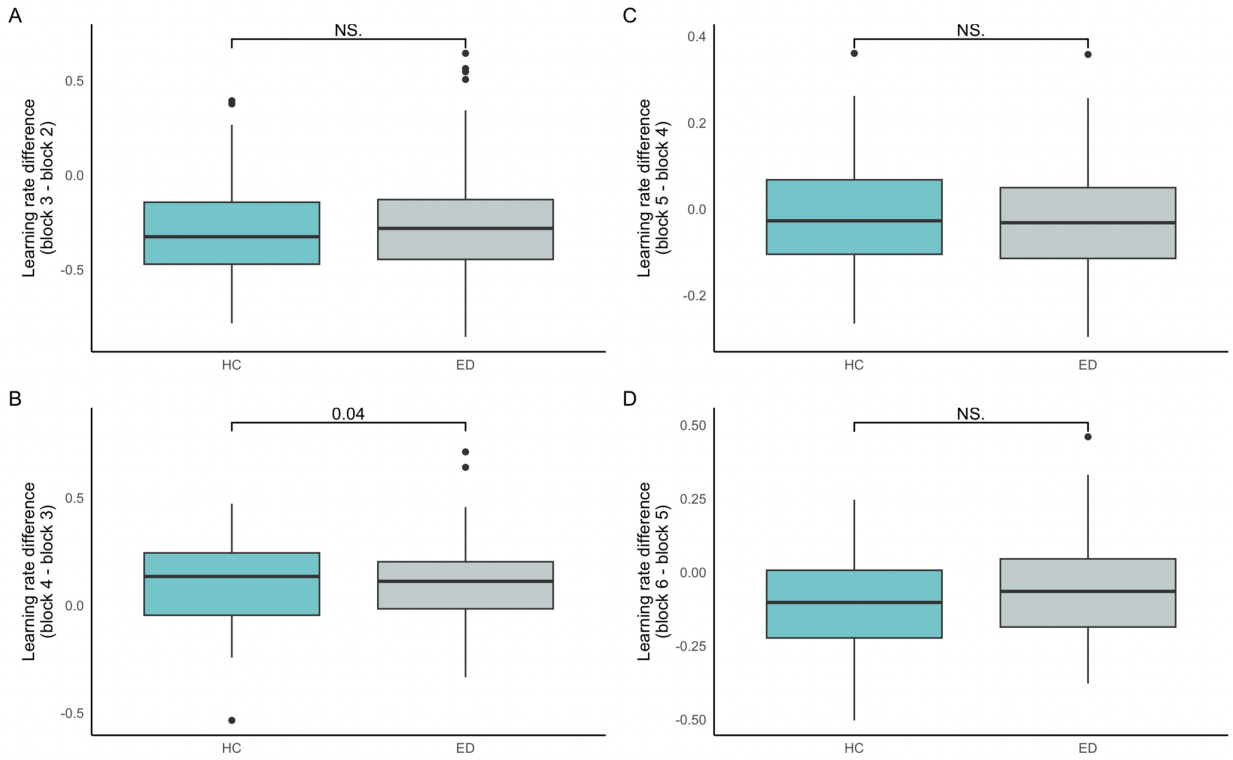


**Figure 4.4** *Shows learning rate difference between blocks, for each group (healthy controls (HC) (light blue), eating disorder (ED) grey).* ***Plot A.*** *Plotting learning rate between blocks 2 and 3, i.e., as noise begins to be manipulated. No significant differences are found between groups.* ***Plot B.*** *Learning rate between blocks 3 and 4 i.e., as the task transitions from a noisy, to a volatile, environment. Here, a nominally significant result is found (β(SE) = 0.03(0.02), p = .041), showing that the ED group may display less learning rate adaptation to increases in volatility (M=0.09, SD=0.18), than the HC group (M=0.12, SD= 0.20).* ***Plot C.*** *Showing learning rate difference between blocks 4 and 5 i.e., as the task begins to simultaneously vary noise and volatility. No significant differences were found here. Finally,* ***Plot D.*** *showing the learning rate difference between blocks 5 and 6. Again, no significant differences were found here.*

# 5 Discussion

The ability to flexibly update beliefs in line with uncertainty inherent in incoming information is a vital cognitive task that when perturbed, may underlie symptoms of mental illness. Inflexible behavioural adaptation to learning environments has been suggested to be an important mechanism underlying symptom of EDs (Berner et al., 2023; Lopez et al., 2008; Roberts et al., 2007; Tchanturia et al., 2011). This "cognitive inflexibility" is thought to result in observable deficits in cognitive functions, such as learning and decision making in response to changes in the environment, outcome contingences, or goals. A primary aim of this study was to provide further insight into the flexibility with which individuals with EDs update their beliefs, in comparison to healthy controls, when confronted with different types of uncertainty. To achieve this, we tested how these individuals adapted their learning in response to changes in both volatility and noise in isolated conditions, and when combined. Results from this study show some support for the hypothesis that ED groups may show a degree of inflexibility in updating. While findings would need to be repeated, given the small effect sizes, individuals with EDs displayed an inflexibility in updating when transitioning from high noise to high volatility environments. Complementary results using performance metrics add to this picture. For example, significantly lower performance in blocks where noise was manipulated was found for ED groups.

Although these findings are novel due to the originality of the experimental task design, previous studies using tasks such as the Wisconsin Card Sort tasks have demonstrated similar effects regarding learning in response to volatility (Lopez et al., 2008; Roberts et al., 2007; Tchanturia et al., 2011). These tasks simulate volatility through un-signalled changes in the underlying probabilistic structure. Such studies have also shown slower adaptation to changes in the environment among individuals with EDs. However, these previous experimental designs have limitations. For example, the task design usually uses one off changes to the contingencies to

simulate volatility, which precludes the ability of the task to investigate adaptation to ongoing changes to the environment. In contrast, this experimental task used a block design, as found in other research (Browning et al, 2015), enabling analysis into the differences between blocks that simulate different types of uncertainty, and evaluation of how learning rates adapt over time. Here, research investigating learning rate adaptation in response to stability (low variance, no mean changes) and high volatility (continuous blocks of trials with regularly changing means) demonstrated that individuals with elevated trait anxiety exhibited lower learning rate adaptation to increased volatility (Browning et al., 2015). The comorbidity between anxiety disorders and EDs, characterized by shared symptoms, risk factors, and underlying mechanisms related to emotion regulation difficulties, may contribute to the similar findings observed in this study (Brewerton et al., 2020; Godart et al., 2007; Kaye et al., 2004; Swinbourne & Touyz, 2007). For example, both disorders are characterized by difficulties in emotion regulation. Individuals with anxiety may engage in disordered eating behaviours to cope with anxiety and exert control over their emotions (Mallorquí-Bagué et al., 2018). Conversely, individuals with EDs may experience heightened anxiety as a result of the fear and distress associated with food, weight, and body image concerns. In fact, the relationship between anxiety and EDs is bidirectional, meaning each condition can influence and exacerbate the other. Anxiety disorders can precede the onset of an ED, as heightened anxiety, perfectionism, and concerns about body image and weight contribute to the development of disordered eating behaviours. On the other hand, the maladaptive thoughts, behaviours, and physical consequences associated with EDs can lead to increased anxiety and exacerbation of existing anxiety symptoms. This overlap may help to explain the similar findings in this study and highlight the need for future studies to control for anxiety symptoms in ED groups.

To garner a more in-depth picture of learning deficit, it is also important to consider how results from this research may interact with one another. For example, ED groups displayed a poorer performance when learning under noise, alongside a difficulty in flexibly adapting learning to increases in volatility. This may imply that individuals with EDs could show a difficulty in learning under noise, which in turn affects the ability to adapt their learning in response to changes in the environment. While this study was unable to show concrete evidence of a specific mechanism for any potential downstream pathways, one hypothesis for future testing is given. It may be that for example, for individuals with EDs poorer performances in the noisy condition was in fact because these individuals had interpreted noise as volatility. As such, instead of placing their estimate close the mean of the distribution and using a wide beam, they instead interpreted noisy information (e.g., far from the mean), and a signal that the mean had changed, leading to rover positions that jumped around, and ultimately lower scores. This interpretation would also lead to ceiling effect in the processing of volatility in the following block. In other words, the individual would not feel the need to update their learning if both the noisy block and the volatile block appeared to be volatile (Piray & Daw, 2021). Future research should work to include multiple types of uncertainty in their experimental design, to explore this hypothesis further.

Although the current study provides valuable insights into aberrant learning under uncertainty in EDs, it is important to note an opposing effect observed in recovered individuals with anorexia (Pike et al., n.d.). These individuals displayed greater learning rate adjustments in response to volatility compared to a stable environment. Specifically, Pike et al., (preprint - *n.d*) showed that individuals who had recovered from anorexia displayed greater learning rate adjustments in response to increases in volatility (vs. a stable environment). Differences in the direction of effect here may relate to several experimental and theoretical variables. For example, (Pike et al., n.d.)

captured LRs as part of a RL model, whereas this study used the beta coefficients from a model predicting signed prediction error from signed position change. The approach taken in this study requires LRs to essentially be averaged for each individual and block, potentially loosing vital information that the trial wise computational modelling in Pike et al (pre-print), was able to capture. Secondly, while Pike et al., (preprint - *n.d*) investigated differences across a number of subtypes, the difference was found specifically in those who had recovered from anorexia, while our sample only included individuals with current diagnoses, and all ED current diagnosis subtypes were grouped together. This may indicate that specific subtypes of EDs, including those with greater pre-morbid vulnerabilities, are in fact differentially affected by abnormalities in learning and decision making under uncertainty. Future research assessing these effects in ED subtypes would help to disaggregate these effects. Finally, the different direction of effect may highlight subtleties relating to learning under different types of uncertainty. Pike et al., (preprint - *n.d*) tested learning rate adaptation in response to changes to volatility only, whereas our study tested learning adaptation between noise and volatility conditions. While the healthy control group behaved according to a normative account of learning, showing both lower learning rates in response to noise, and high learning rates in response to volatility, and increased adaptation of learning rates to increases in volatility from noise, this latter finding was marginally (but significantly) reduced in ED groups.

### *5.1 Limitations and future directions*

It is important to rule out whether core symptoms of EDs are driven by difficulties in the interpretation and/or processing of uncertainty in the environment. While our novel task was designed to measure this, there were several limitations of the task design that may have limited its capabilities in this regard. This is primarily reflected in the exclusion rates, which were

disproportionately high in this study. Authors suggest that this version of the task was reported to be challenging and may have failed to appropriately match the cognitive capabilities of participants. This was shown via anecdotal reporting and reflected in individuals failing to properly play the game i.e., not moving/responding as expected. This is an important consideration of individuals experiencing mental health symptoms specifically, and tasks need to be developed to be maximally accessible, as well as metrics being maximally informative (Katthagen et al., 2022). An additional related factor to consider here is that while online testing enables relatively straightforward testing of large groups (Wise et al., 2023), we were unable to fully ensure that individuals participating in the experiment were completely free of distractions. This lack of experimental control may have also contributed to the large exclusion rates in this data collection. Finally, the smaller sample size generated by issues within the task design described above, may have contributed to the small effect sizes. Given this, these findings must be repeated using a modified task design in larger groups.

As previously mentioned, this study took advantage of a novel task that included readily accessible performance metrics from which it was possible to calculate derived metrics, such as learning rates. One advantage of this approach was that computational modelling was not necessary to access important aspects of learning. While this is useful given the reported complications in the field in relation to robust, reliable and valid computational modelling (Katthagen et al., 2022; Wilson & Collins, 2019), future research could consider applying computational modelling (including simulation and parameter recovery), to this trial wise data. This would enable several advantages. For example, this study averaged performance and learning metrics across blocks, leading to a loss of information. Computational modelling would enable trial wise learning to be assessed, and act as an additional route to further understanding subtle, but mechanistic deficits that may underlie symptoms in eating disorders. Other derived

metrics could also be included. While prediction error was incorporated into the calculation for learning rates, performance error (the difference between the mean of the underlying distribution and the participants trial-wise estimate) could be used to provide insight into the participants ability to acquire the underlying mean.

Finally, future research should also consider accounting for the continuous nature of mental illness, as opposed to the implied binary formulation that assessment of ill (ED) and healthy controls implies. As such, research could account for both a spectrum of ED symptomology and/or, other highly co-occurring mental disorders, such as anxiety, which may provide further disaggregation of deficits and symptoms and importantly, treatment. Similarly, other variables unaccounted for, but theoretically important, such as cognition, are vital to take into account. While this study included a proxy for cognitive ability in the form of education status, future research could include more developed measures, such as standardised intelligence tests (Katthagen et al., 2022). The comorbidity between anxiety and EDs has important implications for treatment. It is crucial to address both anxiety and ED symptoms concurrently to achieve optimal outcomes. Integrated treatment approaches that target both conditions, such as cognitive-behavioural therapy (CBT) and dialectical behaviour therapy (DBT), have shown promise in effectively managing comorbid anxiety and EDs (McElroy et al., 2006; Schaumberg et al., 2021).

## *5.2 Conclusions*

In conclusion, this study provides valuable insights into the flexibility of belief updating among individuals with eating disorders (EDs) in the presence of uncertainty. The results support the hypothesis that individuals with EDs may exhibit increased inflexibility in updating their beliefs compared to healthy controls, particularly when transitioning from high noise to high

volatility environments. Additionally, lower performance observed in noise-manipulated blocks may suggest a specific challenge in learning under noisy conditions, which could subsequently affect adaptive learning in response to environmental changes. Notably, this study contributes to the emerging field of research on learning and decision-making processes in EDs. To advance our understanding, future research should further examine multiple types of uncertainty and their replicability across distinct ED subcategories. This comprehensive approach will enhance our knowledge of the underlying cognitive processes and inform the development of tailored interventions for individuals with EDs.

## 6 Acknowledgements

I would like to thank Dr Margret Westwater-Wozniak for collecting the data, and for support on the analysis of this chapter. I would also like to thank Professor Michael Browning, for input into the analysis – specifically the idea regarding calculation of a proxy for learning rate.

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# 8 Appendix

## *8.1 Task instructions*

**Table 4-4** *Showing task instructions.*

| Name | description | Text prompt – version 1 |
|---|---|---|
| **Introduction** | Intro screen 1 | `It is your first mission with the Intergalactic Space Defenders. However, a near miss has left you marooned on a strange planet in the treacherous Zammer region of sector 13…`, |
| | Intro screen 2 | `Luckily, abandoned spacecraft often drift by the planet dropping bits of space junk from them. You can use this space junk to power your machinery and build a rocket to escape the planet… `, |
| | Intro screen 3 | `The passing spacecrafts will be different sizes. When a passing spacecraft is large, the junk may fall off of it over a larger area. Information at the beginning of each level will give clues about the size of the spacecraft or spacecrafts passing by. `, |
| | Intro screen 4 | `The spacecraft themselves are too high up for you to see them. But you can see the junk that falls off them. Each round you will see a piece fall off. Use this information to move your rover's electromagnet to try and catch the next piece that falls.`, |
| | Intro screen 5 | `You can increase the width of your beam from your electromagnetic (pictured below) by using more power. However, as we are trying to gather enough power for our rocket, you will get LESS points for using MORE power. Remember you will get ZERO points for missing the space junk! Try and catch space junk in the narrowest beam you can to get the best score.`, |
| | Intro screen 6 | `Use the right and left arrows to position the rovers' electromagnet underneath where you think the space junk will fall off. Then use the up and down arrows to increase and decrease its power. Give it a try now!`, |
| | Intro screen 7 | `On a computer left and right can be controlled with the left and right keys and up and down with the up and down keys. Use space to advance or click the play button.` |
| **Block 1** | Practice round screen 1 | PRACTICE ROUND: Move the rover and adjust the electromagnet power using the arrows. Press continue or space when you have positioned the rover and adjusted the power. Press continue to start the next trial.`, |

| | | |
|---|---|---|
| | Practice round screen 2 | `The game can be tricky - if a spacecraft is large junk may fall off over a large area, making it unlikely you'll catch all the junk. But use your experience of where junk has fallen before and this will improve your chances!`, |
| | Practice round screen 3 | REMINDER: The aim of the game is to catch space junk that is falling from different spacecrafts that pass by - using the smallest amount of power possible! Do you want to repeat the tutorial? |
| **Block 2** | Stable learning environment | There is one spacecraft overhead now, and it's dropping loads of junk. Better get to it!", |
| **Block 3** | Learning when the SD changes | Good job! You passed that level! Now there are two old space cruisers over head, one small and one large - but its not clear which order they will come in… Careful - when the large one passes by the space junk could fall over a wider area…', |
| **Block 4** | Learning when the mean changes | Well done! Looks like your lucky day! You have gotten a report that lots of spacecrafts are about to pass by, all of about the same size. Each spacecraft will pass one at a time.', |
| **Block 5** | Learning with combined SD and mean changes | Incoming! There are now many discarded spacecraft of all sizes passing by, one after another. Now's your chance - collect all the junk you can falling from each ship as it passes. Only one ship will go by at a time.', |
| **Block 6** | Learning with combined SD and mean changes Round includes loses. | There are still many discarded spaceships passing by of all different sizes - but now some of the falling junk is heading straight for us! If you don’t catch the junk now, it will damage our equipment and loose us points! But if you do catch it then you will get extra points and get us off this planet as quickly as possible! , |

## *8.2 Contingency distributions*

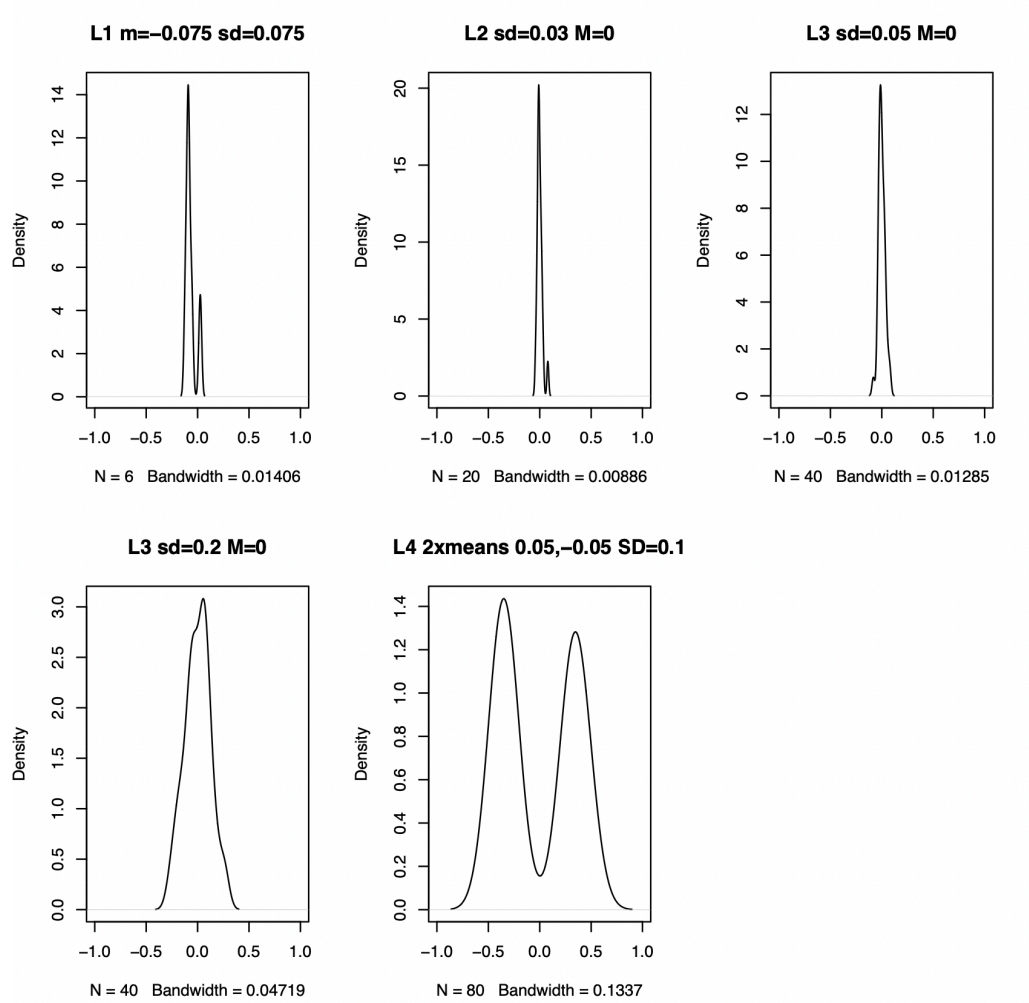


**Figure 4.5** *Showing the distributions of space junk inputs, for each combination of predetermined probability distributions (mean, and SDs). Exact statistical description of the distribution are written above each plot. This figure shows distributions of sampled inputs for blocks 1-4.*

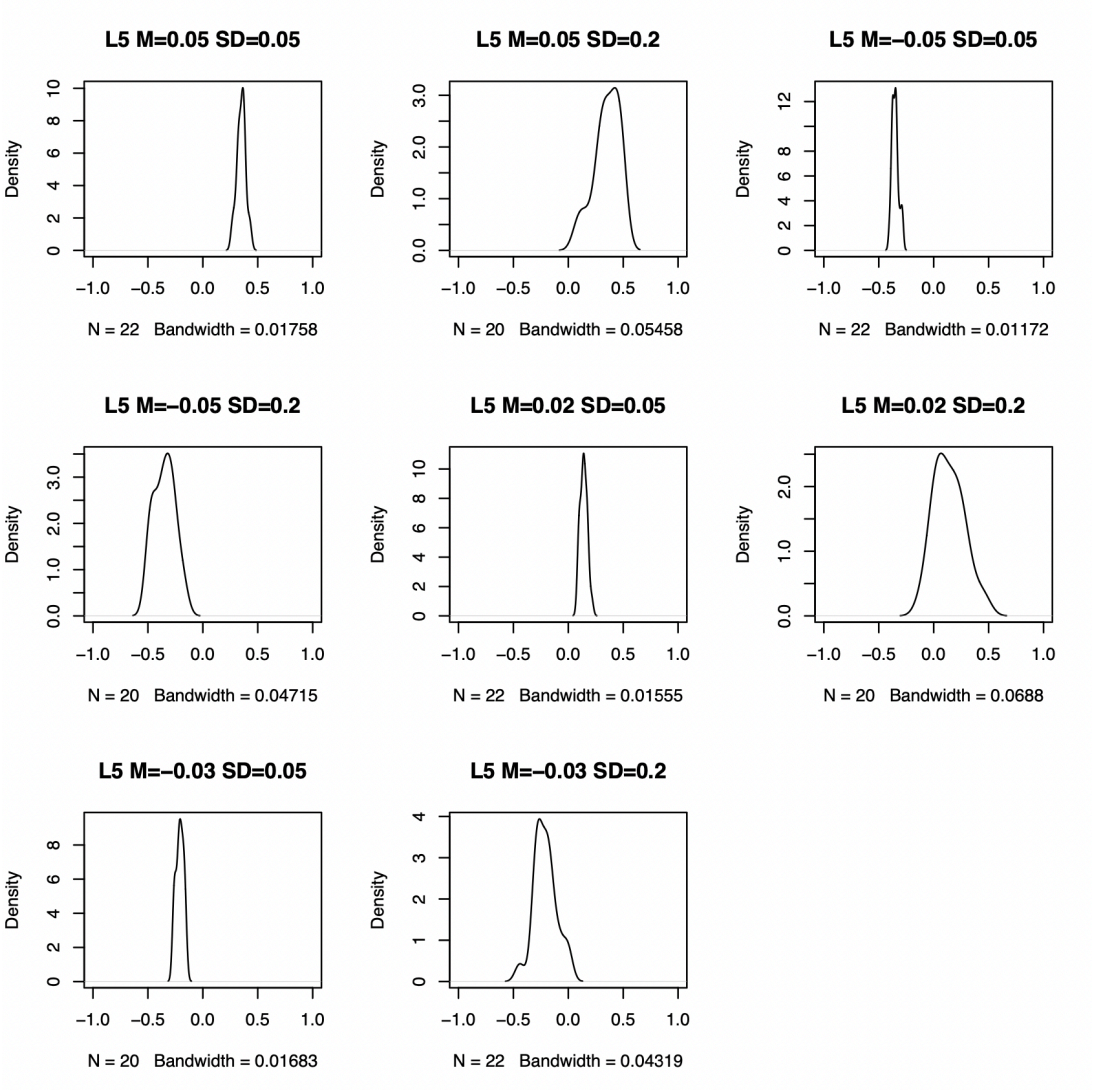


**Figure 4.6** *Showing the distributions of space junk inputs, for each combination of predetermined probability distributions (mean, and SDs). Exact statistical description of the distribution are written above each plot. This figure shows distributions of sampled inputs for block 5, where every 10 trials (+/-) jitter, the mean and/or the SD are updated.*

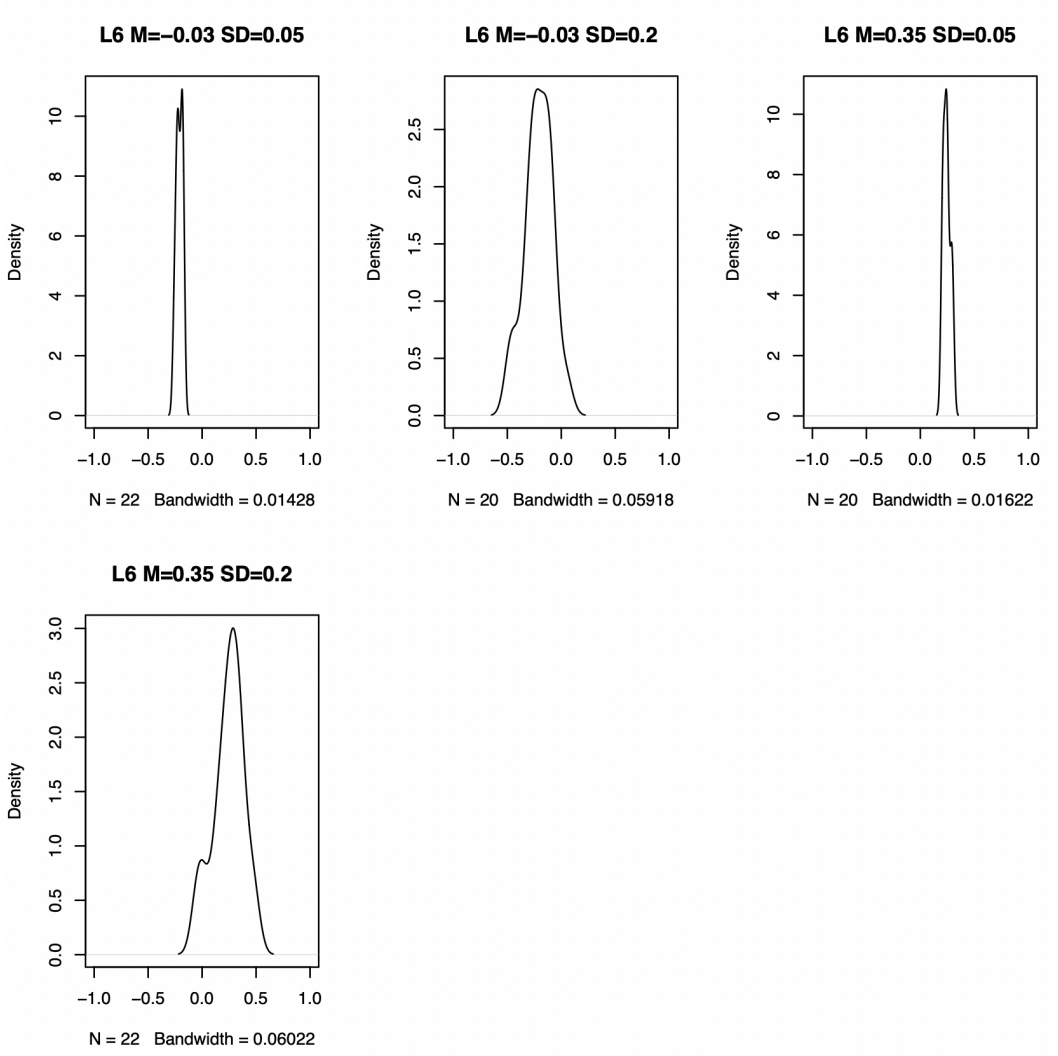


**Figure 4.7** *Showing the distributions of space junk inputs, for each combination of predetermined probability distributions (mean, and SDs). Exact statistical description of the distribution are written above each plot. This figure shows distributions of sampled inputs for block 6, where every 10 trials (+/-) jitter, the mean and/or the SD are updated.*

## *8.3 Identification of appropriate exclusion criteria*

Exclusion criteria for this task are designed to filter out individuals who are not engaging with the task in the expected way. While the criteria is agnostic to why this is occurring, criteria that could be used include metrics describing how participants interact with the task. For example,

movement of the rover, movement of the beam and time to complete the trial. The follow sections look to investigate the relationship between these exclusion criteria and performance in the task. In this way we are able to reliably show how and why individuals are excluded.

Analysis into the possible exclusion criteria reveals that there is a level of relatedness between them (fig 1). In turn, this may mean that these criteria are describing the same participants/group i.e., those not interacting with the task in the correct way. For example, Figure 4.8. Shows the total scores between included (false) and excluded (true), when using a "strict" threshold for exclusion criteria (described in full in the figure legend). These plots indicate movement related criteria e.g., movement of the Y axis (beam), and X axis (rover) follow a similar pattern, with those who would be excluded showing a high density of lower scores. This pattern suggests that it may be superfluous to include multiple movement related exclusion criteria, and instead one criterion describing non movement on both axis could be used.

The same pattern is also observed in the under-time category, again potentially implying that this criterion is also capturing the same group of people. Intuitively, it is sensible to predict a relationship between those with a lack of movement and those that complete many trials in under 1000ms. Interestingly, this metric enables us to interrogate the difference between spamming behaviour and strategy, as it can be hypothesised that a strategy to not move either the beam or the rover would require at least some degree of thought, and therefore time. As such, we can suggest that individuals who both do not move on a certain percentage of trials, and who complete a certain percentage of their trials in less than 1000ms, are likely to be poorly engaging with the game. While spamming behaviour is an interesting behaviour with its own research questions, it is not the focus on this investigation. These findings contrast with the criteria "overtime" which

describes occasion whereby participants spent over 5000ms on a given trial. Overtime trials were not found to show a relationship with score.

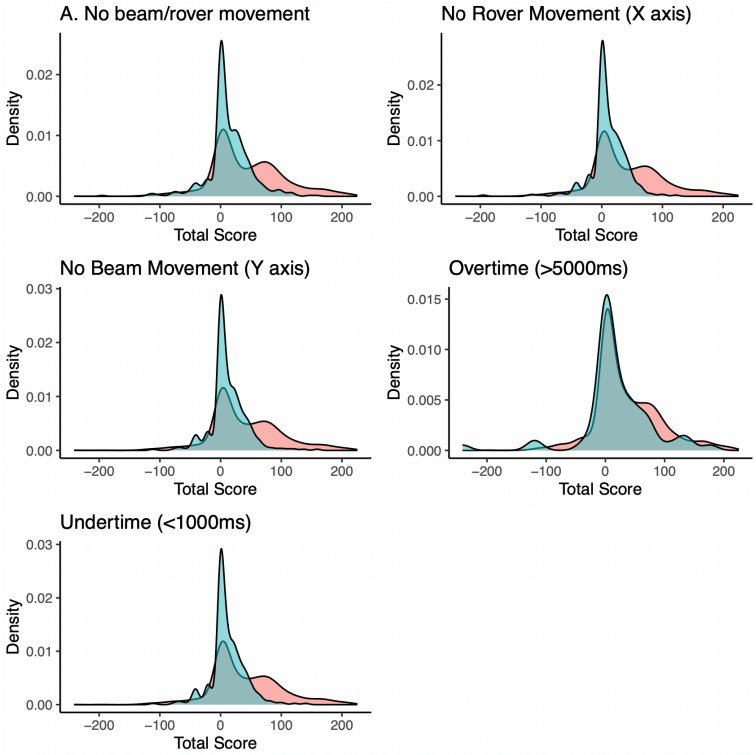


**Figure 4.8** *Density plots showing differences in trial scores for individuals excluded and not excluded according to the strict criteria: no movement in the beam (Y axis) or rover position (X axis) in at least 21 trials (a tenth of trials); no rover movement (X axis) in at least 108 trials (half of trials); no beam movement (Y axis) in at least 108 trials; Overtime = spending longer than 5000ms on each trial in at least 21 trials; Undertime = spending less than 1000ms on each trial in at least 21 trials*

To interrogate these criteria further, we can look at the differences in total score for each criterion on a block-by-block basis. In this way we can see if those performing poorly on the task relate to those we would exclude, and whether there are any blocks that are driving the effect. Again,

we can see that the patterns produced by under-timers (Figure 4.9), and non-movers for the beam and rover (Figure 2), are similar in shape, suggesting that they may be the same group of people (spammers). A correlation analysis supports this point ($r=0.86$; $p<.05$).

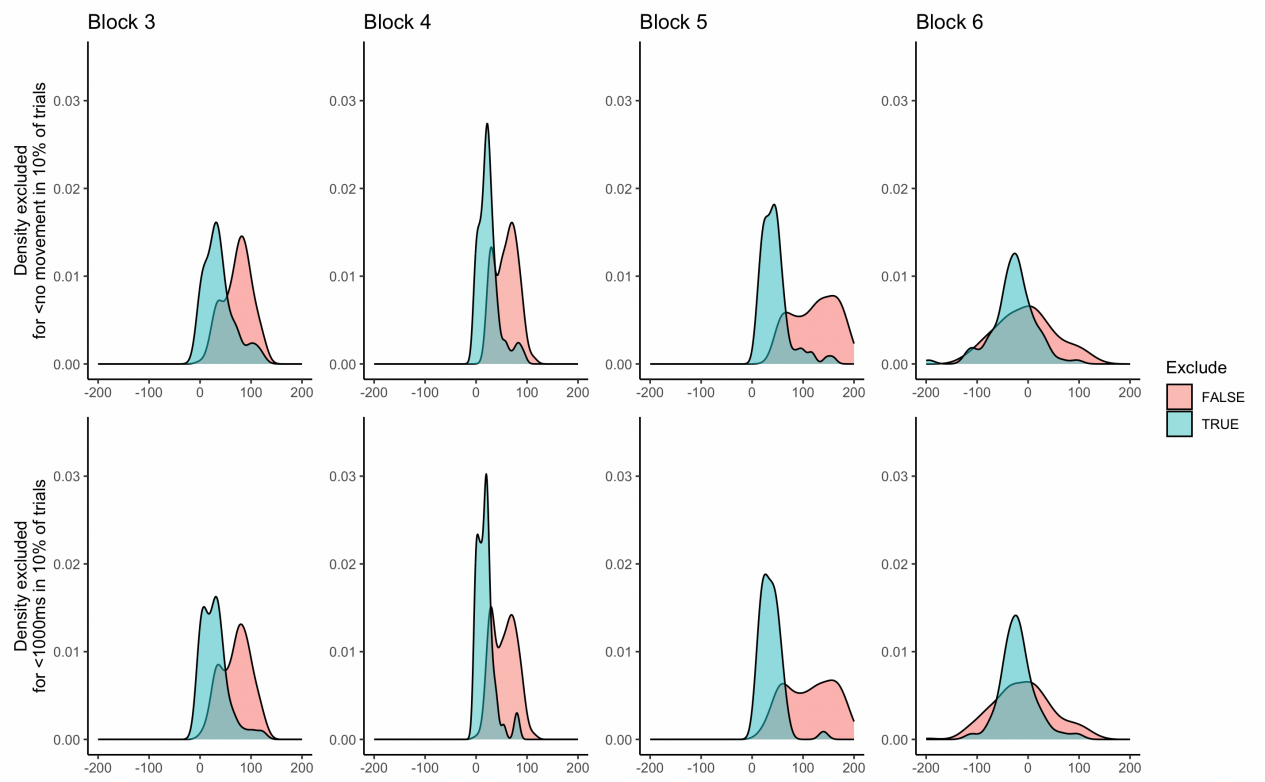


**Figure 4.9** *Top row: Density plots showing total scores for each block between individuals who have been excluded according to the 'strict' exclusion criteria for no movement in the beam or rover position (XY axis) in at least 21 trials (a tenth of trials) and spending less than 1000ms on each trial in at least 21 trials (under-timers). Fig. 2 Bottom row: looks at the total scores for those that have been excluded based on no-movement (beam and rover) labelled "True", compared to those that did not meet the criteria ("False").*

Additional clarification of this point is provided in Table 4-5. Table 4-5 indicates that inclusion of all criteria would exclude 116 individuals, as seen in the "Strict" row of the table. When we

continue to use the strict criteria (behaviour seen on 10% of trials) but only include non-movers (beam and rover) and those who were undertime, the total figure for exclusion is 109. This is evidence that these two criteria cover most of the behaviour that we are trying to identify. Further analysis is provided as to exact which thresholds to use on the identified exclusion criteria: under-timers and non-movements (beam and rover).

### *8.4 Identification of potential thresholds for exclusion criteria*

Table 4-5 provides several exclusion conditions, from "strict" to "lose" as a starting point for defining thresholds on the two chosen exclusion criteria (non-movers and under-timers). An additional exclusion requirement is found for the repeaters – these represent instances where the participant has accidentally repeated sections of the task due to poor internet, for example. As this is a learning task, and previous knowledge of the inputs would skew the data, these have been automatically removed, but included in the table (HC=3; ED=8).

As we can see from the previous plots, under-timers and non-movers represent a similar grouping. We would therefore expect that the thresholds should cumulatively account for this, while still being able to identify those not playing properly. Conditions "split1" and "split2" find that all but one person in the under-time category is accounted for by the nomoveXY criteria, and therefore fit this expectation. Loose criteria (Loose90) require the behaviour to occur in 90% of trials before the participant is excluded. While this is a little unrealistic given the obvious spamming behaviour, it is useful to include this to understand the impacts of using more strict criteria.

**Table 4-5** *Showing the outcome on the sample pool given different exclusion criteria.*

| Exclusion Condition | Criteria | Threshold | Cumulative n reduction (%) | Healthy Control cumulative reduction (% of group) | Eating Disorder cumulative reduction (% of group) |
|---|---|---|---|---|---|
| **Strict** | repeats/incomplete | 1% | 11 | 3 | 8 |
| | nomoveX | 50% | +54 | +12 | +53 |
| | nomoveY | 50% | +7 | +3 | +4 |
| | nomoveXY | 10% | +23 | +8 | +5 |
| | overtime | 10% | +7 | +3 | +15 |
| | undertime | 10% | +14 | +5 | +9 |
| | **total** | **na** | **116 (38%)** | **31 (31%)** | **85(42%)** |
| **Strict 10%** | repeats/incomplete | 1% | 11 | 3 | 8 |
| | nomoveXY | 10% | +81 | +19 | +62 |
| | undertime | 10% | +17 | +7 | +10 |
| | **total** | **na** | **109 (35%)** | **29 (29%)** | **80 (39%)** |
| **Medium 25%** | repeats/incomplete | 1% | 11 | 3 | 8 |
| | nomoveXY | 25% | +64 | +12 | +52 |
| | undertime | 25% | +7 | +2 | +5 |
| | **total** | **na** | **82 (27%)** | **17 (17%)** | **65 (32%)** |
| **Split1** | repeats/incomplete | 1% | 11 | 3 | 8 |
| | nomoveXY | 10% | +81 | +19 | +62 |
| | undertime | 50% | +1 | +0 | +1 |
| | **total** | **na** | **93 (30%)** | **22 (22%)** | **71 (34%)** |
| **Split2** | Repeats/incomplete | 1% | 11 | 3 | 8 |
| | nomoveXY | 25% | +64 | +12 | +52 |
| | Undertime | 50% | +1 | +0 | +1 |
| | **Total** | **na** | **76 (25%)** | **15 (15%)** | **61 (30%)** |
| **Lose 50%** | repeats/incomplete | 1% | 11 | 3 | 8 |
| | nomoveXY | 50% | +47 | +7 | +40 |
| | undertime | 50% | +3 | +1 | +2 |
| | **total** | **na** | **61 (20%)** | **11 (11%)** | **50 (25%)** |
| **Lose 90%** | repeats/incomplete | 1% | 11 | 3 | 8 |
| | nomoveXY | 90% | +18 | +2 | +16 |
| | undertime | 90% | +1 | +0 | +1 |
| | **total** | **na** | **30 (10%)** | **5 (5%)** | **25 (12%)** |

# Chapter 5. Uncertainty estimation deficits across trait level psychopathology: *overlap and distinction in psychosis, depression, and anxiety*

## 1 Abstract

*Background:* The ability to deal with uncertainty inherent in our environments is crucial to our everyday lives. However, research shows that uncertainty impacts learning across a range of mental illness, including psychosis, anxiety, and depression. This overlap highlights how a categorical nosology of mental illness may be hindering our understanding of underlying pathophysiological mechanisms and in turn, improvement of psychological treatments. Novel online experimental testing paradigms, used in conjunction with computational measures of learning, offers a useful way to access large-scale unselected populations with natural variation in psychopathological symptoms.

*Methods:* A novel learning task was used to assess learning under different uncertainty environments (high volatility, high noise, and combined uncertainty conditions) (n=580; M(*SD*)=30.6(5.91); female = 65%). Linear mixed effects models were used to assess whether individuals with elevated psychosis (including paranoia, delusions, and schizotypy traits), depression, and/or anxiety symptoms scores showed differences in: overall performance, in their ability acquire the underlying statistics of the task, and in overall learning rate. To assess ability to flexibly update learning in response to increased volatility, a correlation analysis was computed between symptom severity related and learning rate difference between blocks.

*Results:* Participants generally adhered to a normative account of learning and were able to adapt their learning rates in response to changes in uncertainty. However, individuals with elevated anxiety and psychosis symptomology (including paranoia, delusionary tendencies, and schizotypy traits) demonstrated a decreased ability to flexibly adapt their learning rates to changes in uncertainty. Elevated psychosis symptoms were additionally associated with a non-normative pattern of overall learning rates, and a difficulty in acquiring the underlying statistics of the task. In contrast, individuals with elevated depression symptoms exhibited a performance benefit particularly in response to the introduction of punishments (monetary losses) to the task.

*Conclusion*: overlap and distinction was found between symptom traits. This study shows a shared deficit between elevated anxiety and psychosis traits, that related to an inflexibility in updating to changes in uncertainty. Whereas elevated depression appeared to be uniquely related to differences in learning metrics when punishments were introduced. Authors suggest that additional aberrant learning in elevated psychosis may indicate a more pervasive learning deficits in these groups. Identification of fundamental mechanisms that may underlie multiple aspects of

psychopathology would add to our understanding of mental illness, and important support improved treatment options.

## 2 Introduction

With one in every eight people around the world living with a clinically significant disturbance in their cognition, emotional regulation, and/or behaviour, research strives to aid in the development of improved diagnosis, prevention, intervention, and treatment (WHO, 2017). However, while current nosology (e.g., DSM-5) provide an invaluable resource to clinicians, the categorical approach to describing mental illness may be obscuring underlying pathophysiological mechanisms, and as such, routes toward identification of novel and targeted treatment options (Owen, 2014; Stephan et al., 2016). This is due to the inclusion of categories that appear to combine heterogeneous groups of patients and fail to account for high levels of comorbidity (Insel et al., 2010; Nuckols & Nuckols, n.d.; Reed et al., 2020; Van Os & Tamminga, 2007). In response to this, organisations such as Research Domain Criteria (RDoC) and Hierarchical Taxonomy of Psychpathology (HiToP) have made advances toward identification of more fundamental and mechanistic cognitive deficits across psychopathology (Cuthbert & Insel, 2013; Gauld et al., 2022; Insel et al., 2010; Kapur et al., 2012; Kotov et al., 2021; Michelini et al., 2021). Computational psychiatry, the application of algorithms to describe aberrant behaviour, used in conjunction with large-scale unselected online populations, has emerged as a promising tool for capturing how more fundamental cognitive deficits relate to the continuous, rather than binary (on/off; healthy vs. ill) nature of mental illness (Gagne et al., 2020; Wise et al., 2023; Wise & Dolan, 2020).

One strongly evidenced deficit across psychopathology occurs in relation to learning and decision making (LDM), i.e., the process of adapting one's behaviour to more optimal outcomes (Akpan, 2020). LDM involves the assessment and integration of information. However, uncertainty exists within the information we receive simply because we perceive the world incompletely i.e., in a limited, intermittent way. As such, humans must infer states of the world based on information and processes that are often changeable and hidden (Pulcu & Browning, 2019). Information can be uncertain in multiple ways, affecting LDM differentially. Depending on the agent's assessment of the type and degree of uncertainty in the learning environment, the error between what the agent predicted and what was in fact observed (prediction error) is updated and weighted accordingly. For example, under a normative account of learning, if the agent experiences a prediction error but the incoming information is noisy, it is not weighted heavily, and the rate of learning is low. Alternatively, if the environment is highly changeable (termed volatile), the PE may indicate a meaningful change in the environment – so will cause a high rate of learning. While evidence of this normative account of learning is clear in healthy individuals (Behrens et al., 2007; Pulcu & Browning, 2019), computational modelling approaches applied to psychiatric cognitive task data have shown that the mis-estimation of uncertainty relates to symptoms, symptom dimensions, and disorders (Adams et al., 2013; Gagne et al., 2020; Gillan et al., 2016; Patzelt et al., n.d.; Pike & Robinson, 2022; Sandhu et al., 2023; Sterzer et al., 2018; Wise et al., 2023; Wise & Dolan, 2020). LDM under uncertainty can thus be tested against a normative account of learning either by i) comparing learning between conditions of uncertainty e.g., overall learning rate under stable versus volatile environments; or ii) by assessing the adaptation of learning to changes in the underlying contingencies (volatile learning rate – stable learning rate) (Browning et al., 2015).

Research in the field commonly uses probabilistic (reversal) learning tasks with binary inputs and responses (red/blue square), to simulate noise (no reversals), and volatility (un-signalled reversals). Using this approach, research across the psychosis spectrum shows a generally higher overall level of stochasticity in decision-making behaviour, as well as higher initial estimates of environmental volatility (using for example, hierarchical computational modelling approaches) (Cole et al., 2020; Diaconescu et al., 2020; Katthagen et al., 2020; Reed et al., 2020; Suthaharan et al., 2021). Specific psychotic symptomology can be further disaggregated using characteristics of LDM uncertainty deficits, highlighting the importance of examination of sub-symptomology within the psychosis spectrum. For example, delusions are argued to emerge from initial high estimates of environmental volatility, making non-salient information appear highly relevant and subsequently resistant to change (Adams et al., 2013; Reed et al., 2020; Sterzer et al., 2018), whereas hallucinations are suggested to arise from aberrantly high certainty in perceptual expectations (Powers et al., 2017).

There is a wealth of research using similar experimental task designs in other major mental health disorders such as anxiety and depression, often showing issues around reward responsiveness specifically (Pike & Robinson, 2022 - for review). However, more recently, rather than inducing volatility by switching contingencies once or twice at varying intervals, novel experimental tasks have used a block design to measure learning under volatility (Browning et al., 2015; Gagne et al., 2020). These designs are argued to test differences more effectively because they include entire blocks of volatility and stability as opposed to one or two changes, enabling measurement of how individuals adapt to changes in uncertainty (Browning et al., 2015; Gagne et al., 2020; Pulcu & Browning, 2019; Sandhu et al., 2023). Using these approaches, research has shown that the adaptation of learning rates to changes in volatility has been associated with lower learning flexibility during volatility in trait anxiety (Browning et al., 2015; Gagne et al., 2020), and with

an internalising symptom dimension (trait anxiety and trait depression) (Gagne et al., 2020). Here, anxious and/or depressed individuals did not adapt their learning rates to changes in the underlying volatility contingencies as much as low symptom scorers (Gagne et al., 2020). However, it remains unknown how these individuals would adapt their learning to for example, a noisy environment (Katthagen et al., 2022a; Piray & Daw, 2021).

Further improvements to experimental task design have been suggested (Katthagen et al., 2022 – for review). For example, using continuous inputs drawn from a "ground truth" Gaussian distribution rather than the standard binary approach would enable finetuned manipulation to contingencies that imitate different types of uncertainty. Here, blocks with mean changes would simulate a volatile environment, whereas changes to the variance would prompt learning within a noisy environment. By additionally providing participants with a way to respond in a continuous manner, and with parallel estimates of the volatility and noise, a detailed understanding of uncertainty estimation could be gleaned. While the joint estimation of uncertainty may support the disaggregation of heterogeneity among participants, it remains unclear whether i) learning inflexibility in response to changes in volatility, currently found to relate to an anxiety or an internalising psychopathology factor, can be replicated in elevated psychosis-related traits such as paranoia, delusions and schizotypy personality traits; ii) whether individuals with trait levels of psychopathology adhere to a normative account of learning; and iii) whether there are differences in the acquisition of the statistical uncertainty (mean and standard deviation of the underlying distribution).

In response to these gaps in research, this study will apply a novel task designed to assess LDM under isolated volatility and noise conditions using both a block design, and continuous inputs and responses. Against a normative account of learning, this research will assess overall learning

between uncertainty blocks, as well as the adaptation of learning from noisy to volatile environments across symptoms of psychopathology. To assess whether identified deficits could represent a commonly perturbed mechanism underlying multiple symptoms of psychopathology, the research will assess LDM under uncertainty across multiple symptom traits, including depression, anxiety, and symptoms of psychosis, including delusionary ideation, paranoia, and schizotypal personality traits. Given the exploratory nature of the analysis, research will capitalise on novel online experimental paradigms, providing access to large scale populations. While populations are unselected rather than clinically defined, they will contain natural variation in relevant symptomology as measured by well validated questionnaires. This design will enable data to be gathered at a large enough scale for robust exploration and replication (Wise et al., 2023). Similarly, using online platforms accessible to a wide audience will also allow exploration of psychiatric symptoms in less confounded (but still predictive) populations i.e., without medication and chronic illness. In turn this may provide insight into precipitating subclinical deficits to more serious of chronic illness (Gillan et al., 2016; Patzelt et al., n.d.; Rouault et al., 2018; Seow et al., 2020; Soltani & Izquierdo, 2019; Wise et al., 2023).

# 3 Methods

The study received ethical approval from King's College London ethics committee (25/10/2019; MRSP-19/20-14757). All procedures were conducted in accordance with the committee's guidelines. Informed consent was obtained from all participants. Data collected from this study has been anonymised and processed in compliance with the UK General Data Protection Regulation (GDPR).

## *3.1 Participants*

A total of 631 participants aged 18-40 years old were recruited from Prolific Academic (prolific.ac), an online research participant recruitment platform. Participant eligibility criteria included: UK-based, English as first language, no history of head injury, no diagnosis of cognitive impairment/dementia or autism spectrum disorder. Participants were recruited and assessed over a seven day period.

## *3.2 Procedure*

Prolific Academic (*see* prolific.ac), an online crowd-sourcing platform, was used to recruit all participants anonymously from the UK. Participants were then invited to complete the experiment via Gorilla (*see* gorilla.ac), an online behavioural research platform, with the option to access the tasks via a computer/laptop or mobile phone. Before proceeding with the study, participants provided informed consent and completed a baseline demographic survey. Participants were randomised either to first respond to the symptom questionnaires or to play the Space Game to minimise fatigue effects. Within the demographic questionnaire, participants answered a question on the amount of time that they gamed per week. This was because the research involved them playing a gamified cognitive task, the success of which may be influenced by their familiarity with gaming in general. During the experiment, two attention checks were implemented. During the attention checks participants had to answer a simple question about the colour of a square. On completion of the study, participants were debriefed and each received an average of £6.50 per hour spent on the tasks and an additional performance dependent bonus payment up to £2 in the Space Game. They were also invited to share any feedback or comments that they might have regarding the study.

## *3.3 Materials*

### *3.3.1. Mood and Anxiety Symptom Questionnaire (MASQ)*

The Short-MASQ is a 62-item questionnaire that was used to assess three symptom dimensions of anxiety and depression – general distress, anxious arousal (anxiety-specific) and anhedonia (depression-specific) (Clark & Watson, 1991). The MASQ has been shown to be a valid and reliable instrument, with internal consistencies from 0.85 to 0.92, indicating adequate convergent and divergent properties (Lin et al., 2014). There are a total of 23 items for the General Distress (GD) subscales (11 for General Distress: Anxious Symptoms and 12 for General Distress: Depressive Symptoms), 17 items for the Anxious Arousal (AA) subscale, and 22 items for the Anhedonic Depression (AD) subscale. Two questions related to suicide and death (Q48 and Q61) were excluded from the current study due to ethical considerations. Items in the questionnaire were scored on a five-point Likert scale based on how much the respondent has felt or experienced situations during the past week, ranging from 1 being "*very slightly or not at all"* to 5 being "*extremely*". For the purposes of analysis in this study, the depression related subscales (GDA and AD) and anxiety related subsscales (GDA and AA) were combined.

### *3.3.2 Schizotypal Personality Questionnaire (SPQ)*

Participants completed the SPQ brief (SPQ-B) version questionnaire which assesses schizotypy personality traits (Raine et al., 1997; Raine & Benishay, 2011). The SPQ-B contains 24 questions that fall under three categories of schizotypy factor structure, including cognitive-perceptual, social-interpersonal, and disorganization. Participants answer yes or no to questions such as: *"Some people think that I am a very bizarre person*", and "*I feel I have to be on my*

*guard even with friends*". A total score was calculated across all items for the purposes of this experiment. The SPQ-B questionnaire has been shown to display high levels of convergent and discriminant validity in relation to other psychosis screening tools, across a range of populations including adults and adolescents. The SPQ-B has been extensively studied in relation to a broad range of topics and populations (Aycicegi et al., 2006; Bedwell et al., 2006; Compton et al., 2009; Jahshan & Sergi, 2007; Mata et al., 2005). Analysis of the psychometric properties of the SPQ-B show an internal reliability for the total score of between 0.75 and 0.83. Test-retest reliability ranges from 0.70 to 0.95 (Fonseca-Pedrero et al., 2008, 2009; Mata et al., 2005).

### *3.3.3 Peter's Delusion Inventory (PDI)*

Delusion-proneness was assessed with the Peter's Delusion Inventory (Peters et al., 2004). This questionnaire includes 21 questions incorporating the multidimensionality of delusions, by including measures of distress, preoccupation and conviction of beliefs. The PDI-21 has been shown to be a reliable and valid instrument to measure delusional ideation in the general population (Peters et al., 2004). Participants indicated a yes/no response to each question, and an affirmative response was assigned a score of 1. Total scores were calucated and used for each participant for the purposes of this studty.

### *3.3.4 Green Paranoia Scale (GPTS)*

This GPTS was designed to measure paranoia. The questionnaire includes subscales to assess ideas of social references (16 items) and for persecutory ideas (16 items), alongside the concern, convictions and stress experinced by the indivdiuals in relation to these aspects of paranoia (Green et al., 2008) The GPTS has been validated in clinical and non clinical

populations (Green et al., 2008; *Spanish Adaptation of the Green Paranoid Thought Scales | Psicothema*, n.d.), and has been shown to be a highly informative and valid measure of paranoia in a systematic review (Statham 2019).

### *3.3.5 Novel learning task*

Participants performed a gamified learning task (to see the task, please click here). The task required participants to catch as much falling space junk as possible, so they could build a rocket and escape the planet. However, as the space junk was falling from unseen, hidden, space craft, participants had to infer the location, size, and frequency of change, of the hidden spaceships in order to make successful predictions. To catch the junk, participants were given an electromagnetic rover (adjustable on the x axis) that cast a beam (the power of which was adjustable on the y axis). To conserve fuel for their escape rocket, and to receive the maximum points possible per trial, participants were instructed to maximally catch the junk, using the smallest beam size possible. As such, maximum points per trial would be awarded for successfully catching the junk using the smallest beam width.

Limited information about the size, location and frequency of the incoming unseen space craft was given at the start of every block (see Appendix 8.1: Table 5-4). For example, block 3 pre-play screen provided the information as follows: "INFORMATION: *Number of incoming spacecraft: 1; size of incoming spacecraft: no information, location of information; Location of the incoming spacecraft: one location likely."* On each trial, participants were shown where the last piece of space junk fell. Participants were instructed to use the previous falling space junk location to predict the location of the next piece of junk. The falling junk was presented on each trial for 5000m/s. To indicate their prediction, participants adjusted the rover and beam (which

would appear at a random location on the screen x axis at the start of each trial) using the arrow keys (or WDAS) either on their keyboards or on the screen (left/right for the rover; up down for the beam). Once the participant had indicated their prediction, they were shown the where the junk in fact fell i.e., a prediction error. Feedback was presented in terms of points per individual trial and an ongoing cumulative score in the top right of the screen. Written confirmation e.g. "Well done, you caught it!", "missed", or "timed out!" was also provided on a trial-wise basis. Each trial could score a maximum of ten points. The score was shown after each trial and between each block. Bonus points were award for every 250 points, and each bonus point earned the participant an additional 50p on top of the payment for completing the experiment.

The task included 219 trials (ITI: 1000-5000ms) overall, split into six blocks that differed in their configurations of volatility and noise, via manipulations to the underlying probability distribution that the junk was sampled from. The task was counterbalanced to avoid ordering effects. Here, each block was simply presented in the opposite direction i.e., the task included a forward, and reverse, condition. Distributions were designed in line with a previous study (Berniker et al., 2010; see Table 5.1; Figure 5.1b). Block one was a practice round that included three practice trials and required successful completion i.e., to catch every piece of junk, before the participant could continue. If the participant did not pass the practice round, they would be directed back to the start of the instructions to begin again. Block two (n=10 trials) was a stable learning environment i.e., no mean changes. Based on the counterbalancing condition, half of participants were exposed to high noise during block two (SD=0.12), whereas the other half had low noise (SD=0.03). In block three, the noise was manipulated in an isolated condition i.e., there were no mean changes (Mean=0.01), but the variance was altered. Depending on the counterbalancing condition, participants were exposed to a condition of low noise (SD=0.03; n=20 trials), and a high noise (SD=0.12; n=20 trials). Block four (n=40 trials) tested learning under isolated

volatility. Volatility was manipulated by the inclusion changes to the mean of the underlying distribution from which the junk was drawn (see Table 5-1; Figure 5.1), alongside a stable variance (SD=0.01). Here, the probability distribution switched between two previously unseen means. The switch rate for mean change was computed at a 0.25 chance every 5 trials, resulting in 5 overall mean switches across the block (see Table 5-1; Figure 5.1B) as seen in Berniker et al., 2010). Blocks five (n=84 trials) and six (n=40 trials) updated the mean and SD of inputs every ten trials (plus jitter), resulting in continuous high volatility, and periods of high and low noise. In each case, two previously seen means were used alongside two new means i.e., block five used the two means from block four, plus two new means etc. While learning requirements were the same across blocks five and six, blocks differed in terms of its reward policy, described below. To access the task online, please click here.

**Table 5-1** *Showing the details of the contingencies underlying the task for each block.*

| **Screen** | | **Contingency Information** | | | |
|---|---|---|---|---|---|
| **Name** | **Description** | **Trials (n)** | **Mean** | **SD** | **Rules** |
| **Block 1** | Practice round screen 1 | 3 | -0.07 | 0.045 | Option to repeat |
| **Block 2** | Stable learning environment | 10 | 0 | 0.12 or 0.03 | 50% participants SD=0.12; 50% participants SD=0.03 |
| **Block 3** | Learning when the SD changes (high and low noise) | 40 | 0 | 0.12 or 0.03 | SD changes halfway through. Fixed mean. Counterbalanced condition is reversed. |
| **Block 4** | Learning when the mean changes (high volatility) | 40 | 0.35, -0.35 | 0.06 | A 25% chance of changing to the distribution with the second mean, every four turns. |
| **Block 5** | Learning with combined SD and mean changes | 84 | 0.35, -0.35, 0.14, -0.21 | 0.12 or 0.03 | Each SD/mean combination changes every 10trial+/-jitter of around 3 trials. |

| | | | | | |
|---|---|---|---|---|---|
| **Block 6** | Learning with combined SD and mean changes. Block includes loses. | 42 | 0.35, -0.21 | 0.12 or 0.03 | Each SD/mean combination changes every 10+/-jitter of around 3 trials. Randomly ordered. Extra points for catching. Loose points for missing/using a larger beam. |

*Abbreviations: SD=standard deviation*

### *2.4.1 Outcome measures*

Overall performance was measured by score. Score was calculated as a function of both catch success i.e. whether they caught the junk on that trial, and the size of the beam used to capture it (i.e., screen size), and was presented to participants as a score out of ten on each trial. In block six, participant could receive double points for a catch, or could lose points if they were unsuccessful at catching the space junk. Losses were calculated in the same way as rewards, but reversed. As such, missing the space junk with a wider beam led to a loss of more points than missing the space junk with a small beam. Beam width, the amount of the screen taken up by the beam) could also be taken as a separate measure, and while related to score, provided some additional information about the ability of participants to acquire the underlying variance of the distribution.

Derived metrics included performance error, that could be calculated by subtracting the participants estimate of the mean of the distribution i.e., rover position, from the mean of the underlying distribution. Performance error, as related to the mean of the underlying distribution, provides insight into whether the individual is learning the underlying mean. The averaged standardised beta coefficients from a model predicting the signed prediction error (participant rover position – space junk position at $t_1$), from the signed rover position change indicated

(participant rover position $t_1$ – participant rover position $t_2$), was used as an index of learning rate across participants.

## *3.4 Analysis*

### *3.4.1 Quality control*

Data was subject to quality control screening to account for potential inattentive behaviour i.e. where a participant is deemed to not be attending to the task in the expected or necessary way. Criteria was pre-determined and is fully explained in Figure 5.1.

### *3.4.2 Models for performance metrics*

Overall performance was measured by score, averaged across each block. Acquisition of the underlying statistics was measured using comparison between blocks for the averaged performance error (learning of the mean). Whereas acquisition of the variance was measured by comparing beam width, averaged across the blocks and the noise conditions (high vs low). For example if a block included both high and low noise, participants for that block would have a value for each.

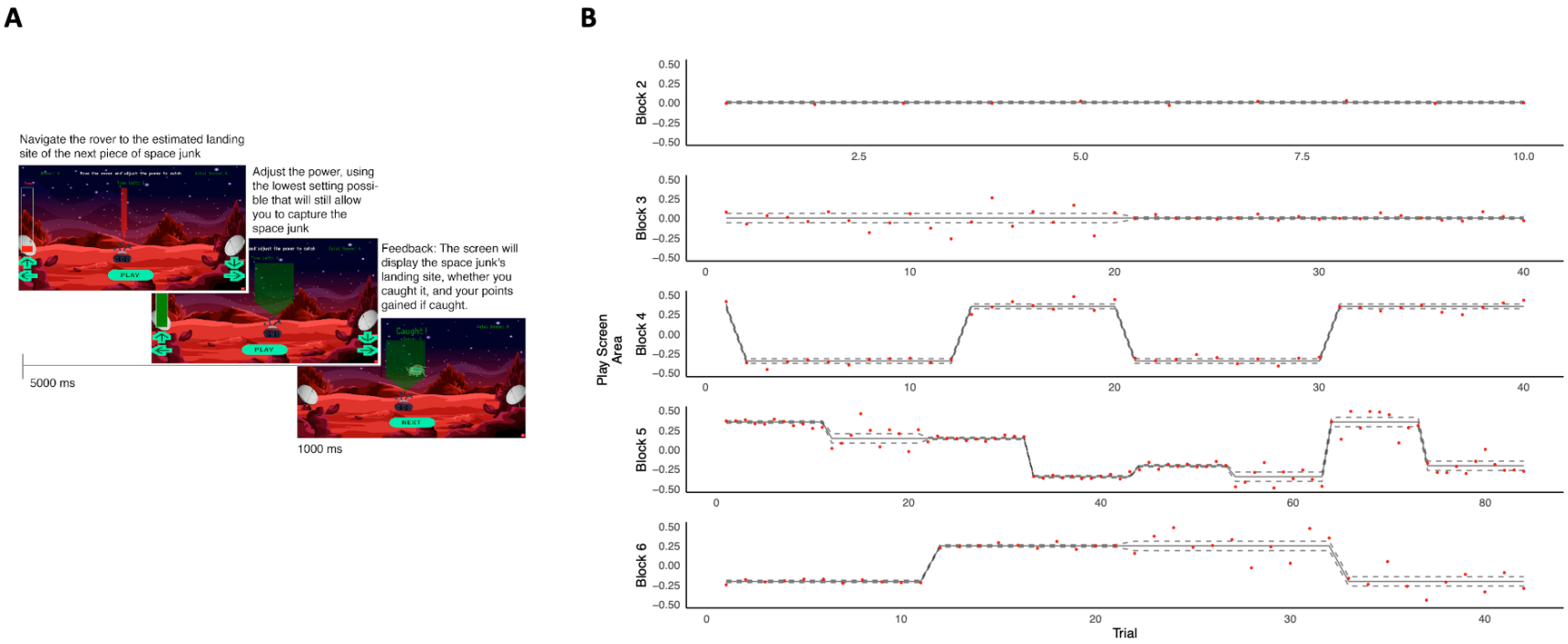


**Figure 5.1 A**. Showing trial structure. Here, once the participant is exposed to the cue for a maximum of 5000m/s, participants are then instructed to make an estimate of the mean, using rover positioning; and variance using manipulation of the beam width. Feedback i.e., another piece of space junk drawn from the same distribution, is then presented to the participant (1000m/s). **B.** The black solid line shows the mean(s) used for each block (see Table 3.1 for further details), indicating both the stability of the mean over trials (x axis), and the location of the mean on the play screen area. The standard deviation used to simulate noise in the space junk locations is shown using the black dashed line (see Table 3.1 for further details). Here, the width of the dashed line around the mean indicates both the width of the SD used, and the area of the

play screen available for space junk locations to be drawn from. The red dots show the actual space junk positions that the participants were exposed to, in accordance with the underlying probability distributions

Analysis was carried out using R 4.2.1 GUI 1.79 High Sierra build (8095) (R. Team, 2014). Full analysis code available here. Linear mixed effects models were computed for the task's main outcome measures (Meteyard & Davies, 2020). The structure of the data included both within and between subject factors, including nested elements. It was necessary for the model to include multiple nested and non-nested random effects. As such, the r package "lme4" was used, and random slopes and intercepts were fit for relevant variables, in order to account for the structure of the data (Bates, 2010). Specifically, all models included random effects of i) participant, and ii) the counterbalancing condition (forward, reverse, priming block high or low) nested within block (block 3-6). This was to i) inform the model that each participants' data was interrelated within each subject, but different between subjects, and ii) to inform the model that for example, block 2 data from counterbalancing condition forward was allowed to differ from block 2 reversed (and so on). Fixed effects were fit for each dependent variable using model selection, and therefore small variations in the included fixed effects between models, but in general included device type (mobile, computer), gender (male, female, non-binary), and an interaction between block (3:6) and whether or not the participant was a gamer (yes/no). Specific fixed effects are reported in the results section.

Each block of the task represented a different learning environment. To compare metrics between each learning environment, backwards contrasting methods were employed. As such, each block was statistically compared to the block before i.e. block 4 (high volatility) compared to block 3 (high noise); block 5 (high noise and volatility) compared to block 4. Noise and volatility blocks remained stable across block 5 and 6, with the difference being a shift in reward polices, as such block 6 (introduction of losses and increased gains) was compared to block 5 (standard rewards) (see Table 5-2). As these were planned comparisons, multiple corrections analysis was not

computed. However a sensitivity analysis for findings relating to the response variable: score, is provided.

**Table 5-2** *Showing planned backwards contrasts.*

| Planned Contrasts | Description of comparison |
|---|---|
| Block 4 vs block 3 | High volatility vs. high noise |
| Block 5 vs block 4 | High volatility + noise vs. high volatility |
| Block 6 vs block 5 | High volatility + noise + losses + increased gains vs. High volatility + noise |

### *3.4.3 Model Selection*

Model selection was carried out to identify the best model for each metric. To directly compare the models, an information theoretic approach (AIC) (Akaike, 1973) was used. This approach is noted for its conservative approach due to the penalties it imposes on model complexity, such as additional fixed effects, as well as its ability to compare nested models (Wagenmakers & Farrell, 2004; Vrieze, 2012). To enable this comparison of models, given that we wanted to compare models with differing numbers of fixed effects, and that the data was nested, the log likelihood was used (Verbyla, 2019) . However, Maximum Restricted Maximum Likelihood (REML) was the choice of estimation method used once the best model had been identified because of the inclusion of nested random effects (Corbeil & Searle, 1976). The reported results were read from the models that had the lowest AIC values of the models compared, including the simplest model (fixed effects set to 1), showing that the simpler models was least informative. A chi square difference test was also used to statistically test whether the models were significantly improved from baseline i.e., the most simple model. Chi square tests

for model selection are used when comparing nested models, i.e., where the differences between models lies in the number of fixed effects (Schermelleh-Engel et al., 2003).

### *3.4.4 Learning rate analysis*

The averaged standardised beta coefficients from a model predicting the signed prediction error (participant rover position – space junk position at t+1), from the signed rover position change indicated (participant rover position $t_1$ – participant rover position $t_2$), was used as an index of learning rate across participants. Using the back-contrasted method described in the previous section, average learning rates were compared between blocks. A secondary analysis for learning rates included analysis of the learning rate difference. Here the difference in learning rate (beta coefficients) between blocks, were correlated against the continuous symptoms core measures. Results are provided for learning rate differences between block three (only including trials with a wide SD, n=20) (isolated high noise) and four (isolated volatility); and block three (only including trials with a narrow SD, n=20), and block four (isolated volatility).

# 4 Results

## *4.1 Quality control*

In this experiment 24 individuals were excluded for failing to meet these predetermined "spamming" quality control standards (see Figure 5.2), along with a further 14 individuals for failing to meet all three attention checks (n=1) and/or incomplete data due to a technology issue e.g. internet connection (n=13). Participants were also excluded if they identified as having a learning or neurological disorder (n=12). Finally, one individual was excluded on the basis of using a tablet device type, as opposed to a mobile or computer/laptop. Overall, 51 individuals

were excluded, leading to a total of 580 participants for analyses ($M$ = 30.6 years; $SD$ = 5.91; female = 65%; for full details of sample characteristic please see Table 5-3.).

## *4.2 Task validation*

*Normative account of learning.* A normative account of learning suggests that individuals will display higher learning rates during periods of volatility, compared to periods of low volatility/stability/or noise. Noisy environments elicit lower learning rates because they are non-meaningful data points. To assess whether learning rates mirrored a normative account of learning and as such provide evidence that the task has worked as expected, average learning rates were compared across blocks. A model was built that back-contrasted each block, and included fixed effects of device type, age, gamers (interacting with block), combined MASQ depression questionnaire, interaction between SPQ scores and block, and random effects of participant, and trial name nested in block. A main effect of block was found, supporting the case that the task was able to assess measures of learning. For example, as expected, average learning rates significantly increased in response to conditions of high volatility (block four) and were lower in conditions of high noise (block 3) (β(SE) = 0.299(0.01), $p$<.001; Figure 5.3).

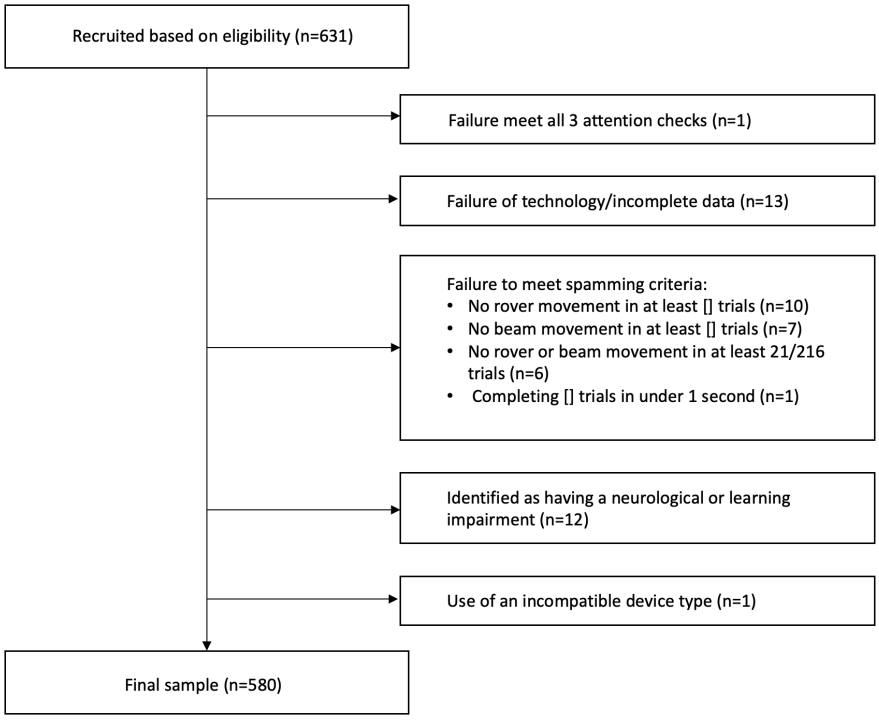


**Figure 5.2** *Showing a flow diagram of the exclusion criteria used in this study, and the number of participants excluded for each criterion.*

**Table 5-3** *Participant characteristics (N = 580)*

| **Participant Characteristic** | ***n*** | **%** |
|---|---|---|
| **Gender** | | |
| Male | 198 | 34 |
| Female | 376 | 65 |
| Non-binary | 6 | 1 |
| **Ethnicity** | | |
| White (English, Welsh, Scottish etc.) | 501 | 86 |
| Asian (Indian, Pakistani, Bangladeshi, Chinese etc.) | 39 | 7 |
| Black (African, Caribbean etc.) | 27 | 5 |
| Mixed or multiple ethnic groups | 13 | 2 |
| **Education** | | |

| | | |
|---|---|---|
| No qualifications | 5 | 0.9 |
| GCSE | 50 | 9 |
| AS Levels/ A Levels or equivalent diplomas | 167 | 29 |
| Undergraduate degree (BSc/BA) | 253 | 44 |
| Postgraduate degree (MSc/MA/MRes/PhD) | 92 | 18 |
| **Employment** | | |
| Full time | 316 | 55 |
| Part time | 98 | 17 |
| Student | 61 | 11 |
| Carer/parent | 36 | 6 |
| Unemployed (short term) | 19 | 3 |
| Unemployed (long term) | 37 | 6 |
| Prefer not to say | 13 | 2 |
| **Device type** | | |
| Computer/laptop | 469 | 81 |
| Mobile phone | 111 | 19 |
| **Gamer** | | |
| Over 5 hours per week | 190 | 33 |
| Under 5 hours per week | 390 | 67 |

| **Participant Characteristic** | ***M*** | ***SD*** |
|---|---|---|
| **Age** | 30.6yrs | 5.91 |

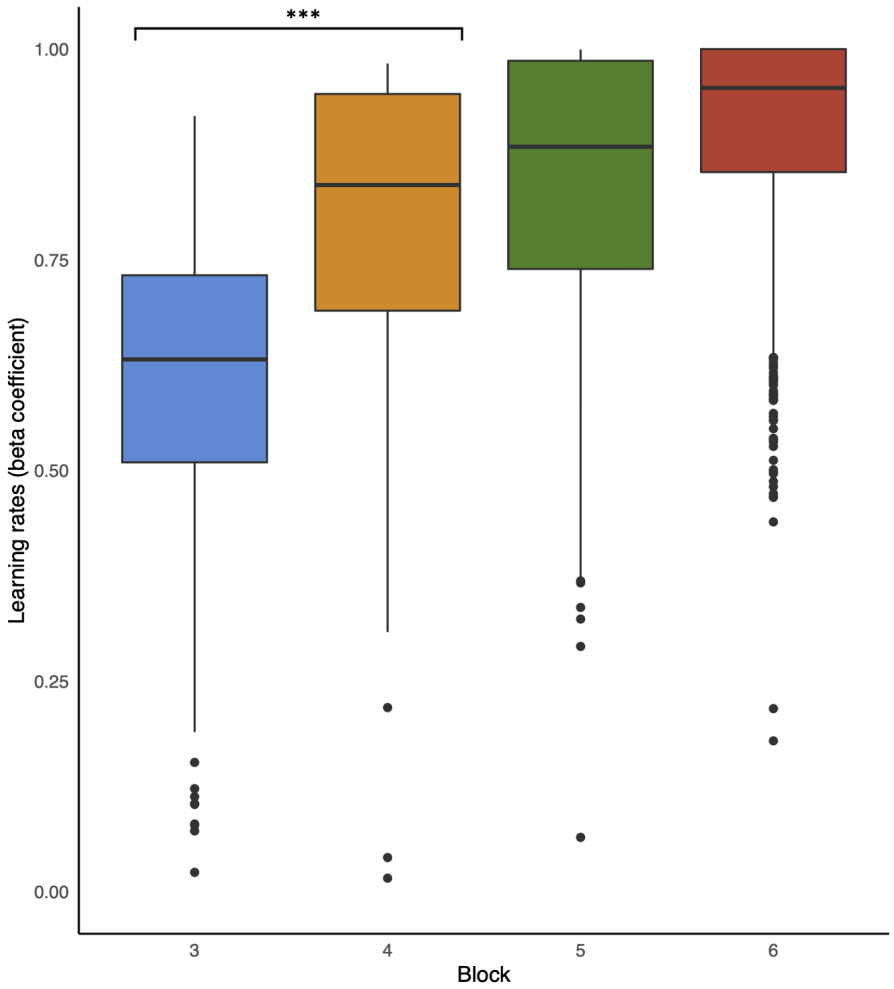


**Figure 5.3** *Showing learning rate across all participants, for each block. Learning rate is calculated as the beta coefficient of a model predicting signed prediction error from signed position change. A significant difference was found between blocks three (M=0.61; SD=0.17) and four (M=0.83; SD=0.11) i.e., as volatility increased (β(SE) = 0.299(0.01), p<.001).*

*Construct validity.* For each person, beam widths were averaged across both block and the underlying noise condition (low or high). This was done to capture how participants used the beam width under differing noise conditions specifically. The model included fixed effects of gender, the MASQ anxiety scales, the MASQ depression scales, as well as the Green Paranoia scale. Random effects remained constant. High noise conditions across the task led to the use of

a wider beam, as expected (β(SE) = -8.57(1.52), $p$<.001). Similarly, participants showed acquisition of the mean of the underlying distribution, in around three trials (Figure 5.4), indicating that the rover was being used appropriately, to indicate the estimate of the mean.

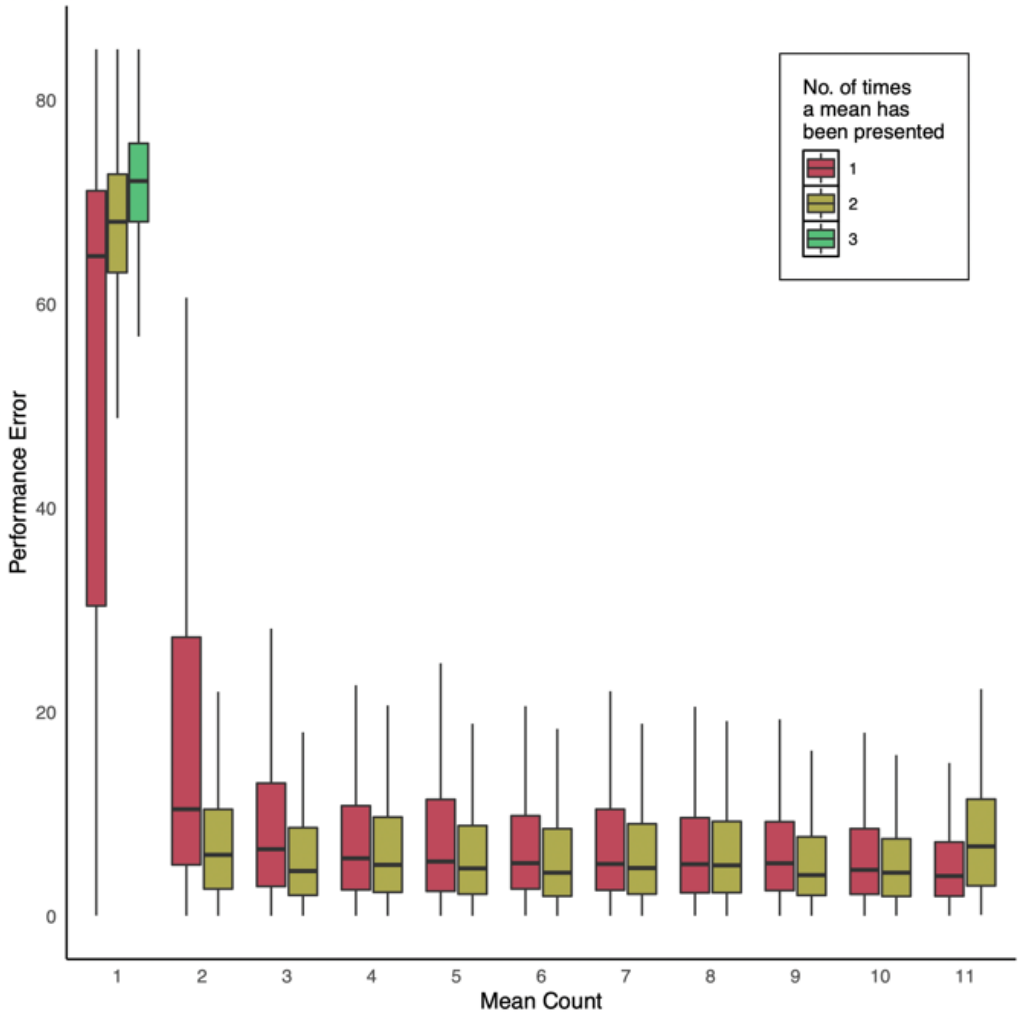


**Figure 5.4** *Shows performance error (participant estimate – mean of the distribution) across trials where a mean change occurs (1), alongside subsequent trials after a mean change (2-11). Colours indicate how many times the mean in question has been seen by the participant. Data displayed here is from block four, where volatility was increased i.e., the mean changed between two previously unseen means, but the variance remained small and unchanging.*

### *3.2.3 Acquisition of the underlying statistics*

*Performance error.* The average of the log performance error was used to account for non-normally distributed data. Fixed effects included in the winning model were: device type, gender, gamers, combined MASQ anxiety questionnaire, combined MASQ depression questionnaires, the GPTS, and an interaction between PDI scores and block. Random effects remained the same. A model that included interactions terms was identified to significantly improve model fit (X2(df) = 7.30(2), p=.026).

Using a mobile device significantly increased performance errors overall (β(SE) = 0.16(0.02), $p$<.001). Whereas being male significantly decreased performance errors overall (β(SE) = -0.09(0.02), $p$<.001). Isolated volatility block (block 4) predicted significantly higher performance errors than the isolated noise block (block 4 vs block 3: (β(SE) = 0.50(0.30), $p$<.001). This was also the case for blocks of high noise and volatility, when compared to blocks of high volatility alone (block 5 vs block 4: (β(SE) = 0.10(0.03), $p$<.001).

Individuals scoring higher on the Green Paranoia Scale showed significantly higher overall performance errors across the whole game, with no interactions with any specific block (β(SE) = 0.01(0.00), $p$ =.001). Whereas elevated depression scorers showed an opposing effect of lower overall performance errors across the whole game (β(SE) = -0.01(0.00), $p$<.001; Figure 5.5).While there was no differences in performance errors between high and low scorers on the PDI questionnaire, there was a significant interaction found between elevated delusion symptomology and performance errors in block 4 (high volatility) compared to block 3 (noise/low volatility). This interaction suggests that in contrast to the mainstay of individuals in the dataset, elevated PDI scorers showed lower performance errors under the volatility only block

(block 4), and higher performance errors during the noise only block (block 3) i.e., in opposition to what would be expected (see Figure 5.5).

*Beam Width.* For each person, beam widths were averaged across both block and the underlying noise condition (low or high). A model including interaction terms significantly improved model fit (X2(df) = 522.15(3), $p<.001$), and showed the lowest AIC value. The model included fixed effects of gender, and the high noise condition interacting with block, the combined MASQ anxiety, and depression scales, as well as the Green Paranoia scale. Random effects remained constant.

Males showed significantly smaller beamwdiths over the whole game (β(SE) = 4.26(1.25), $p<.001$). The high noise conditions across the task led to use of a wider beam, as expected (β(SE) = -8.57(1.52), $p<.001$). High scoring individuals on the MASQ depression questionnaire used a significantly smaller beam size over the whole game (β(SE) = 0.07(0.03), $p$ =.008), and showed a significant negative interaction with the high noise conditions, indicating that they calibrated their beam width sizes appropriately by using a wider beam in higher noise conditions (β(SE) = -0.07(0.03), $p$ <.001). Individuals scoring higher on the Green paranoia questionnaire on the other hand, where shown to use a significantly narrower beam in response to conditions of high noise, indicating poor calibration of beam width to noise (β(SE) = -0.05(0.02), $p$ =.017) (Figure 5.6).

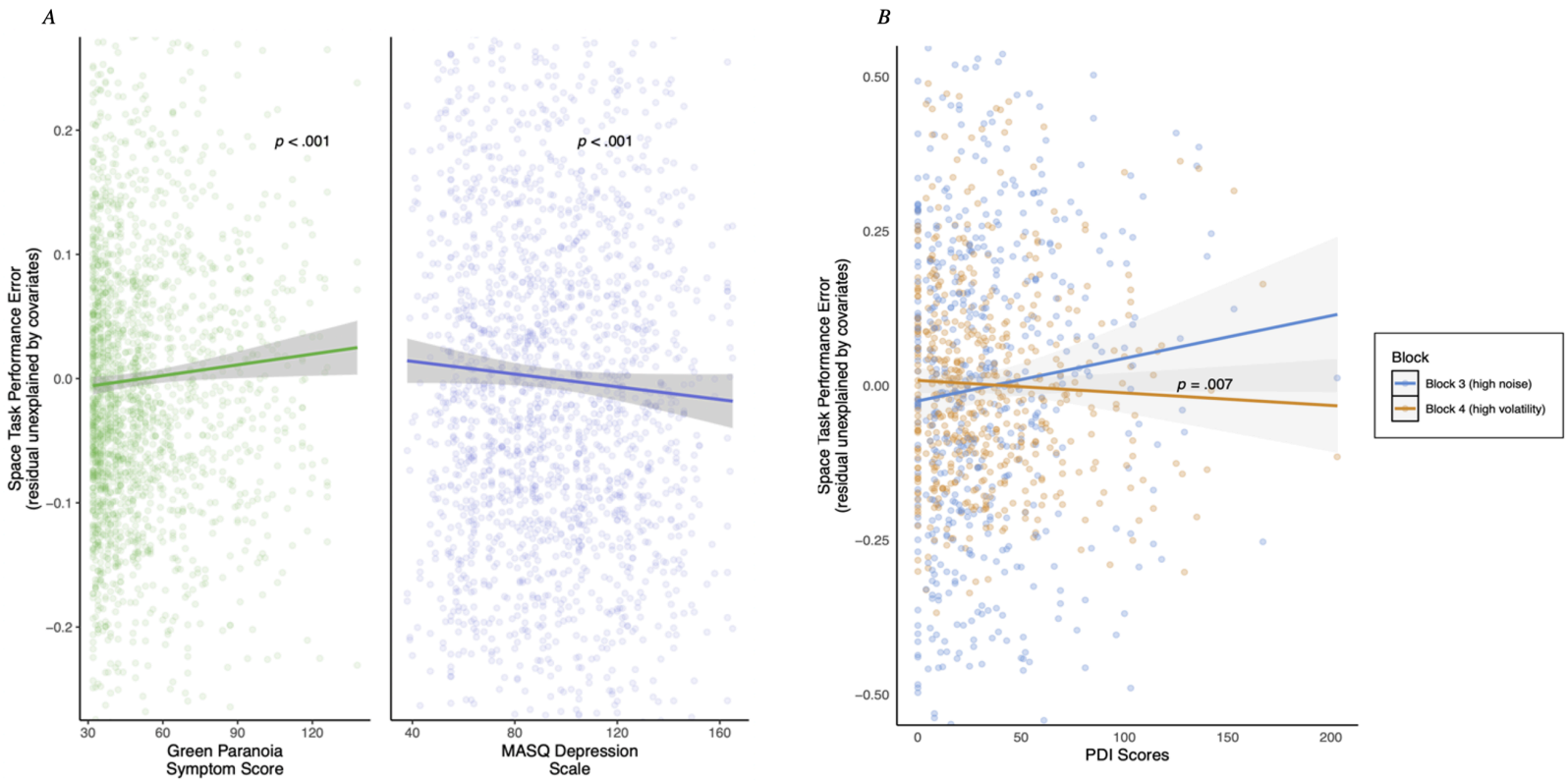


**Figure 5.5A** *Showing the relationship between symptom scores on the MASQ depression subscales, and the Green Paranoia symptom scale, and performance errors across the task as a whole. Each dot represents the average performance error for each block, for each participant. A linear model line is drawn to show the strength of relationship between these variables, and the standard error is shown in grey, around the line. Here, elevated paranoia is associated with higher performance errors across all blocks (p<.001). Whereas the opposite effect is seen in*

*individuals with elevated depression (p<.001).* **Figure 5.5B**. *Shows the interaction found between blocks 3 and 4, and PDI scores. This interaction effect suggests that, in contradiction to a normative model of learning, elevated delusion symptoms are associated with increased performance errors during increased noise (block 3), and decreased performance errors during increased volatility (block 4) (p=.007). Both figures display the unexplained residuals of the fitted model, once all other covariates have had their variance explained.*

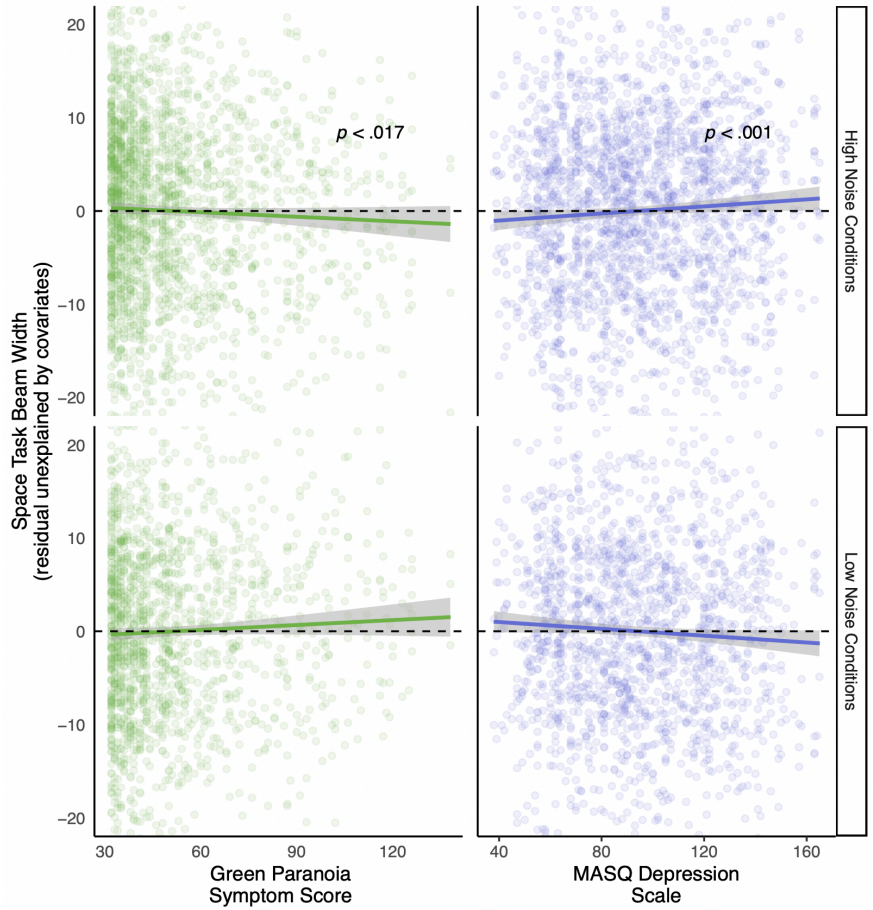


**Figure 5.6** *Shows the relationship between beam width and symptom scales for paranoia and depression. Each coloured dot in the plot represents the average beam width used by each participant, for each block. A linear model line is drawn to show the strength of relationship between these variables, and the standard error is shown in grey, around the line. Figures display the unexplained residuals of the fitted model, once all other covariates have had their variance explained. Plots are further differentiated by the specific noise condition (high: SD = 0.12;*

*low: SD = 0.03) across the whole task. In high noise conditions a sensible strategy is to use a wider beam, and vice a versa for low noise conditions. However, here we see that in high noise conditions, symptoms of elevated paranoia are significantly associated with use of a narrower beam (p=.017), whereas individuals with elevated depression showed appropriate wide beam use during high noise (p<.001).*

## *4.3 Task performance and acquisition of statistics*

### *4.3.1 Performance metric: score*

A winning model for score included random effects of participant, and counterbalancing condition nested in block. Fixed effects included device type (mobile/computer), gender (male, female, non-binary), an interaction between gamer (yes/no) and block, an interaction between the combined MASQ depression scales and back contrasted block, and an interaction between the Green Paranoia Scale and block. Inclusion of an interaction term within the model significantly improved model fit (X2(df) = 8.80(3), $p$=.031).

Significantly higher average scores were found in individuals identifying as gamers (>5hrs per week) (β(SE) = 0.22(0.09), $p$ = .018), and those who were male (β(SE)=0.41(0.09), $p$<.001). Whereas using a mobile phone to play the game, rather than a computer or laptop showed significantly decreased overall scores (β(SE)=-0.30, $p$=.001). Planned contrasts between blocks revealed that as the game progressed to combined noise and volatility environments, scores significantly decreased (block 5 vs block 4: (β(SE)=-0.57(0.22), $p$=.012). This pattern of decreased scores was also observed between blocks differing in reward policies (block 6 (losses and increased gains) vs. block 5 (gains only) (β(SE)=-0.50(0.19), $p$=.011).

Performance (scores) in individuals with elevated depression scores were significantly higher than those with lower depression scores (β(SE)=0.01(0.00), $p$<.001; see Figure 5.7). The opposite effect was found in individuals with elevated paranoia symptomology, who instead showed significantly lower scores than individuals with low paranoia symptoms (β(SE)=-0.01(0.00), $p$<.001) (see Figure 5.7). A significant interaction was observed between elevated depression

symptomology and differences in scores between blocks 6 and 5, indicating that while these individuals obtained higher scores overall, this was additionally emphasised in the block 6 compared to block 5 (β(SE)=0.01(0.00), *p*=.001) (see Figure 5.8). And in contrast to the overall trend of progressively worsening scores as the game went on for the mainstay of other participants.

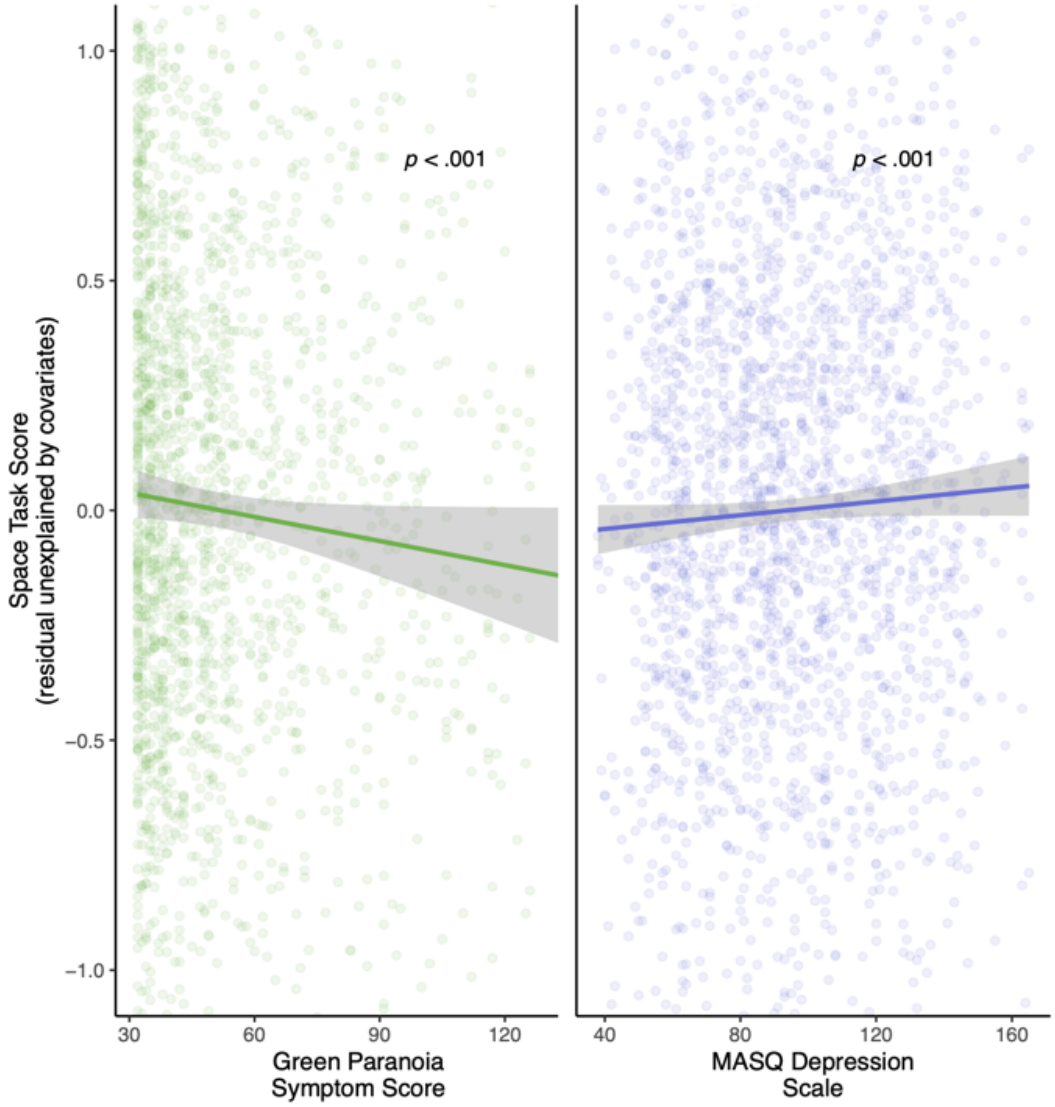


**Figure 5.7** *Showing the relationship between paranoia and depression scores, and the unexplained residuals of the fitted model, once all other covariates have had their variance explained i.e., depicting the effect of overall score as described by the model. Each coloured dot*

*in the figure represents the block-wise average for task score, for each individual. A linear model line is drawn to show the strength of relationship between these variables, and the standard error is shown in grey, around the line. Here, a significant negative relationship is shown with increasing paranoia scores (p<.001), and the opposite effect is found for those with elevated depression scores (p<.001).*

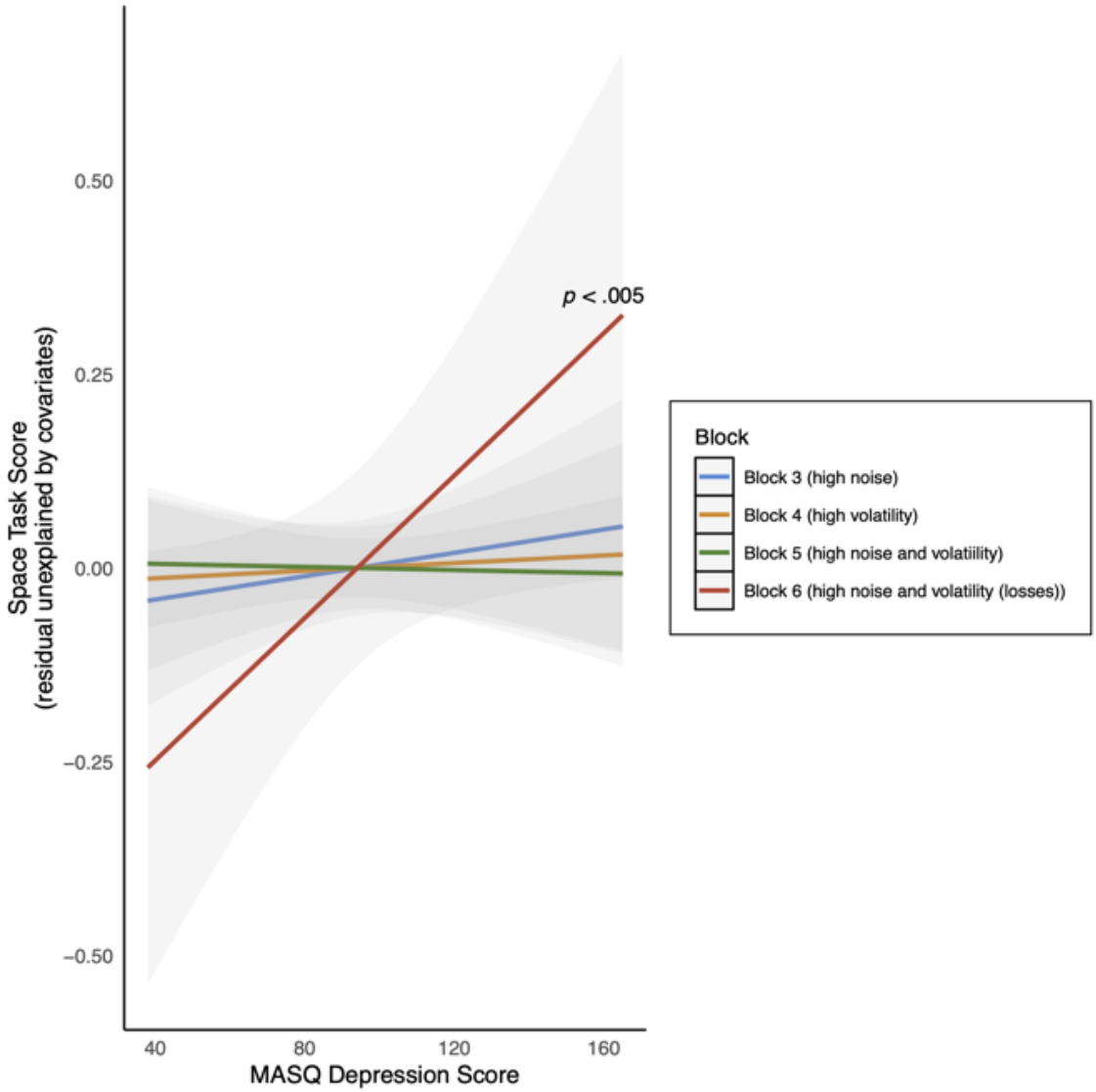


**Figure 5.8** *Showing the relationship between depression symptom scores, as measured by the MASQ, and scores on the task. Blocks are indicated by colour and described in the key. The figure displays the unexplained residuals of the fitted model, once all other covariates have had their*

*variance explained i.e., depicting the effect of overall score as described by the model. A linear model line is drawn to show the strength of relationship between these variables, and the standard error is shown in grey, around the line. The figure shows that elevated depression is associated with higher scores (p=.005).*

## *4.4 Learning rates*

### *4.4.1 Overall learning rates*

Learning rates were calculated by taking the beta coefficient value from a model predicting signed prediction error from the signed position change. Learning rates were averaged across person and block. Fixed effects included in the winning model were: device type, age, gamers (interacting with block), combined MASQ depression questionnaire, interaction between SPQ scores and block. Random effects of participant, and trial name nested in block were also used. A model that included interactions terms was identified to significantly improve model fit (X2(df) = 7.30(2), $p$ =.016).

In line with a normative account of learning (Behrens et al, 2010), average learning rates significantly increased in response to conditions of high volatility (block four) and were lower in conditions of high noise (block 3) (β(SE) = 0.299(0.01), $p$ <.001). As the game increased in difficulty i.e., as volatility and noise conditions are combined, average learning rates were found to be significantly higher (block five vs. block four: (β(SE) = 0.13(0.01), $p$ < .001). Finally, the introduction of losses and increased gains in block six also gave rise to increased average learning rate as compared with block five, where the only change in learning environment was reward policy (β(SE) = 0.01(0.01), $p$ < .001)

A significant relationship between age and averaged learning rates (β(SE) = -0.01(0.00), $p$ = .031), and mobile device type and averaged learning rates, was identified (β(SE) = -0.03(0.01), $p$ <.001). While there was no significant overall association with gaming status (p=.722), a significant interaction was found between gamers and higher average learning rates when comparing block four (high volatility) to block three (high noise) (β(SE) = 0.04(0.01), $p$ =.001), and block five (combined volatility and noise) to block four (high volatility), although the latter was nominal (β(SE) = 0.12(0.01), $p$ = .046). No differences in averaged learning rates were found between block six and five ($p$ =.233).

A main effect of group was identified for the MASQ depression scale and averaged learning rates. This finding indicated higher average learning rates overall in individuals with elevated depressive symptomology (β(SE) = 0.01(0.01), $p$ = .005). An interaction was also identified between elevated SPQ scores and averaged learning rates between the high isolated volatility block (block four), and the high isolated noise block (block three) (β(SE) = -0.01(0.01), $p$ = .001). This finding indicated that elevated SPQ scorers showed higher average learning rates in response to increased isolated noise, and lower average learning rates in response to high isolated volatility (see ***Figure 5.9***) i.e., the opposite pattern than i) theoretically expected, and ii) to findings from this experiment. No main effect of SPQ group was found ($p$ =.382).

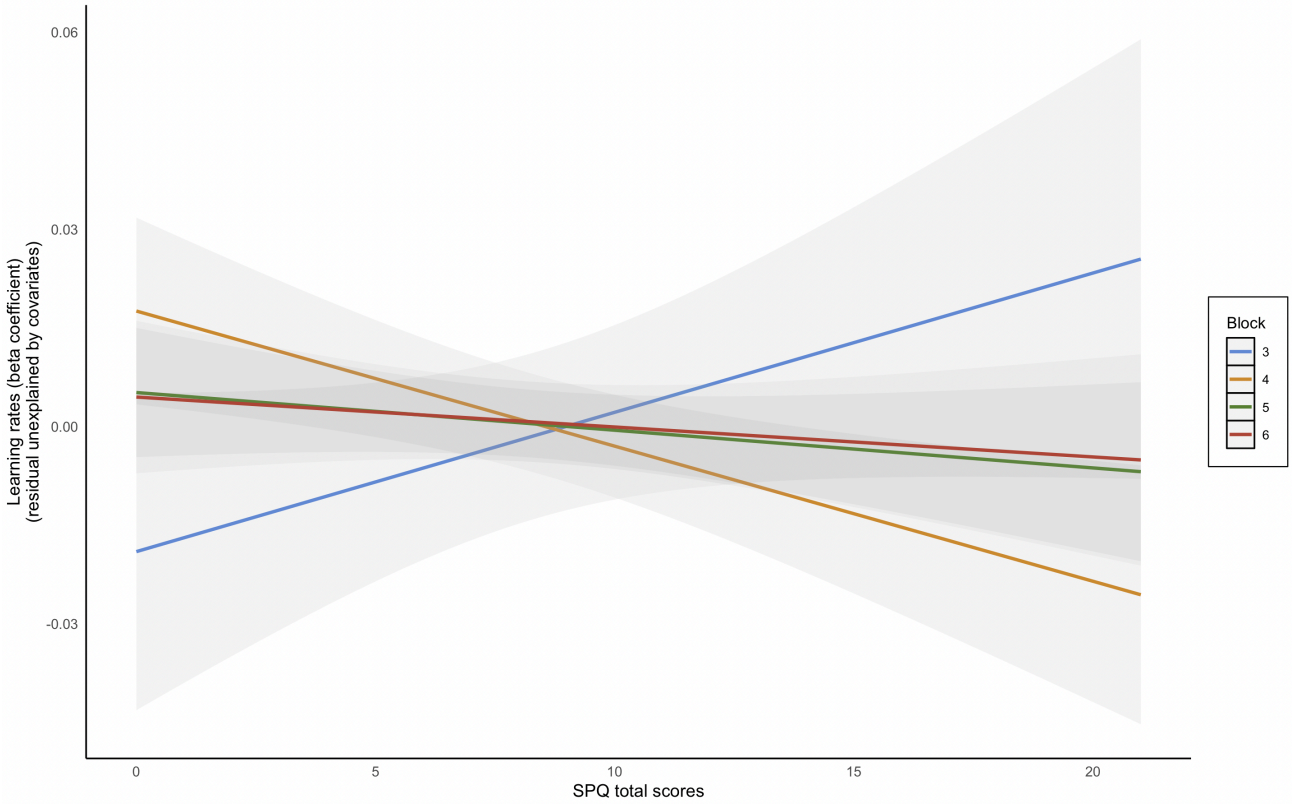


**Figure 5.9** *Showing the interaction found between SPQ scores (schizotypy personality traits), and averaged learning rates for each block. The y axis shows learning rates, specifically learning rates residuals from the model in question, and uses the unexplained residuals of the fitted model, once all other covariates have had their variance explained. The x axis shows the SPQ score for each participant. Each line indicates the relationship (linear model) between SPQ scores and learning rates for each block. A linear model line is drawn to show the strength of relationship between these variables, and the standard error is shown in grey, around the line. Here we see, contrary to the mainstay of individuals in the sample, increased learning rates in response to noise, and decreased learning rates in response to volatility, as SPQ symptoms increase.*

### *4.4.2 Learning rate adaptation to uncertainty*

The differences in learning rates were compared between conditions. For example, conditions were compared where the mean was changing only, with no variance changes (i.e., isolated volatility – block 4), against conditions where the variance was wide, and there were no mean changes (i.e., isolated noise). Elevated trait symptom scores were associated with a reduced change in learning rate between volatile and stable conditions for trait anxiety ($r(549) = -0.13$, $p=.003$), paranoia ($r(549) = -0.10$, $p=.018$), and delusionary ideation (trend level significance) ($r(549) = -0.06$, $p=.060$). Learning rate differences were also taken between conditions with high volatility (and now noise), and high noise (with low volatility) (see Figure 5.10. Again, elevated trait symptoms scores were associated with reduced change between high volatility and high noise, specifically schizotypy ($r(549) = -0.12$, $p=.005$), paranoia ($r(549) = -0.10$, $p=.025$), delusionary ideation ($r(549) = -0.06$, $p=.060$), and a nominal significance with elevated trait anxiety scores ($r(549) = -0.09$, $p=.037$) (see Figure 5.11).

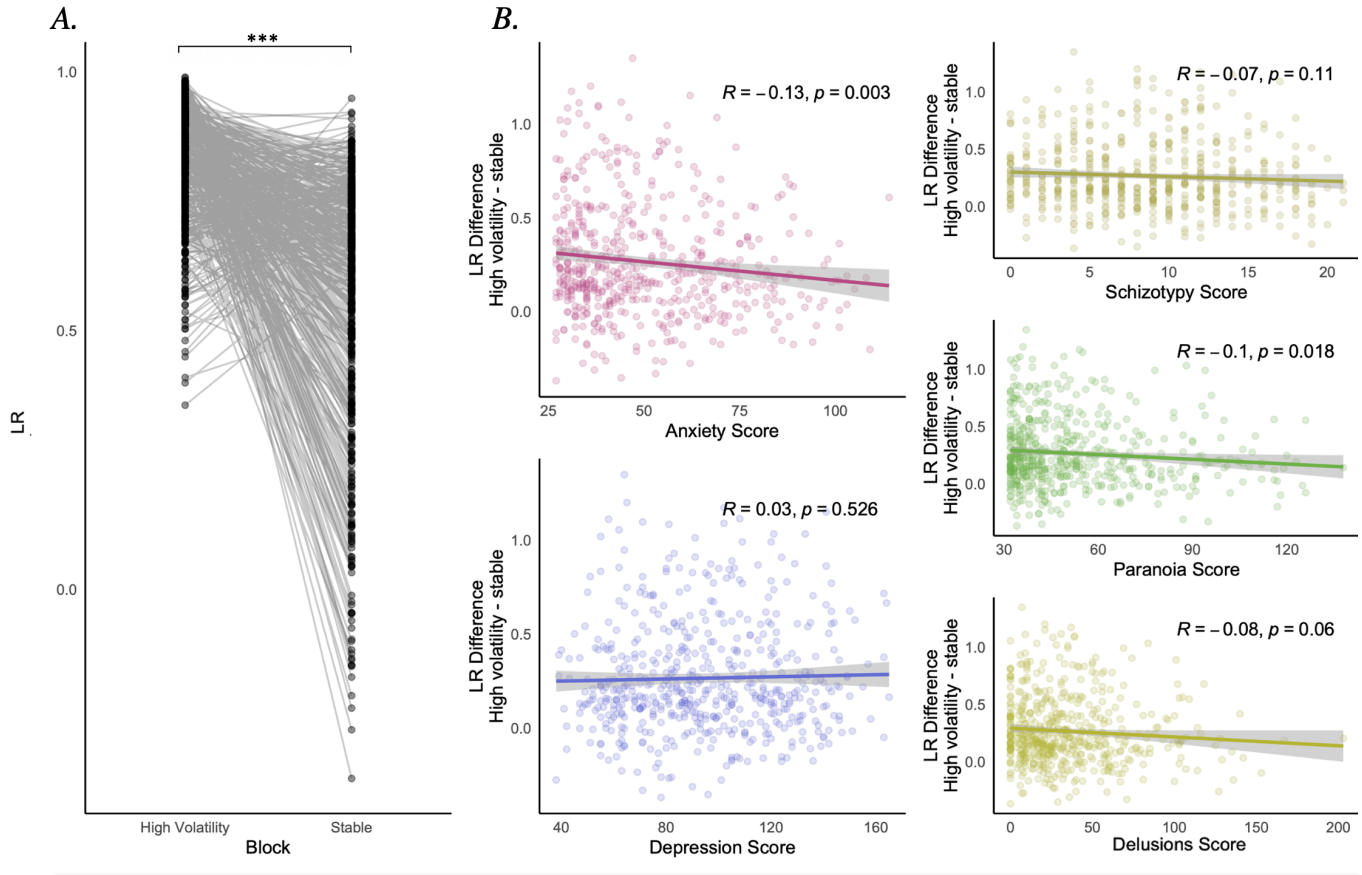


**Figure 5.10A** *Showing the change in learning rates (beta coefficient) between conditions of high volatility (block 4), and stable conditions (block 2 small variance). Dots on the plot represents the average LR coefficient for participants during high noise, and high volatility conditions. The grey lines show how for each individual, these LR coefficients change, and specifically display the direction of change. A linear model line is drawn to show the strength of relationship between these variables, and the standard error is shown in grey, around the line.*

*Here, we find that LRs are significantly higher in higher volatility blocks, as compared with stable blocks i.e., low volatility and noise*. **Figure 5.10B.** *Showing the relationships between the learning rate difference (between LRs in high volatility and stable conditions), and a range of symptom scales. Symptom scales include: anxiety (as measured by the MASQ, depression (MASQ), schizotypy (SPQ), paranoia (GPTS), and delusions (PDI). Each coloured dot represents a participant. The figure demonstrates that anxiety, paranoia, and delusion scales all correlated negatively with learning rate difference between high volatility and stable conditions.*

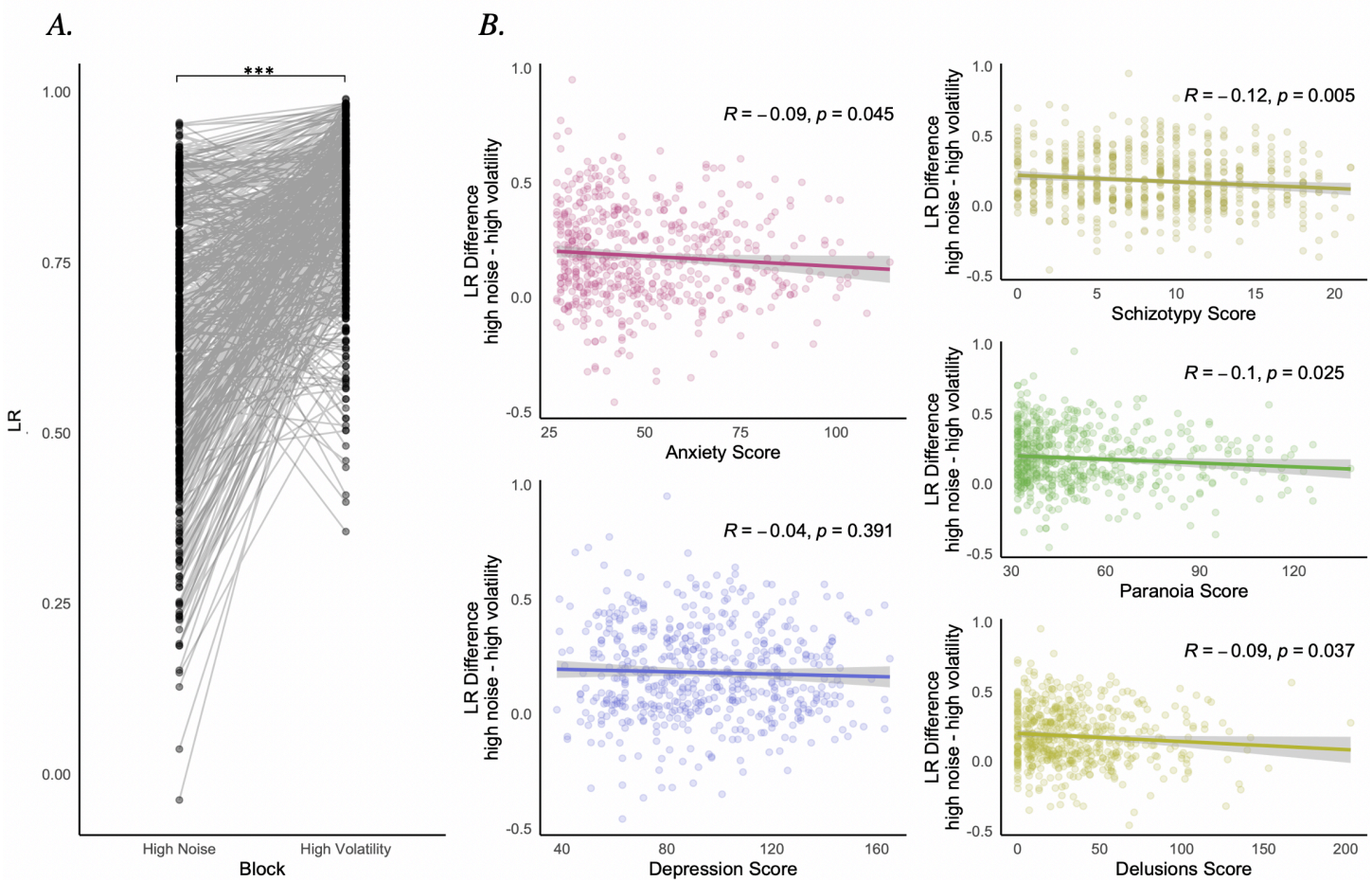


**Figure 5.11A** *Showing the change in learning rates (beta coefficient) between conditions of high volatility (block 4), and isolated high noise conditions (block 2, wide variance). Dots on the plot represents the average LR coefficient for participants during high noise, and high volatility conditions. The grey lines show how for each individual, these LR coefficients change, and specifically display the direction of change. A linear model line is drawn to show the strength of relationship between these variables, and the standard error is shown in grey, around the line.*

*Here it is possible to see that as the environment changes from high noise to high volatility, LRs significantly increase, as expected.* **Figure 5.11B.** *Shows the relationships between the learning rate difference (between LRs in high volatility and high noise conditions), and symptoms scales include anxiety (as measured by the MASQ, depression (MASQ), schizotypy (SPQ), paranoia (GPTS), and delusions (PDI). Here, we can see that elevated delusions, paranoia, schizotypy, and anxiety are all associated with a lower LR difference between high noise and high volatility conditions.*

# 5 Discussion

This online large-scale study utilised a novel learning task designed to capture variations in learning under high volatility, high noise, and combined uncertainty conditions. Outputs from the task included general performance, ability to acquire statistics inherent in the contingency probability distributions, and learning rates. These metrics were used to measure i) overall learning under different types of uncertainty, and iii) adaptation to changes in uncertainty. The primary aim was to investigate whether outputs from the task related to natural variation in anxiety, depression, and psychosis-related trait symptomology (delusions, schizotypy, paranoia) in the general population. The disaggregation of noise and volatility conditions supported potentially important, but subtle, overlap and distinction in learning deficits in symptom groups. For example, while both anxiety and psychosis groups shared a deficit concerning the inflexible adaptation of learning rates to changes in uncertainty, elevated psychosis-related symptomology additionally included abnormal overall learning in response to uncertainty i.e., in opposition to a normative model, potentially suggesting a more pervasive learning deficit. In contrast, elevated depression symptoms were associated with a performance benefit, and showed no overlap with other symptoms or learning deficits.

While a normative account of learning should describe the patterns of learning rates across different conditions of uncertainty (Behrens et al., 2007), it also indicates that individuals must be able to adapt learning rates dynamically and flexibly in response to the environment (Yu and Dayan, 2005). Findings from this study show that individuals generally adhere to a normative account of learning and can rationally adapt learning to changes in uncertainty. However, an impoverished ability to adapt to changes in uncertainty was identified across several groups with elevated anxiety, paranoia, and delusionary tendencies. While these findings replicate previous

research in trait anxiety groups (Browing et al., 2015; Huang et al., 2017), this is a relatively novel finding for psychosis symptomology. The study advances these findings by additionally relating an inflexible learning deficit to changes in uncertainty from noisy to volatile environments (as opposed to stable and volatile only). Individuals with psychosis related disorders including schizotypy, delusionary tendencies, and paranoia, showed an impoverished ability to adapt learning from high noise to high volatility, while trait anxiety disorder also showed a small (but significant) effect size in this regard (further evidence required).

Leaving aside the question of causation, comorbidity between anxiety and psychosis-spectrum disorders has been reported (Huppert and Smith, 2005; Braga et al., 2013; Wilson et al., 2020;). This relationship is reflected in clinical treatment for both disorders, for example, treatment for safety behaviours in anxiety and paranoid thinking is the same (Birchwood et al., 2007; Hartley et al., 2013; Heavens et al., 2019; Aunjitsakul et al., 2022). This close relationship has also been identified sub-clinically and has been suggested to relate to the pluripotent nature of symptomology at pre-clinical stages (Hatmann et al., 2021; Shah et al., 2022; Ratheesh et al., 2023). While findings from this study indicate a potential overlap between subclinical symptom groups, previous research has also shown that these groups show an insensitivity to volatility, and/or a difficulty adapting to changing uncertainty contingencies specifically (Beltzer et al., 2019, Browning et al., 2015, Hearnaus et al., 2018, Huang et al., 2017), leading to suboptimal decision making.

Higher order modelling studies have however indicated a potential disaggregation of effects showing that for anxiety related disorders, learning deficits may relate to the belief about volatility itself (Hein et al., 2021), whereas psychosis disorder may additionally show increased estimates of the volatility inherent in the environment (Cole et al., 2020, Reed et al., 2020,

Suthaharan et al., 2021). Results from this study show evidence of a similar overlap and disaggregation in symptomology and learning deficit. While we see that the adaptation of learning rates to changes in uncertainty is disrupted in anxiety (stable-volatile), and psychosis (stable-volatile; noisy-volatile), additional deficits were noted for those experiencing elevated psychosis symptoms. These differences implied that psychosis disorder groups also displayed non-normative learning behaviour when learning under noise and volatility conditions, shown via overall learning rates. In contrary to the behaviour of the mainstay of individuals in the study who displayed normative learning behaviour, individuals with elevated schizotypy symptomology showed increased learning rates when learning in a noisy environment and decreased learning rates when learning in a volatile environment. Elevated delusion and paranoia symptomology also showed increased performance errors (distance from the mean) during noise, and decreased performance errors during volatility (delusions), and overall larger performance errors (paranoia). While an optimal strategy for the task is to place the rover as close to the unseen mean as possible, these individuals showed overall higher performance errors (distance from the mean), as well as a poor understanding of the noise of the environment via consistently incorrect use of the beam (paranoia), presumably providing some explanation for this groups uniquely poor performance overall. As such, these additional deficits present in elevated psychosis symptomology may be evidence of a deeper alteration in belief updating in dynamic environments. For example, a difficulty in acquiring the mean when learning under noise, may indicate the misinterpretation of noise for volatility, as has been previously hypothesised (Piray & Daw, 2021).

Traditional probabilistic belief updating tasks have reliably shown evidence of poorer performance in patients with psychosis spectrum disorder including schizophrenia groups and individuals who have experienced a first episode of psychosis (Deserno et al., 2017; Fromm et

al., 2023, Schlagenhauf et al., 2014, Reed et al., 2020, Suthaharan et al., 2021). However, theories describing the mechanism underlying this poor performance differ (Corlett et al., 2009; Barch & Dowd, 2010; Friston et al., 2014; Adams et al., 2016; Heinz et al., 2016; Howe & Nour, 2016; Feeney et al., 2017; Sterzer et al., 2018; Katthagen et al., 2022; Deserno et al., 2023). Use of isolated uncertainty conditions has enabled further insight into these deficits. In this study we are able to see that elevated psychosis symptomology was associated with i) lower learning rates under isolated volatility and importantly, increased learning rates under noise, and ii) poor adaptation both in response to changes from stable to volatile environments, and from noisy to volatile environments. One hypothesis for these findings is that higher-order uncertainty i.e., an intuition about the volatility of the volatility influences these individuals' assessment of learning, and subsequently decision making. For example, if one expects the world to be highly changeable, then when the world increases in volatility (noise to volatility conditions) learning rates may not increase between conditions. Learning under isolated volatility would also not increase learning and appear lower than average (Hein et al., 2021, Cole et al., 2020). To further develop these findings application of a computational model that parameterises multiple types of uncertainty and their place within a hierarchy, such as the hierarchical gaussian filter, could be applied to capture the beliefs about volatility at different levels, and also the individual's belief about the noise (Mathys et al., 2011; 2014). Using this approach would help to discern whether these individuals are over estimating volatility, or misinterpreting volatility for noise (Katthagen et al., 2022).

Finally, elevated depression symptoms were associated with no adaptation deficits. This is at odds with recent research from clinical depression research which have shown poorer overall behavioural performances in PLTs (Dombrovski et al., 2019). However, research has shown that individuals with depression show increased learning from negative feedback across subclinical,

self-reported and clinical depression (Cavanagh et al., 2019; Cooper et al., 2014; Pike & Robinson, 2022). Authors speculate that the increased performance benefit found in block six, where losses are introduced, may indicate that these individuals were influenced by the feedback paradigm in a positive way – i.e., feedback from losses increased their acquisition of the underlying statistic of the task evidenced via their decreased overall performance errors, and appropriate use of the beam, and as such led to a performance benefit. One interpretation of findings form this study could be that these individuals were responding more to instances when a loss was triggered, leading them to successfully update in response to these trials, and as such, show an improved performance. However, importantly, while learning rates were higher for depressed individuals overall, there was no interaction with block, and as such, we do not find evidence of increased learning rates in response to feedback valance, on average. Further interrogation using trial-wise analysis may shed further light on this.

Finally, a lack of overlap between anxiety and depression symptoms, and specific learning deficits, was also surprising given the high rates of comorbidity between these symptom groups traditionally (Cummings et al., 2014). For example, a recent study showed that an internalising symptom dimension (clustered anxiety and depression subclinical symptom scores) related to lower learning rate differences between stable and volatile learning environments. However, while there may be a feedback related deficit associated with anxiety (perhaps specifically in relation to the changeability of feedback – see Pulcu & Browning, 2017), recent research within the field of computational psychiatry has also found dissociating effects that position depression disorder in relation to deficits associated with feedback specifically, for example, learning more in response to aversive feedback and less from rewards (Cooper et al., 2014; Kumar et al., 2018; Dombrovski et al., 2019; Takano et al., 2019; Cavanagh et al., 2019); and anxiety disorders in relation to difficulties in processing and learning during volatility (Li et al., 2014; Browning et

al., 2015; Beltzer et al., 2019, Hernaus et al., 2018, Huang et al., 2017; Gagne et al., 2021). It may be that when using a task capable of capturing the joint estimation of uncertainty, the overlap between anxiety and depression symptomology is no longer apparent.

### *5.1 Limitations and future considerations*

There were several important limitations of this research. Firstly, the learning rate, a key measure relating to the ability for an individual to utilise the error in their previous prediction to update their current prediction, used here is the beta coefficient between a model predicting the position change from the prediction error. This is different to other research that uses either a computational model like the Rescorla Wagner (Browning et al., 2015), or calculates them directly, for example in Nassar et al., (2010; 2012; 2021) (PE/PC). While this research did apply the approach previously published by Nassar et al., (2021), we found that due to small prediction errors i.e., close to zero, some learning rates were extreme outliers. While approaches to deal with this have included truncating all learning rates over and below zero and one to zero and one, this i) led to an abnormal bimodal distribution and ii) introduced a risk of overlooking important aspects of behaviour. While use of the beta coefficient learning rate has not been used previously, we felt it provided a useful proxy to learning rate that captured the intended aspects of behaviour. Regardless of the methods used, behavioural measures will remain distant proxies of underlying cognitive processes.

In terms of the analysis, measures were averaged across conditions rather than trial-wise, leading to the disadvantage of information loss. While the study did apply mixed models using participant as a random effect in an attempt to account for the variance associated with individuals learning, application of a computational modelling approach would extract trial level variability.

Application of generative modelling would also support the process of explicitly specifying the underlying cognitive process and provide a more complete summary of data. Effect sizes were small, and given the exploratory nature of this study, results need to be replicated. However, given the large size of the sample, and high degrees of freedom, some confidence can be ascribed to the findings. While tentative recent research has shown that parameters describing learning are relatively reliable over time (Weigard et al., 2021; see for discussion: Browning et al., 2020; Karvelis et al., 2023), use of longitudinal designs would enable researchers to assess the construct validity and reliability of parameters of learning within individuals and in relation to symptoms. Clinically this could provide insight into both the progression of illness, and for example, metrics that describe treatment response or relapse propensity.

One benefit of the study is the use of an online experimental paradigm to capture natural variation in large scale general population samples, and further studies should continue to capitalise on this design to enable further robust exploration of replication of findings. One disadvantage that needs to be acknowledged in this approach, however, is that online administration of tasks and symptom scales leads to a lack of control over levels of attention, participant state of mind i.e., substance use during the study, and the ability to control for distractions. While this is a general disadvantage of the online experimental paradigm, this study sought to provide some protection from these effects by i) recruiting a large sample, and ii) applying strict data driven exclusion criteria. The task was also developed to encourage continued and sustained attentions via monetary rewards and the gamified nature of the task.

There may also be important explanatory variables across findings in this research that were not accounted for in this study. For example, being more attentive in general to an online experiment, or having differences in cognitive ability (education status was controlled for), or even

differences in socioeconomic status (Baker et al., 2019). While this study attempted to control for variables that seemed logical, for example, gaming time per week, and education, a detailed measure of cognition or socioeconomic status was not included. As such, future studies should control for these effects more coherently.

Finally, this study was attempting to provide insight into overlap and distinction between symptom groups and as such, aside from ensuring that standard correlations between symptom items were appropriately low, this study did not account for the relatedness between elevated symptom scorers between symptom scales. Future research should capitalise on approaches used in, for example, Gagne et al., (2020), and apply clustering and/or latent modelling approaches to reduce the dimensionality of symptom data and provide insight in to the relationship between behaviours measures of dimensions of psychopathology.

## *5.2 Conclusion*

In summary, this study indicated that elevated trait anxiety and psychosis may share a deficit relating to the ability to flexibly update learning to increases in volatility. However, elevated trait psychosis groups also indicated a non-normative response to overall learning, when tested in isolated conditions of uncertainty, potentially suggesting a more pervasive learning deficit that may also related to the level of noise present. Elevated trait depression scores related to an efficient acquisition of the underlying statistics of the task leading to an overall a performance benefit, particularly in blocks where losses were present. This may indicate a distinction between depression and anxiety/psychosis disorders, placing feedback responsiveness as a more central issue for depression, and difficulties in adapting to, and/or interpreting uncertainty as being related to anxiety and psychosis symptoms.

## 6 Acknowledgements

I would like to thank all students that helped collect the data for this chapter.

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# 8 Appendix

## *8.1 Instructions*

**Table 5-4** *Showing the instructions and information given in the Space task for each screen.*

| Screen Name | description | Text prompt – |
|---|---|---|
| **Introduction** | Intro screen 1 | `It is your first mission with the Intergalactic Space Defenders. However, a near miss has left you marooned on a planet that deals with all the waste and rubbish from the surrounding planets!' |
| | Intro screen 2 | "Old spacecraft of all shapes and sizes are flown into orbit above you, one at a time. As they disintegrate, useful parts fall off them. Your job is to catch the parts so you can build a rocket and escape." |
| | Intro screen 3 | "Each spacecraft will be too high for you to see. To successfully capture the falling parts you will have to estimate two things:<br><br>1. The location of the passing spacecraft. This will help you estimate where the parts will be falling from. ii) The size of the passing spacecraft. For example, if the parts are falling from a large space craft, they are likely to be more spread out.<br><br>You will be given information about the incoming spacecraft at the start of each level that will help you to figure out the sizes and locations of the spacecraft." |
| | Intro screen 4 | "You have an electromagnetic ray to capture the falling parts and bring them in, so you can build the rocket. IMPORTANT: You only have a small amount of fuel, so you must use the least amount of power possible to bring the parts in (the smallest ray possible)." |
| | Intro screen 5 | You will get a HIGHER SCORE for catching the falling parts with a SMALLER ray - but remember you will get zero points if you miss it! |
| | Intro screen 6 | After seeing  where the last spacecraft piece fell, turn the ray ON by pressing UP and then press the RIGHT and LEFT arrows to position the electromagnet. Use the UP and DOWN arrows to increase and decrease its power.<br><br>Give it a try now!' |

| | | |
|---|---|---|
| | Intro screen 7 | On a computer you can use the LEFT and RIGHT keyboard keys. Press enter, space or click to continue.' |
| **Block 1** | Practice round screen 1 | PRACTICE ROUND: You have 5 seconds to complete each turn. You must pass all 3 turns in the practice round to continue.<br><br>Turn the electromagnetic ray ON (red to green) by pressing UP, and then press the RIGHT and LEFT arrows to position the electromagnet. Use the UP and DOWN arrows to increase and decrease its power.<br><br>PRACTICE ROUND INFORMATION:<br><br>Number of incoming spacecraft: 1<br><br>Size of incoming spacecraft: Small<br><br>Location of incoming spacecraft: ONE location likely |
| | Practice round screen 2 | Good job! A quick reminder:<br><br>The Spacecraft will pass overhead one at a time - but may be different sizes, and in different locations. Information at the start of each level will help you to figure this out. |
| | Practice round screen 3 | "'Catch the parts that fall off the passing spacecraft using the smallest ray you feel is possible. This will earn you the most points. Every time you earn 500 points you get a bonus payment!. Do you want to repeat the tutorial? " |
| **Block 2** | Stable learning environment | Level 1 INFORMATION:<br><br>Number of incoming spacecraft: 1<br><br>Size of incoming spacecraft: No information<br><br>Location of incoming spacecraft: One location likely |
| **Block 3** | Learning when the SD changes | Level 2 INFORMATION:<br><br>Number of incoming spacecraft: 2<br><br>Size of incoming spacecraft: One large, one small. No information on the order they will pass.<br><br>Location of spacecraft: One location likely |

| | | |
|---|---|---|
| **Block 4** | Learning when the mean changes | Level 3 INFORMATION:<br><br>Number of incoming spacecraft: Multiple<br><br>Size of incoming spacecraft: All around the same size<br><br>Location of incoming spacecraft: Multiple locations likely |
| **Block 5** | Learning with combined SD and mean changes | Level 4 INFORMATION<br><br>Number of incoming spacecraft: A large amount<br><br>Size of incoming spacecraft: All different sizes<br><br>Location of incoming spacecraft: Multiple locations likely |
| **Block 6** | Learning with combined SD and mean changes<br>Round includes loses. | Level 5 INFORMATION:<br><br>Number of incoming spacecraft: A large amount<br><br>Size of incoming spacecraft: All different sizes<br><br>Location of incoming spacecraft: Multiple locations likely<br><br>IMPORTANT: If the falling spacecraft parts are not caught in this round you will LOOSE points, and potentially LOOSE the money you have earnt. BUT if you do catch the falling parts you will earn DOUBLE POINTS! Catch the parts in the smallest ray possible and earn 20 points each time! |

# *Chapter 6.* Belief updating in schizotypy: *application of computational modelling to a novel learning task*

## 1 Abstract

*Background:* Individuals with psychotic symptoms experience functional impairment, increased risk of suicide and premature mortality. Efforts have been made to identify individuals in the prodromal phase of illness to prevent the onset of psychosis. Cognitive deficits thought to underlie symptoms include the processing of structural uncertainty of information, specifically the volatility and noise. Individuals experiencing psychosis spectrum disorders have been shown to over-estimate volatility, and display noisiness (stochasticity) in decision making. However, it is unclear how noise within an environment affects belief updating and/or interacts with volatility estimation. This study aimed to use a novel experimental task and computational modelling approach to investigate aberrant volatility estimation in relation to both volatile and noisy learning environments. A second aim was to investigate how noise perception was integrated into both belief updating and decision making.

*Methods:* This study used a novel task that was able to probe belief updating in response to both noisy and volatile environments by drawing inputs from continuous "ground truth" probabilities,

that differed in their configurations (mean, variance) underlying the task. The task also procured trial wise parallel estimates of the noise (i.e., the variance) and volatility (i.e., the mean), and provided a sense of uncertainty via an overarching narrative and block wise instruction. Individuals from the general population that were shown to display high (n=81) and low (n=66) levels of schizotypy symptoms (as measured by the schizotypy personality questionnaire), completed the novel task. Linear mixed effects models were used to compare groups across performance metrics including score and (a proxy for) learning rate. The Hierarchical Gaussian Filter was applied to the task data, using a novel method that was able to independently capture learning about noise and volatility (Jumping Gaussian Estimation).

*Results:* Behavioural, performance-based metrics, showed no differences between groups. Volatility estimation was found to be intact across both high and low schizotypy groups. However, a significant difference was identified between groups in their use of their belief about the noise. Here, individuals with elevated schizotypy continued to show increased use of their belief about the noise, despite a change in environment from high noise and low volatility to low noise and high volatility. This contrasted with the low schizotypy group that instead appropriately adjusted the use of their belief about the noise, in response to the decrease in noise.

*Conclusions:* To our knowledge, this is the first study probing the computational mechanisms underlying the parallel, hierarchical learning about volatility as well as noise in relation to subclinical psychotic experiences. We found that under a volatile environment, learning mechanisms remained intact but groups differed in their use of learned knowledge for decision making. More specifically, high schizotypy subjects showed an incongruous use of noise belief during a high volatility, low noise environment. While these findings need to be replicated, it may be that a lack of confidence in a model of world when learning under volatility could lead

these individuals to implement a type of safety strategy. In this case, the safety-type response included overloading themselves with superfluous information about the noise of the environment, when this was not relevant. In turn this could lead to ongoing issues in belief updating, as the environment becomes more complex, and/or symptom severity increases.

## 2 Introduction

Individuals experiencing psychotic symptoms, such as hallucinations and delusions, suffer significant functional impairment, increased risk of suicide, and premature mortality (Fusar-Poli et al., 2014; Saha et al., 2007; Walker et al., 2015). Given the extent of disability, and considerable associated direct and indirect costs to public health services, effort has been directed into preventative measures, such as the identification of individuals in the prodromal phase of illness (Csillag et al., 2016). Evidence shows that individuals with schizotypy personality traits display an increased probability of developing symptoms of psychosis (Kwapil et al., 2013; Poulton et al., 2000). This offers researchers the opportunity to study individuals with a vulnerability to psychosis spectrum disorders, expressed as a multidimensional personality organisation, prior to the appearance of clinical manifestations (Fusar-Poli et al., 2017; McGorry et al., 2018; Racioppi et al., 2018).

Altered belief updating and processing of environmental uncertainty has been related to symptoms of clinical and attenuated non-clinical psychosis, including paranoia, delusionary ideation, and schizotypy personality traits in the general population (Baker et al., 2019; Fromm et al., 2023; Katthagen et al., 2020; Reed et al., 2020; Schlagenhauf et al., 2014; Suthaharan et al., 2021). Computational psychiatry, the use of algorithmic formulations to mechanistically describe psychopathological behaviours, can depict belief updating in relation to prediction error

i.e., the idea that beliefs are tested against observations and updated according to the size of the error in the prediction (Friston, 2022; Montague et al., 2012). The weight that is given to a prediction error while updating the belief is termed learning rate (Diederen & Fletcher, 2021). Within a Bayesian (hierarchical) framework, the update magnitude depends on/is weighted by, the precision of the prior belief and/or sensory evidence i.e., how certain the agent is of this information. A highly certain (or precise) PE indicates a true change in the environment and is weighted more strongly leading to a larger belief update. Importantly, whether the computational framework is Bayesian or not, agents must infer hidden states of the world due to the incompleteness of sensory information. As such, uncertainty estimation is thought to be a pervasive and important aspect of information processing that can differ between individuals, despite the same sensory inputs (Pulcu & Browning, 2019; Sandhu et al., 2023). Consequently, it becomes important to assess as a potential perturbed mechanism underpinning psychosis-related symptomology.

As precision-weighted PEs have been shown to be encoded by dopamine, the neurotransmitter repeatedly implicated in psychosis-spectrum disorder, it has been argued that elevated presynaptic striatal dopamine synthesis (and release) in psychosis spectrum disorders may lead to aberrant salience towards irrelevant cues (Howes et al., 2020; Howes & Kapur, 2009; Howes & Nour, 2016; Kapur, 2003; Winton-Brown et al., 2014). Theoretically, this process would subjectively feel as though the world is constantly changing (volatile), leading to the need to regularly update beliefs. Evidentially, support for this hypothesis is shown behaviourally, via a bias towards irrelevant information (Katthagen et al., 2020; Livet et al., 2020; Stuke et al., 2017), as well as a tendency to perform poorly in probabilistic reversal learning tasks, increased win switch rates, lower overall learning rates, and/or more “random” or stochastic choices (Culbreth et al., 2016; Kaplan et al., 2016; Li et al., 2014; Murray et al., 2008; Schlagenhauf et al., 2014;

Waltz et al., 2013). Hierarchical computational modelling approaches, such as the Hierarchical Gaussian Filter (HGF) build on these behavioural findings using the idea of a hierarchical inference processes. Here, higher-level beliefs, that may be abstract and complex, are updated according to incoming lower-level, sensory information. The HGF not only captures sensory perception (level 1) and beliefs (level 2), but additionally incorporates the individuals' belief about the environmental volatility (level 3). Findings from the HGF specifically show i) a tendency for *a priori* enhanced higher-level beliefs about initial environmental volatility (level 3) (Cole et al., 2020; Deserno et al., 2020), as well as, ii) increased coupling between higher and lower levels of learning (level 2-level 3) (Deserno et al., 2020; Reed et al., 2020; Suthaharan et al., 2021), leading to enhanced lower-level belief updating about action-outcome contingencies. One hypothesis integrating these findings suggests that the tendency not to stabilize beliefs, but to constantly update them (interpret as volatile), leads to a failure in reaching an equilibrium in higher level beliefs, which would enable these individuals to downplay noise (Katthagen et al., 2022).

However, although multiple theoretical accounts propose that altered volatility estimation may underpin (at least some) psychotic symptoms, volatility is just one way in which information can be uncertain. Information can also be uncertain because it is noisy. Noisiness, often referred to as expected uncertainty, refers to the fact that while we may know the probability of an event occurring, this does not necessarily mean that we can predict an outcome with complete certainty (Pulcu & Browning, 2019). While the ability to learn from feedback has been tested in regards to noise *or* volatility, the joint estimation of both noise and volatility is yet to be tested. For example, previous studies have mostly incorporated expected uncertainty via probabilistic reinforcement contingencies for binary stimuli that reversed completely which signalled volatility, but the specific noise levels did not need to be tracked (Cole et al., 2020; Deserno et

al., 2020; Reed et al., 2020; Suthaharan et al., 2021). In contrast, when studies focused on learning about noise with metric inputs and responses, the environment remained stable (Haarsma et al., 2020). The joint estimation of uncertainty is important because the speed with which a belief is updated i.e., the learning rate, is in fact jointly determined by both the noise and volatility (Piray & Daw, 2021). While these components are individually well understood, important insights are potentially concealed by not considering the full problem facing the learner: simultaneous estimation of volatility and noise (Piray & Daw, 2021).

To address this, our study sought to experimentally test both learning about volatility *and* noise in isolated and combined testing conditions. To achieve this, a novel task using metric inputs (in a continuous space), drawn from ground truth probability distributions, was used. The statistics describing these distributions were manipulated to simulate noise (standard deviation (SD)), and volatility (mean changes). Continuous responses were indicated via a parallel estimate of both the mean and SD on a trial wise basis, which signified whether successful inferences were made. Crucially, both information, mean and SD, needed to be tracked in order to perform successful in the task. Preliminary analysis using computational modelling and specifically, a version of the HGF, was used. The study aimed to firstly, replicate findings on higher order beliefs about the volatility of the environment under different uncertainty learning environments. It was hypothesised that individuals with elevated schizotypy would show increased coupling between higher and lower levels of learning (level 2 and 3). As these hypothesised findings would in turn cause enhanced lower-level belief updating about the action outcome contingencies, it was also expected that this would negatively impact performance for high schizotypy groups. Secondly, while we consistently see that psychosis-related disorders are associated with noisy/stochastic decision making, the study sought to explore the role that beliefs about the noise of an environment play in an individual's decision making. To achieve this, a free parameter capturing

an individual's noise belief was implemented within the decision model of the HGF. Finally, we were interested in the role of both volatility and noise on belief updating. As such, a novel version of the HGF was used that was able to capture both sources of uncertainty independently (Jumping Gaussian Estimation Task (JGET)), rather than simply representing uncertainties of higher vs lower-level beliefs about the occurrence of (usually binary) inputs and responses (as in the classic HGF (Mathys et al., 2014)). To the author's knowledge this is the first study to infer parallel noise and volatility beliefs for metric inputs (task feedback) and outcomes (participants' responses), using the HGF, and specifically the JGET package (Mathys et al., 2011; Mathys et al., 2014).

# 3 Methods

Ethical approval was obtained using a REMAS (MRA-19/20-19444) via King's College London. Individuals were given information detailing the study and provided their informed consent via Gorilla. Data collected via Gorilla was compliant with EU GDPR2016 and Gorilla's 'Data Processing Agreement' (consistent with NIHR guidance).

## *3.1 Participants*

One thousand participants were collected using an online platform Qualtrics (prolific.co) Participants completed the Schizotypal Personality Questionnaire (SPQ) questionnaire and provided demographic information. The top and bottom 10% of scorers (n=164; top scorers: n=81, M(SD)= 28.2(6.40); bottom scorers: n=66; M(SD)=31.5(5.51); see Table 6-3.) were selected and asked to take part in further cognitive testing on the online platform Gorilla (*see* gorilla.sc). Participants were eligible to take part in the study if they resided in the UK currently,

spoke English as their first language, were aged between 18 and 40yrs and had no history of serious head injury or neurological disorder.

The sample size calculation was based on the effect size found in a pilot study (N=2,020) using a version of the novel prediction task in a population sample. A power analysis for general linear modelling with two groups, anticipating a small effect size (0.02), suggests that a sample of 450 will have 91.2% probability of finding an effect that is there (using G*Power R package). An additional 100 participants were added to the total, to account for exclusions. This is consistent with other large scale, online population testing (Wise & Dolan, 2020). Data was additionally subject to quality control screening, where a participant is deemed to not be attending to the task in the expected or necessary way. Quality control measures included: failure of technology, failure to move the beam and rover in at least 10% of trials (n=21) and/or completion of at least 10% of trials in less than 1000m/s.

### *3.2 Procedure*

This was a cross-sectional population study. Participants were provided a webpage link to an online testing platform "Gorilla" (https://gorilla.sc/). Participants could use their own internet-accessible devices including smartphones, and computers. Before proceeding with the study, participants provided informed consent and completed a baseline demographic survey. On completion of the study, participants were paid £6.00 for their time and could earn additional payments of up to £1.50 during the task in performance-based bonuses.

### *3.3 Materials*

### *3.3.1 Schizotypal Personality Questionnaire (SPQ)*

Participants completed the SPQ brief (SPQ-B) version questionnaire which assesses schizotypy personality traits (Raine et al., 1997; Raine & Benishay, 2011). The SPQ-B contains 24 questions that fall under three categories of schizotypy factor structure, including cognitive-perceptual, social-interpersonal, and disorganization. Participants answer yes or no to questions such as: *"Some people think that I am a very bizarre person*", and "*I feel I have to be on my guard even with friends*". A total score was calculated across all items for the purposes of this experiment. The SPQ-B questionnaire has been shown to display high levels of convergent and discriminant validity in relation to other psychosis screening tools, across a range of populations including adults and adolescents. The SPQ-B has been extensively studied in relation to a broad range of topics and populations (Aycicegi et al., 2006; Bedwell et al., 2006; Compton et al., 2009; Jahshan & Sergi, 2007; Mata et al., 2005). Analysis of the psychometric properties of the SPQ-B show an internal reliability for the total score of between 0.75 and 0.83. Test-retest reliability ranges from 0.70 to 0.95 (Fonseca-Pedrero et al., 2008, 2009; Mata et al., 2005).

### *3.3.2 Novel learning task: The Space Game*

Participants performed a gamified learning task (to play the task, please click here). The task required participants to catch as much falling space junk as possible, so they could build a rocket and escape the planet. However, as the space junk was falling from unseen, hidden, space craft, participants had to infer the location, size, and frequency of change, of the hidden spaceships in order to make successful predictions. To catch the junk, participants were given an electromagnetic rover (adjustable on the x axis) that cast a beam (the power of which was adjustable on the y axis). To conserve fuel for their escape rocket, and to receive the maximum

points possible per trial, participants were instructed to maximally catch the junk, using the smallest beam size possible. As such, maximum points per trial would be awarded for successfully catching the junk using the smallest beam width.

Limited information about the size, location and frequency of the incoming unseen space craft was given at the start of every block (see Appendix: Table 6-4). For example, block 3 pre-play screen provided the information as follows: "INFORMATION: *Number of incoming spacecraft: 1; size of incoming spacecraft: no information, location of information; Location of the incoming spacecraft: one location likely."* On each trial, participants were shown where the last piece of space junk fell. Participants were instructed to use the previous falling space junk location to predict the location of the next piece of junk. The falling junk was presented on each trial for 5000m/s. To indicate their prediction, participants adjusted the rover and beam (which would appear at a random location on the screen x axis at the start of each trial) using the arrow keys (or WDAS) either on their keyboards or on the screen (left/right for the rover; up down for the beam). Once the participant had indicated their prediction, they were shown the where the junk in fact fell i.e., a prediction error. Feedback was presented in terms of points per individual trial and an ongoing cumulative score in the top right of the screen. Written confirmation e.g. "Well done, you caught it!", "missed", or "timed out!" was also provided on a trial-wise basis. Each trial could score a maximum of ten points. The score was shown after each trial and between each block. Bonus points were award for every 250 points, and each bonus point earned the participant an additional 50p on top of the payment for completing the experiment.

The task included 219 trials (ITI: 1000-5000ms) overall, split into six blocks that differed in their configurations of volatility and noise, via manipulations to the underlying probability distribution that the junk was sampled from. The task was counterbalanced to avoid ordering effects. Here,

each block was simply presented in the opposite direction i.e., the task included a forward, and reverse, condition. Distributions were designed in line with a previous study (Berniker et al., 2010; see Table 6-1; Figure 6.1b). Block one was a practice round that included three practice trials and required successful completion i.e., to catch every piece of junk, before the participant could continue. If the participant did not pass the practice round, they would be directed back to the start of the instructions to begin again. Block two (n=10 trials) was a stable learning environment i.e., no mean changes. Based on the counterbalancing condition, half of participants were exposed to high noise during block two (SD=0.12), whereas the other half had low noise (SD=0.03). In block three, the noise was manipulated in an isolated condition i.e., there were no mean changes (Mean=0.01), but the variance was altered. Depending on the counterbalancing condition, participants were exposed to a condition of low noise (SD=0.03; n=20 trials), and a high noise (SD=0.12; n=20 trials). Block four (n=40 trials) tested learning under isolated volatility. Volatility was manipulated by the inclusion changes to the mean of the underlying distribution from which the junk was drawn (see Table 6-1; Figure 6.1), alongside a stable variance (SD=0.01). Here, the probability distribution switched between two previously unseen means. The switch rate for mean change was computed at a 0.25 chance every 5 trials, resulting in 5 overall mean switches across the block (see Table 6-1; Figure 6.1b; as seen in Berniker et al., 2010). Blocks five (n=84 trials) and six (n=40 trials) updated the mean and SD of inputs every ten trials (plus jitter), resulting in continuous high volatility, and periods of high and low noise (see Table 6-1; Figure 6.1b). In each case, two previously seen means were used alongside two new means i.e., block five used the two means from block four, plus two new means etc. While learning requirements were the same across blocks five and six, blocks differed in terms of its reward policy, described below.

**Table 6-1** *Showing the details of the contingencies underlying the task for each block.*

| Screen | | Contingency Information | | | |
|---|---|---|---|---|---|
| **Name** | **Description** | **Trials (n)** | **Mean** | **SD** | **Rules** |
| **Block 1** | Practice round screen 1 | 3 | -0.07 | 0.045 | Option to repeat |
| **Block 2** | Stable learning environment | 10 | 0 | 0.12 or 0.03 | 50% participants SD=0.12; 50% participants SD=0.03 |
| **Block 3** | Learning when the SD changes (high and low noise) | 40 | 0 | 0.12 or 0.03 | SD changes halfway through. Fixed mean. Counterbalanced condition is reversed. |
| **Block 4** | Learning when the mean changes (high volatility) | 40 | 0.35, -0.35 | 0.06 | A 25% chance of changing to the distribution with the second mean, every four turns. |
| **Block 5** | Learning with combined SD and mean changes | 84 | 0.35, -0.35, 0.14, -0.21 | 0.12 or 0.03 | Each SD/mean combination changes every 10trial+/-jitter of around 3 trials. |
| **Block 6** | Learning with combined SD and mean changes. Block includes loses. | 42 | 0.35, -0.21 | 0.12 or 0.03 | Each SD/mean combination changes every 10+/-jitter of around 3 trials. Randomly ordered. Extra points for catching. Loose points for missing/using a larger beam. |

*Abbreviations: SD = standard deviation.*

*3.3.2.1 Outcome Measures*

Overall performance was measured by score. Score was calculated as a function of both catch success i.e. whether they caught the junk on that trial, and the size of the beam used to capture it (i.e., screen size), and was presented to participants as a score out of ten on each trial. In block six, participant could receive double points for a catch, or could lose points if they were unsuccessful at catching the space junk. Losses were calculated in the same way as rewards, but reversed. As such, missing the space junk with a wider beam led to a loss of more points than

missing the space junk with a small beam. Beam width, the amount of the screen taken up by the beam) could also be taken as a separate measure, and while related to score, provided some additional information about the ability of participants to acquire the underlying variance of the distribution.

Derived metrics included performance error, that could be calculated by subtracting the participants estimate of the mean of the distribution i.e., rover position, from the mean of the underlying distribution. Performance error, as related to the mean of the underlying distribution, provides insight into whether the individual is learning the underlying mean. The averaged standardised beta coefficients from a model predicting the signed prediction error (participant rover position – space junk position at $t_1$), from the signed rover position change indicated (participant rover position $t_1$ – participant rover position $t_2$), was used as an index of learning rate across participants. To access the task online, please click here.

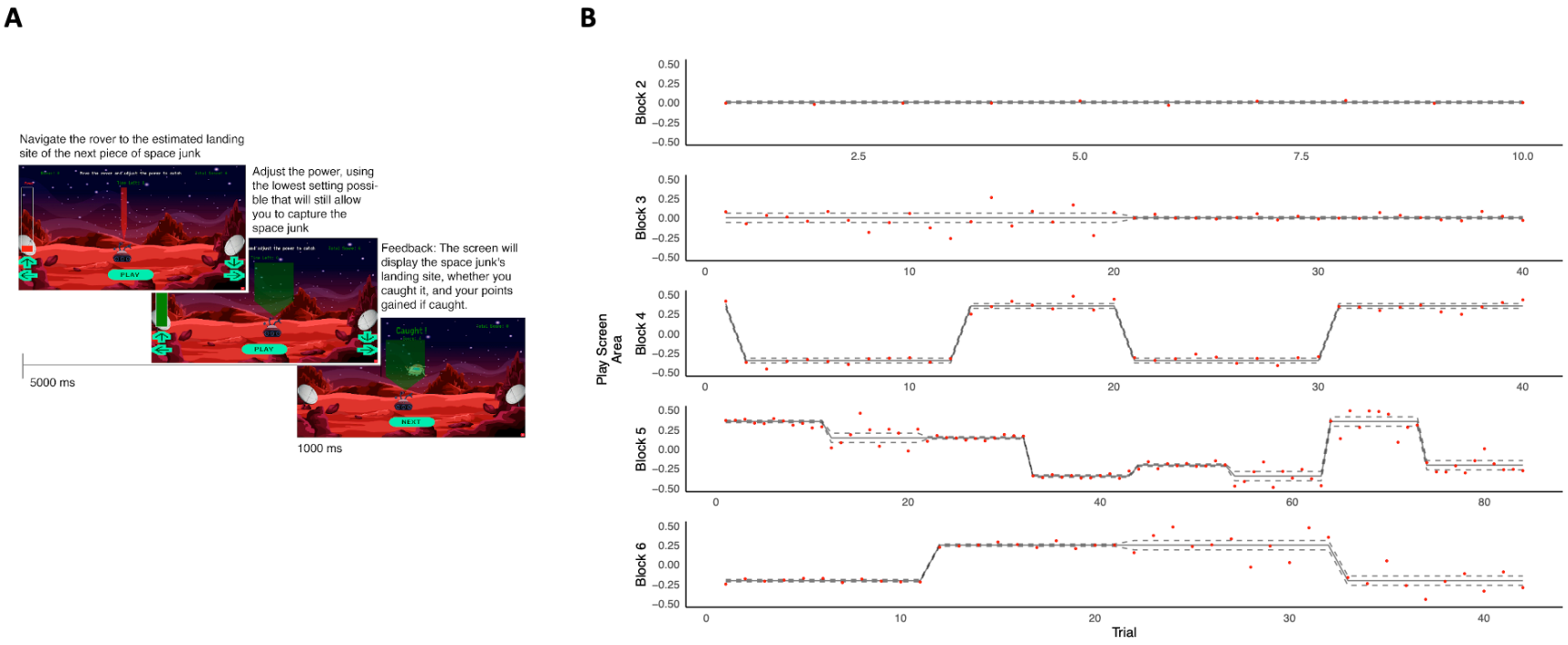


**Figure 6.1 A**. *Showing trial structure. Here, once the participant is exposed to the cue for a maximum of 5000m/s, participants are then instructed to make an estimate of the mean, using rover positioning; and variance using manipulation of the beam width. Feedback i.e., another piece of space junk drawn from the same distribution, is then presented to the participant (1000m/s).* **6.1B.** *The black solid line shows the mean(s) used for each block (see Table 3.1 for further details), indicating both the stability of the mean over trials (x axis), and the location of the mean on the play screen area. The standard deviation used to simulate noise in the space junk locations is shown using the black dashed line (see Table 3.1 for further details). Here, the width of the dashed line around the mean indicates both the width of the SD used, and the*

*area of the play screen available for space junk locations to be drawn from. The red dots show the actual space junk positions that the participants were exposed to, in accordance with the underlying probability distributions*

## *3.4 Analysis*

### *3.4.1 Quality control*

Data was subject to quality control screening, where a participant is deemed to not be attending to the task in the expected or necessary way. Exclusion criteria included: failure of technology, failure to move the beam and rover in at least 10% of trials (n=21) and/or completion of at least 10% of trials in less than 1000m/s.

### *3.4.2 Performance*

Overall performance was measured by score, averaged across each block. Acquisition of the underlying statistics was measured using comparison between blocks for the averaged performance error (learning of the mean). Whereas acquisition of the variance was measured by comparing beam width, averaged across the blocks and the noise conditions (high vs low). For example if a block included both high and low noise, participants for that block would have a value for each.

Analysis was carried out using R 4.2.1 GUI 1.79 High Sierra build (8095). Full analysis code available here. Linear mixed effects models were computed for the task's main outcome measures. The structure of the data included both within and between subject factors, including nested elements. It was necessary for the model to include multiple nested and non-nested random effects. As such, the r package "lme4" was used, and random slopes and intercepts were fit for relevant variables, in order to account for the structure of the data. Specifically, all models included random effects of i) participant, and ii) the counterbalancing condition (forward,

reverse, priming block high or low) nested within block (block 3-6). This was to i) inform the model that each participants' data was interrelated within each subject, but different between subjects, and ii) to inform the model that for example, block 1 data from counterbalancing condition forward was allowed to differ from block 1 reversed (and so on). Fixed effects were fit for each dependent variable using model selection, and therefore small variations in the included fixed effects between models, but in general included device type (mobile, computer), gender (male, female, non-binary), and an interaction between block (3:6) and whether or not the participant was a gamer (yes/no).

Each block of the task represented a different learning environment. To compare metrics between each learning environment, backwards contrasting methods were employed. As such, each block was statistically compared to the block before i.e. block 4 (high volatility, low noise) compared to block 3 (high noise, no volatility); block 5 (high noise and volatility) compared to block 4. Noise and volatility blocks remained stable across block 5 and 6, with the difference being a shift in reward polices, as such block 6 (introduction of losses and increased gains) was compared to block 5 (standard rewards) (see Table 6-2). As these were planned comparisons, multiple corrections analysis was not computed.

*Table 6-2 Showing planned backwards contrasts.*

| **Planned Contrasts** | **Description of comparison** |
|---|---|
| Block 4 vs block 3 | High volatility vs. high noise |
| Block 5 vs block 4 | High volatility + noise vs. high volatility |
| Block 6 vs block 5 | High volatility + noise + losses + increased gains vs. High volatility + noise |

### *3.4.3. Model selection*

Model selection was carried out to identify the best model for each metric. To directly compare the models, an information theoretic approach (AIC) (Akaike, 1973) was used. This approach is noted for its conservative approach due to the penalties it imposes on model complexity, such as additional fixed effects, as well as its ability to compare nested models (Wagenmakers & Farrell, 2004; Vrieze, 2012) To enable this comparison of models, given that we wanted to compare models with differing numbers of fixed effects, and that the data was nested, the log likelihood was used (Verbyla, 2019). However, Maximum Restricted Maximum Likelihood (REML) was the choice of estimation method used once the best model had been identified (Corbeil & Searle, 1976). The reported results were read from the models that had the lowest AIC values of the models compared, including the simplest model (fixed effects set to 1), showing that the simpler models was least informative. A chi square difference test was also used to statistically test whether the models were significantly improved from baseline i.e., the most simple model. Chi square tests for model selection are used when comparing nested models, i.e., where the differences between models lies in the number of fixed effects (Schermelleh-Engel, et al., (2003).

### *3.4.4 Learning rate*

The averaged standardised beta coefficients from a model predicting the signed prediction error (participant rover position – space junk position at $t_1$), from the signed rover position change indicated (participant rover position $t_1$ – participant rover position $t_2$), was used as an index of learning rate across participants. Using the back-contrasted method described in the previous section, average learning rates were compared between blocks.

### *3.4.3. Computational modelling – preliminary analyses*

The HGF is a generative model where learning takes place via precision-weighted prediction errors on multiple levels. Within this learning hierarchy, the upper-level refers to a volatility belief that determines how much weight is given to the lower-level prediction errors caused by deviating inputs (Mathys et al., 2011; Mathys et al., 2014). In the "classic" application of the HGF, both sources of uncertainty, *systematic* volatility and *unsystematic* noise (or: outcome uncertainty) are not independently estimated but simply represent the uncertainties of the respective higher- vs. lower-level beliefs about the occurrence of (mostly binary) inputs (Mathys et al., 2014). This circularity probably comes close to the true challenges of the mind, i.e., to dissociate what is real change and what is noise from the same input. However, it also impedes the interpretation of the estimated learning signatures and parameters, especially concerning the question of what might be the core deficit in aberrant belief updating, overestimating volatility or underestimating noise. In our space task paradigm, we aimed to better disentangle both concepts via introducing metric inputs (positions where the space junk falls) that are drawn from a *ground truth* probability distribution. Crucially, these have changing means and SDs and subjects who successfully infer both of these can adapt their performance over positioning the rover (mean) and widening the beamwidth (SD). So far, no study has been published inferring parallel noise and volatility beliefs for metric inputs (task feedback) and outputs (participants' responses) using the HGF. However, there already is a respective HGF script within the tapas toolbox as part of the TNU package: the Jumping Gaussian Estimation Task (JGET; name of script: 'tapas_ehgf_jget'). The JGET model is perfectly applicable to our paradigm because it is characterised by a 2-branches HGF that "learns" about (1) the current mean value ($x_1$) and (2) its variance ($\alpha_1$) of the input stream ($u$). It is – of course – also hierarchical; there are volatility

"parents" for the variation of mean values ($x_2$) and the variance ($\alpha_2$). As in the classic HGF applications, there are the same free parameters that capture inter-individual differences, e.g., $\kappa$ for the coupling between levels or the level-wise $\omega$ determining the constant step-size for trial-wise updating (Mathys et al., 2011; 2014). Unlike in the previous HGF applications, both streams for learning about $x$ and $\alpha$ emerge from an additional, common level that brings together beliefs about $x_1$ and $\alpha_1$. We used the latter trajectories in order to predict (and thereby fit) the trial-by-trial responses: belief about $x_1$ → rover position and belief about $\alpha_1$ → beam width. Specifically, we assumed that predicted responses were drawn from Gaussian distributions with the respective belief as the mean and an individual noise parameter $\zeta$ as the variance (modified version of the 'tapas_gaussian_obs'-script). For the noise (or variance) belief, we introduced an additional free coefficient parameter $\beta$ capturing the general tendency of an individual to use the acquired knowledge (belief) for their beam width adaptation (see Figure 6.2).

Given that there is no literature on the JGET package, we had no prior knowledge on the range of the (free) parameters. We therefore consulted the experts and carried out simulations for visual inspection in order to choose task priors that produced reasonable learning trajectories and behavioural responses that matched the 'raw data' behaviour (rover positioning and beam width). The novelty of the approach taken also emphasises the fact that these analyses and results are preliminary evidence and need to be expanded on and repeated. Due to the differing statistical contingencies underlying each block, these simulations were conducted in a block wise fashion (see Figure *6.6*, for simulated responses). Priors then ended up differing between all blocks, apart from only blocks 5 and 6 that both had close similarity in ground truth contingencies (see Appendix: Table 6.5, for an overview of exact priors used).

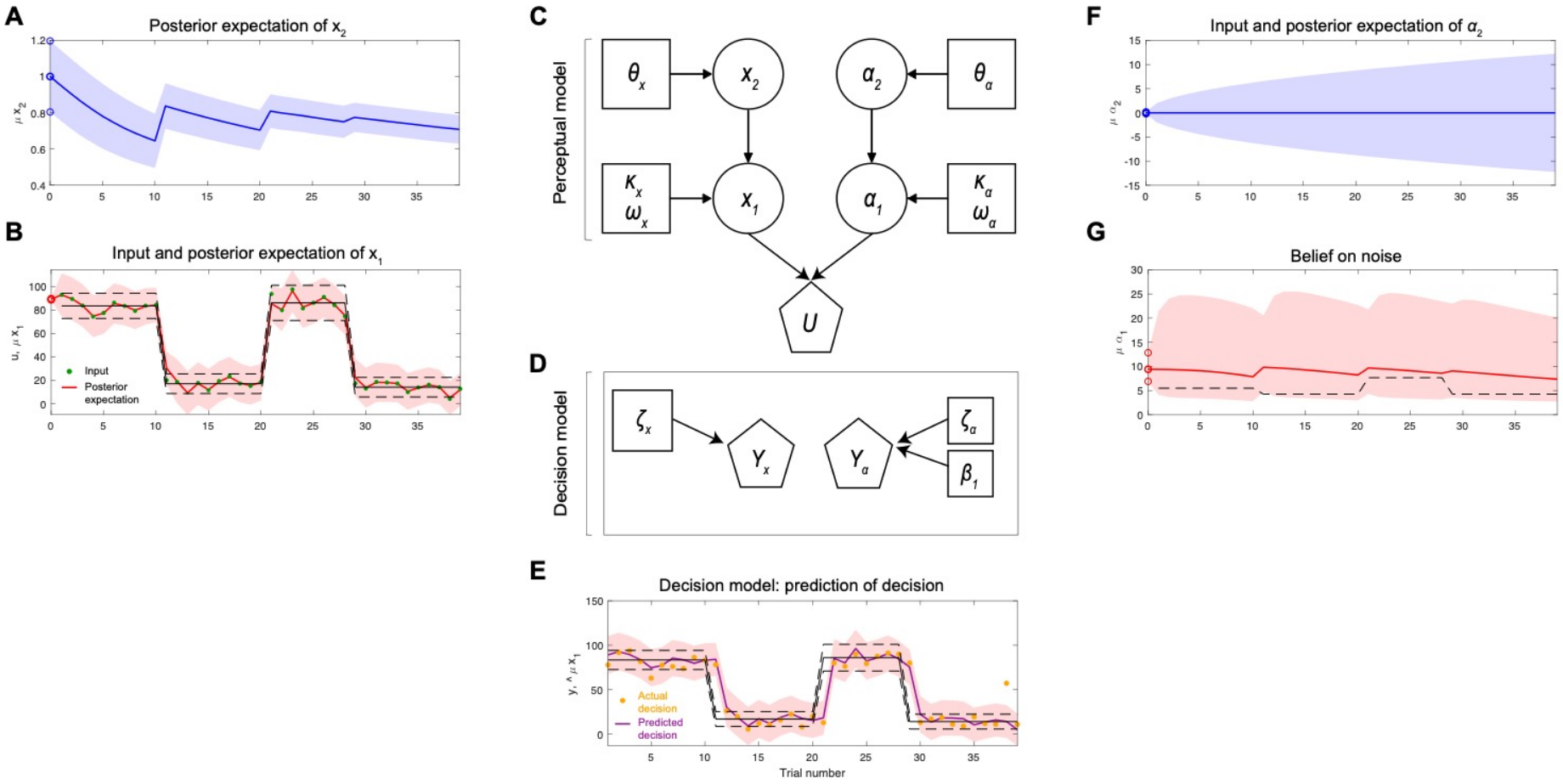


**Figure 6.2** *Showing a depiction of the Jumping Gaussian Estimation Task modelling process used in this study. This version of an extended HGF model captured learning about the mean (x) and variance (a) independently. Pentagons represent trial-by-trial input ($y_x$ = rover*

*positions; $y_a$ = beam widths). Squares represent the modelling parameters, relating to learning about the mean (x) and noise (a) separately: $\theta$ refers to the constant step-size in volatility learning ($\mu^2$), $\omega$ is the equivalent on the lower-level belief and $\kappa$ determines the coupling strength between levels. Parameters for u (see Appendix Table 6.5) refer to the lowest level, where beliefs about noise and mean are combined for a common prediction about the mean. The decision model (grey) includes $\zeta_x$ and $\zeta_a$ for determining the decision noise or SD when drawing from a Gaussian distribution around the respective belief ($\mu_1$) about mean and noise. The $\beta_1$ parameter captures how much an individual makes use of her belief about noise when adapting the beam width.*

# 4 Results

## *4.1 Quality control*

In this experiment 12 individuals were excluded for failing to meet these predetermined task-related quality control standards. For example, individuals were excluded if they 1) failed to move either made no movement (either of the rover or the beam) in over >10% of trials (n=8), and/or 2) completed over >50% of trials in under 1000ms (n=0), leading to a total of 8 exclusions. Further, seven individuals were excluded because of incomplete data due to a technology issue e.g. internet connects, or use of a tablet (n=3). Overall, 18 individuals were excluded, leading to a new total of 147 participants (high SPQ = 81; low SPQ = 66; *M =29.7* years; *SD = 6.21*; female = 69.39%).

**Table 6-3** *Participant characteristics table*

| **Participant Characteristic** | **Group** | |
|---|---|---|
| | ***High SPQ (n81) (%)*** | ***Low SPQ (n66) (%)*** |
| **Gender** | | |
| Female | 70.37 | 68.18 |
| **Ethnicity** | | |
| White (English, Welsh, Scottish etc.) | 80.25 | 76.00 |
| Asian (Indian, Pakistani, Bangladeshi, Chinese etc.) | 11.11 | 4.55 |
| Black (African, Caribbean etc.) | 3.70 | 7.58 |
| Mixed or multiple ethnic groups | 4.94 | 3.03 |
| **Education** | | |
| GCSEs or A levels | 29.63 | 18.18 |
| Undergraduate degree (BSc/BA) | 60.49 | 51.52 |
| Postgraduate (MSc/MA/MRes/PhD) | 9.88 | 32.80 |
| **Employment** | | |
| Employed | 27.16 | 18.18 |

| | | | | |
|---|---|---|---|---|
| Unemployed | 72.84 | 81.82 | | |
| **Device type** | | | | |
| Computer/laptop | 72.84 | 69.70 | | |
| Mobile phone | 27.16 | 30.30 | | |
| | ***M(SD)*** | ***M(SD)*** | ***F*** | ***p*** |
| **Age** | 28.2(6.40) | 31.5(5.51) | 10.93 | **.001**** |

## *4.2 Acquisition of underlying statistics*

### *4.2.1 Performance error*

Performance errors were averaged for subjects and blocks. The winning model included random effects for participants, and counterbalancing condition nested in block, with a fixed effects of education, device type and block (X2(df) = 46.95(6), $p$=<.001). Results showed that use of a mobile phone to complete the game increased average overall performance errors ((β(SE)=0.09(0.04), $p$=.025; Figure 6.3). Average performance error was also increased during high volatility and low noise environments (block 4), compared with high noise and low volatility environments (block 3) (β(SE)=0.47(0.04), $p$=<.001). No other differences between blocks were observed, nor interactions with SPQ group.

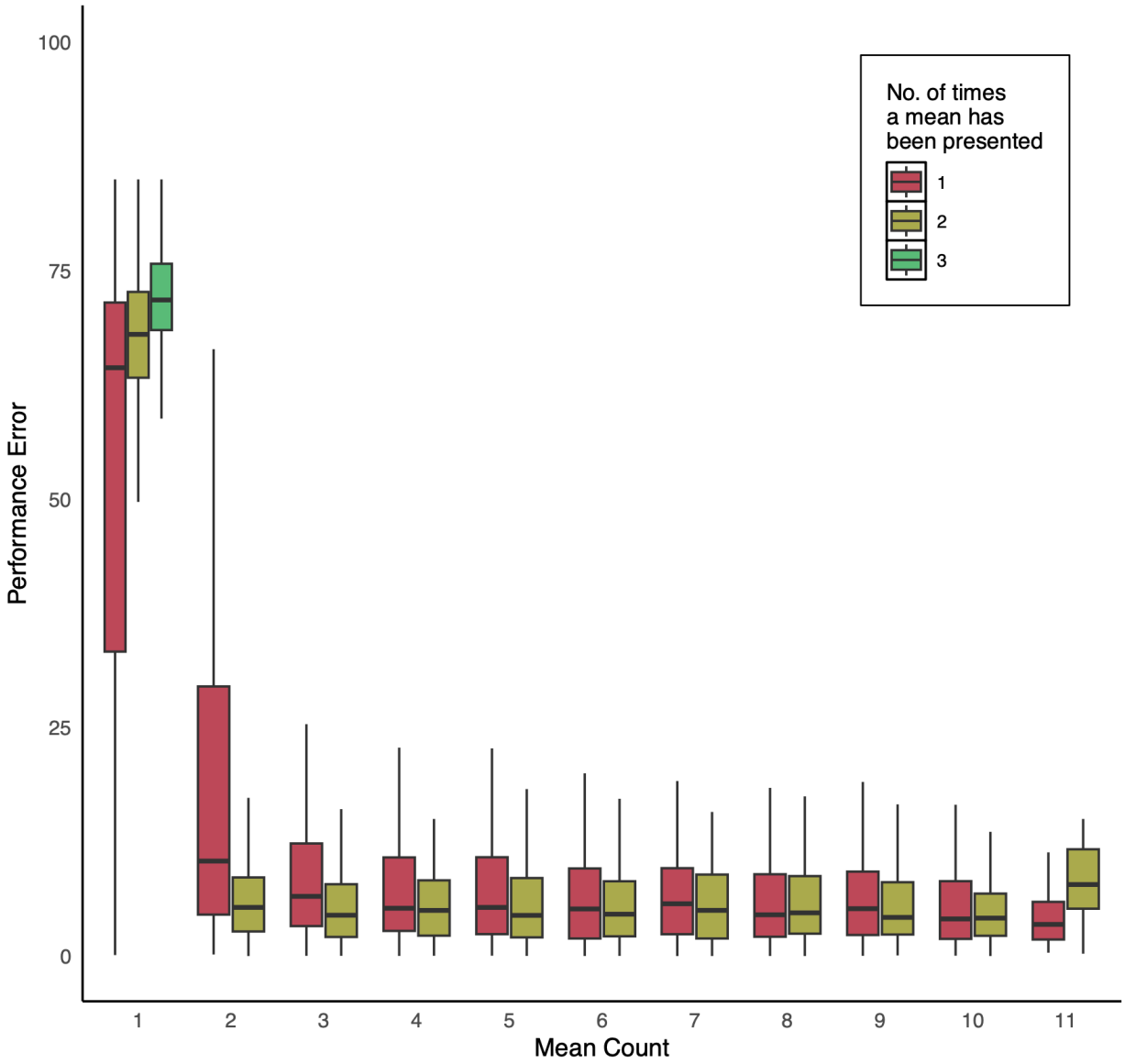


**Figure 6.3.** *Showing performance error (participant estimate – mean of the distribution) across trials where a mean change occurs (1), alongside subsequent trials after a mean change (2-11). Colours indicate how many times the mean in question has been seen by the participant. Data displayed here is from block four, where volatility was increased i.e., the mean changed between two previously unseen means, but the variance remained small and unchanging.*

### *4.2.2 Beam width*

For each person, beam widths were averaged across blocks and the underlying noise condition (low or high). A model including interaction between block and underlying noise significantly improved model fit (X2(df) = 157.50(6), p<.001), and showed the lowest AIC value. Results showed that the noise condition (high/low) significantly affected the use of the beam. Specifically, participants used a significantly wider beam during period of high noise and vice versa (β(SE)=-10.15(1.027), *p*<.001; see ***Figure 6.4***). There was a significant decrease in beam size between blocks 3 (noise) and 4 (volatility), as expected (β(SE)=-6.56(1.39), *p*<.001). Beam widths increased as the task condition changed to combined noise and volatility (block 4 to block 5; (β(SE)=-9.52(1.61), *p*<.001; and blocks 5 to 6 (β(SE)=-10.37(1.39), *p*<.001)). No group effects were found.

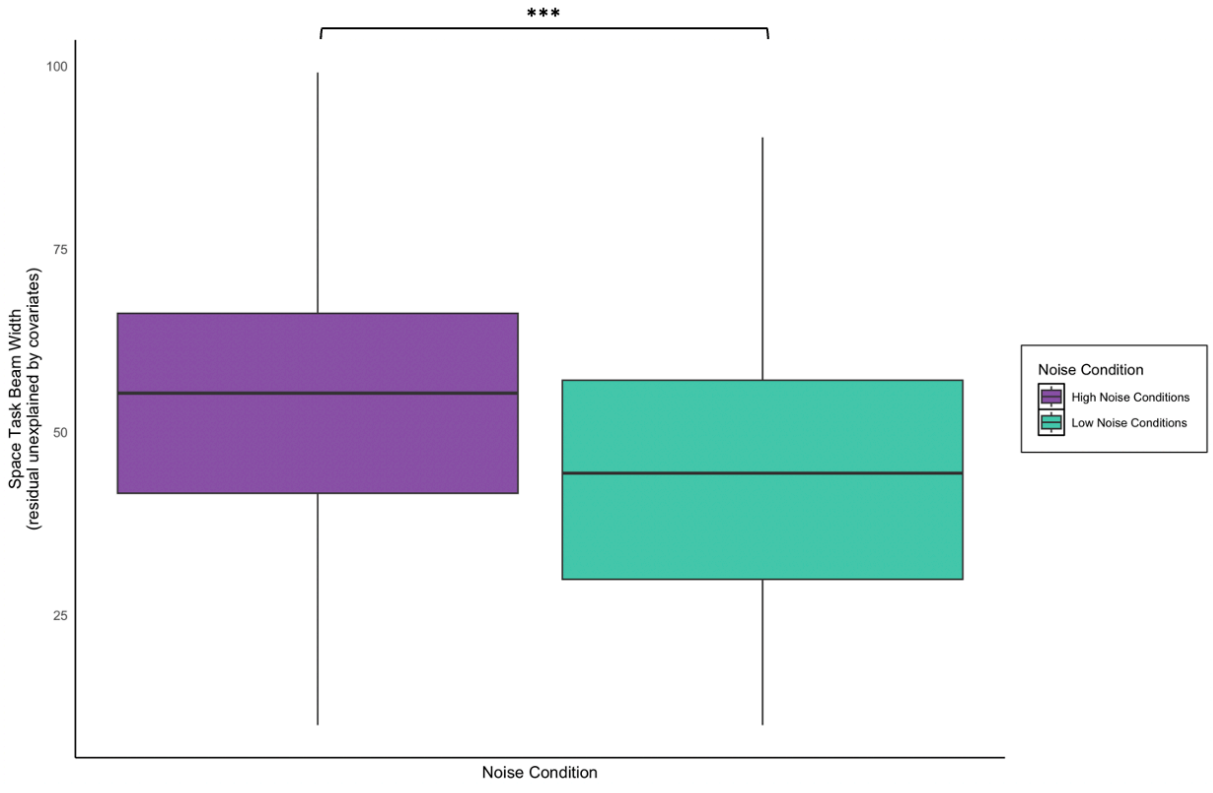


**Figure 6.4** *Showing average beam widths used in conditions of high (purple; SD=0.12) and low (green; SD=0.03) noise. The figure uses the unexplained residuals of the fitted model, once all*

*other covariates have had their variance explained. The model finds that high noise conditions (M=52.7; SD=18.2) led to use of significantly wider beam widths than low noise conditions (M=43.3; SD=18.1; (β(SE)=-10.15(1.027), p<.001).*

### *4.3 Performance (score)*

Scores were averaged across person and block. The winning model included random effects for the factor participant, and counterbalancing condition (forward/reversed) nested in block, with a fixed effect of block (back-contrasted) (X2(df) = 24.95(3), $p$<.001). Averaged score decreased between all back contrasted blocks, including between block 3 (noisy) and block 4 (volatility) (β(SE)=- 0.37(0.11), $p$=.003), block 4 (volatility) and 5 (noise and volatility) (β(SE)=-0.83(0.12), $p$<.001), and between blocks 5 (noise and volatility + rewards) and 6 (noise and volatility + losses) (β(SE)=-0.80(0.11), $p$<.001). No significant effect or interaction with SPQ group was observed.

### *4.4 Learning rate*

Learning rates were calculated using the beta coefficient from a model predicting the signed position changes from the signed prediction error, averaged across blocks. The winning model included random effects of participants, and counterbalancing condition nested in block, with fixed effects of gender, education, ethnicity, and back-contrasted block (X2(df) = 28.07(10), $p$=.002). Females displayed significantly higher learning rates overall than males (β(SE)=0.04(0.01), $p$=.010). Whereas education group “high school graduate”, and ethnicity types “Asian or Asian British” and “Black of Black British” showed significantly decreased overall learning rates (high school graduates: β(SE)=-0.04(0.01), $p$=.012; ethnicity Asian:

β(SE)=-0.05(0.02), *p*=.034; ethnicity Black: β(SE)=-0.05(0.02), *p*=.028). As expected, learning rates increased in conditions of high volatility (block four) compared to high noise (block three) (β(SE)=0.19(0.01), *p*<.001; see ***Figure 6.5***). Learning rates were also found to be higher between combined noise and volatility conditions with losses and increased rewards (block six), when compared with combined noise and volatility with the normal reward policy structure (β(SE)=0.09(0.01), p=.020). No group, or group by block interaction was found.

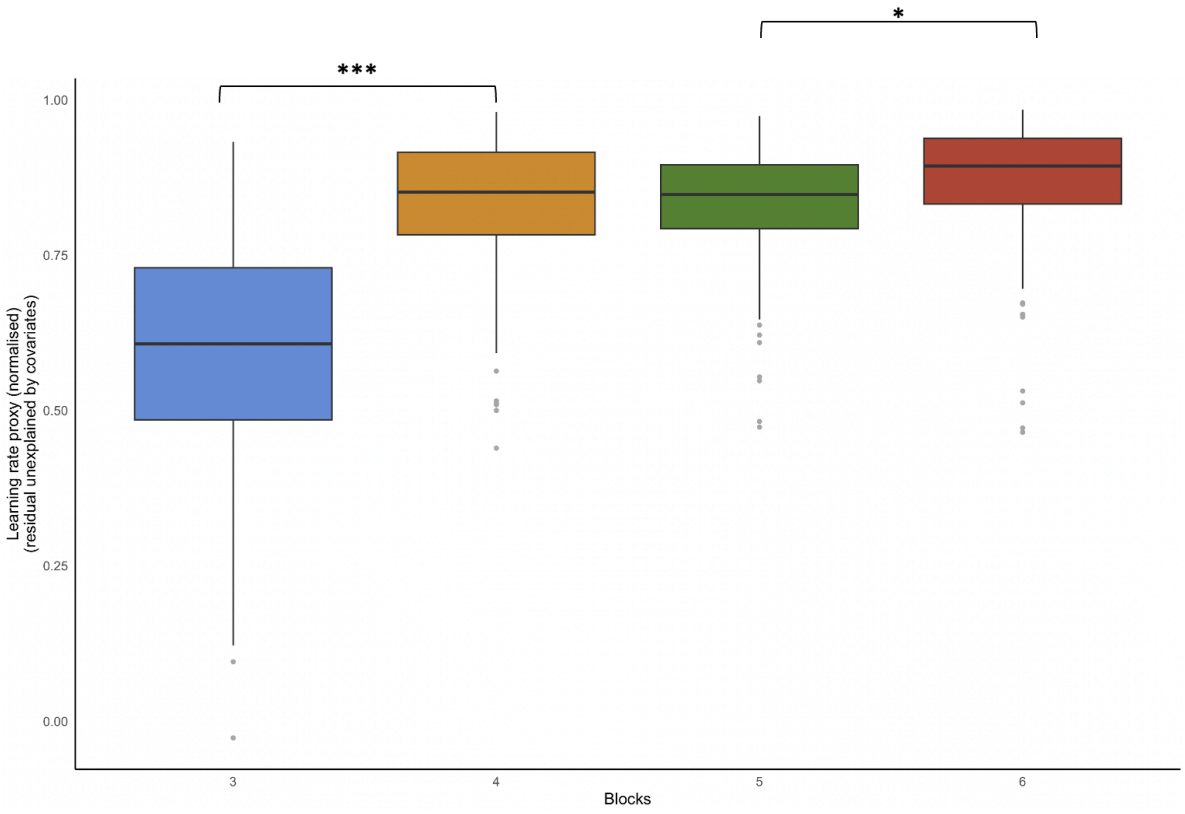


**Figure 6.5** *Showing learning rate across all participants, for each block. Learning rate is calculated as the beta coefficient of a model predicting signed prediction error from signed position change. A significant difference was found between blocks three (blue; M=0.59; SD=0.17) and four (yellow; M=0.83; SD=0.11) i.e., as volatility increased (p<.001). Learning rates were also found to increase between blocks four and (green; M=0.83; SD=0.09) and five (red' M=0.86; SD=0.10) (p=.020).*

## *4.5 Computational modelling – preliminary findings*

### *4.5.1 Model simulations and fit*

Priors were adapted for block three, four separately, whereas blocks five and six used the same set of priors. We can see from Figure *6.6*, that the simulated predictions of blocks 3-6 capture the data well, both in terms of the (median) participants estimate of the junk positions, and their (median) beam widths. The total number of individuals excluded due to poor fit overall was 10, (block 3 n= 1; block 4 n= 6; block 5 n=2; block 6 n=2). These individuals were excluded from further analysis.

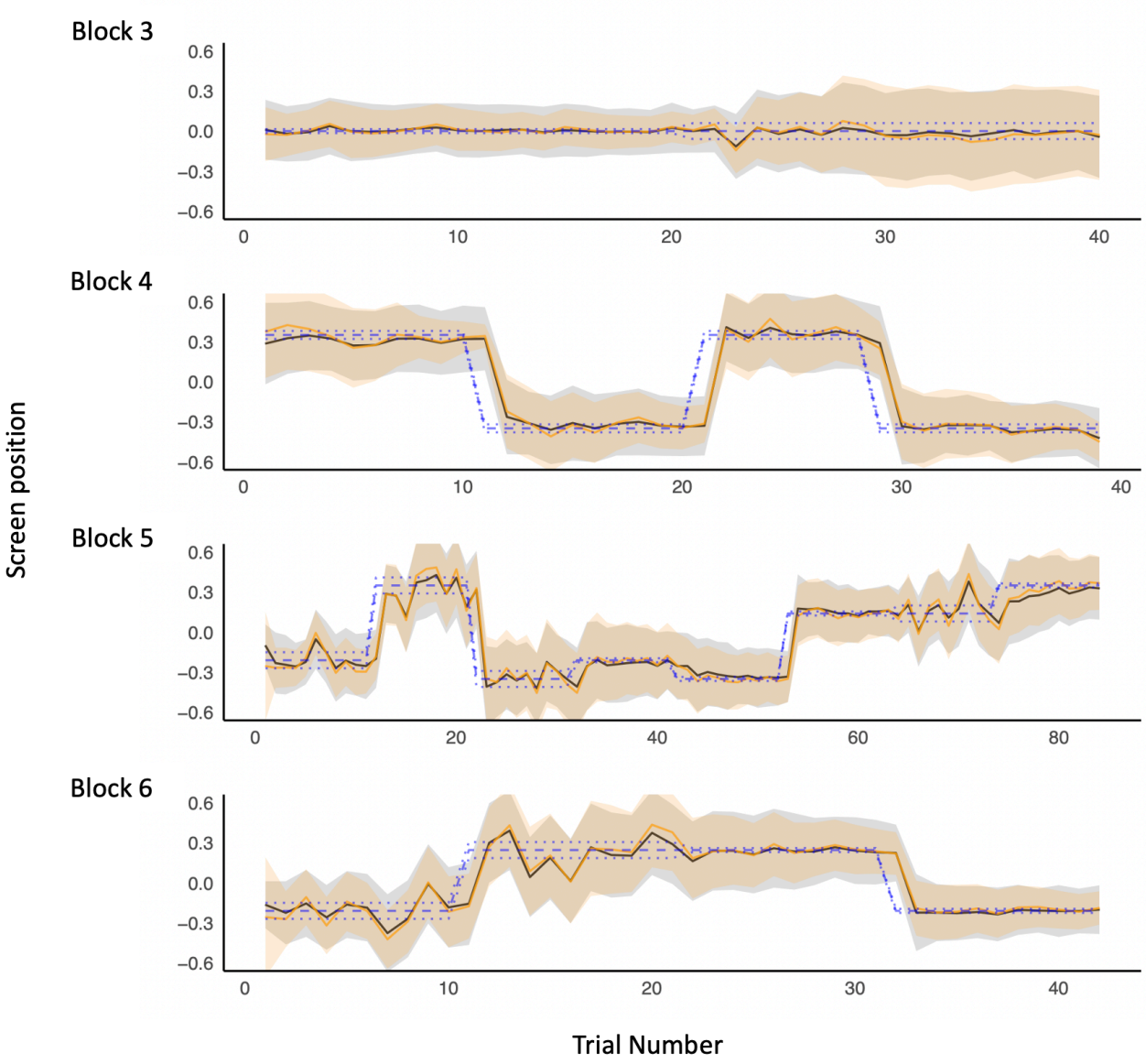


**Figure 6.6** *Showing a comparison between participant estimates, and estimates made via the model simulations, across blocks 3 to 6 (A to D). The x axis displays the trial number for each block. The y axis shows the screen position scale. Here, 0 indicates the middle of the screen, while positive and minus figures show the right- and left-hand sides of the screen respectively. In this way, mean estimates (rover positions) and noise estimates (beam widths) can both be displayed as positions on the screen. The contingencies of the probability distributions underlying each block are illustrated using blue dotted and dashed lines. For example, figure A (block 3) consisted of a stable unchanging mean of 0 throughout the block – indicated by the*

*dashed line, alongside an increase in the size of the standard deviation/noise halfway through the block – indicated by the blue dotted line increasing in width at trial 20. Median participant estimates of the mean i.e., rover positions, are indicated by the black solid lines. Median simulated estimates of the mean based on the JGET HGF model are shown in orange. The median participant's noise estimate (beam width) for each trial is shown using the width of the screen in black/grey. The median simulated noise estimate is shown as a width in orange.*

### *4.5.2 Computational modelling: extracted parameter comparison*

Exploratory analysis was conducted to assess whether differences between high and low SPQ groups existed for parameters of interest (noise belief *($\beta_1$)*, and kappa (*$\kappa$)* for mean (*kax)*, and $\kappa$ for the variance (*kaa*). Blocks 3 and 4 used different priors, while block 5 and 6 used the same priors. Similarly, not all blocks allowed $\kappa$ parameters (mean and SD) to vary, i.e., when there was no volatility in noise the $\kappa$ for noise was fixed to 0 (please see Appendix: Table 6.5). As such, while noise belief could be compared across all blocks, $\kappa$ associated with the mean, and $\kappa$ associated with the variance, were not mixed.

Use of noise belief ($\beta_1$) was assessed using a linear mixed effects model with a random effect of participant, and fixed effects including age, ethnicity, education, and an interaction between block and group. While it must be acknowledged that priors differed between some blocks, it was legitimate to build on the advantages of a linear mixed effects model design ask if, once variance across all blocks and participants is accounted for, whether there was an interaction between block and group, in free parameters of interest. However, this necessarily meant that the main effect of block was not relevant from these analyses.

No main effect of group was identified (p=.333). However, given the differences in priors for block 3 and 4 this was not the main focus of this analysis. No covariates were significantly associated with $\beta_1$. Preliminary findings however, did show a significant interaction between group and block 4 (β(SE)=0.02(0.01), $p$=.026), potentially indicating that elevated schizotypy was associated with an increase in noise belief as the task moved from block 3 (high noise, low volatility) to block 4 (high volatility, low noise) (see Figure 6.7). The same approach was taken for the $\kappa$ values for the mean (*kax)* and the variance (*kaa).* No significant interaction was identified between group and block for either parameter. Mean score overall showed a negative relationship with $\beta_1$, but this was not significant (Appendix: Figure 6.9a). There was no association between mean scores for each block and noise belief for either group (see Figure 6.8). Further information can be found in the appendix (see Appendix Figure 6.9- Figure 6.14) regarding the relationships between mean scores and PEs with other free parameters studied in this research.

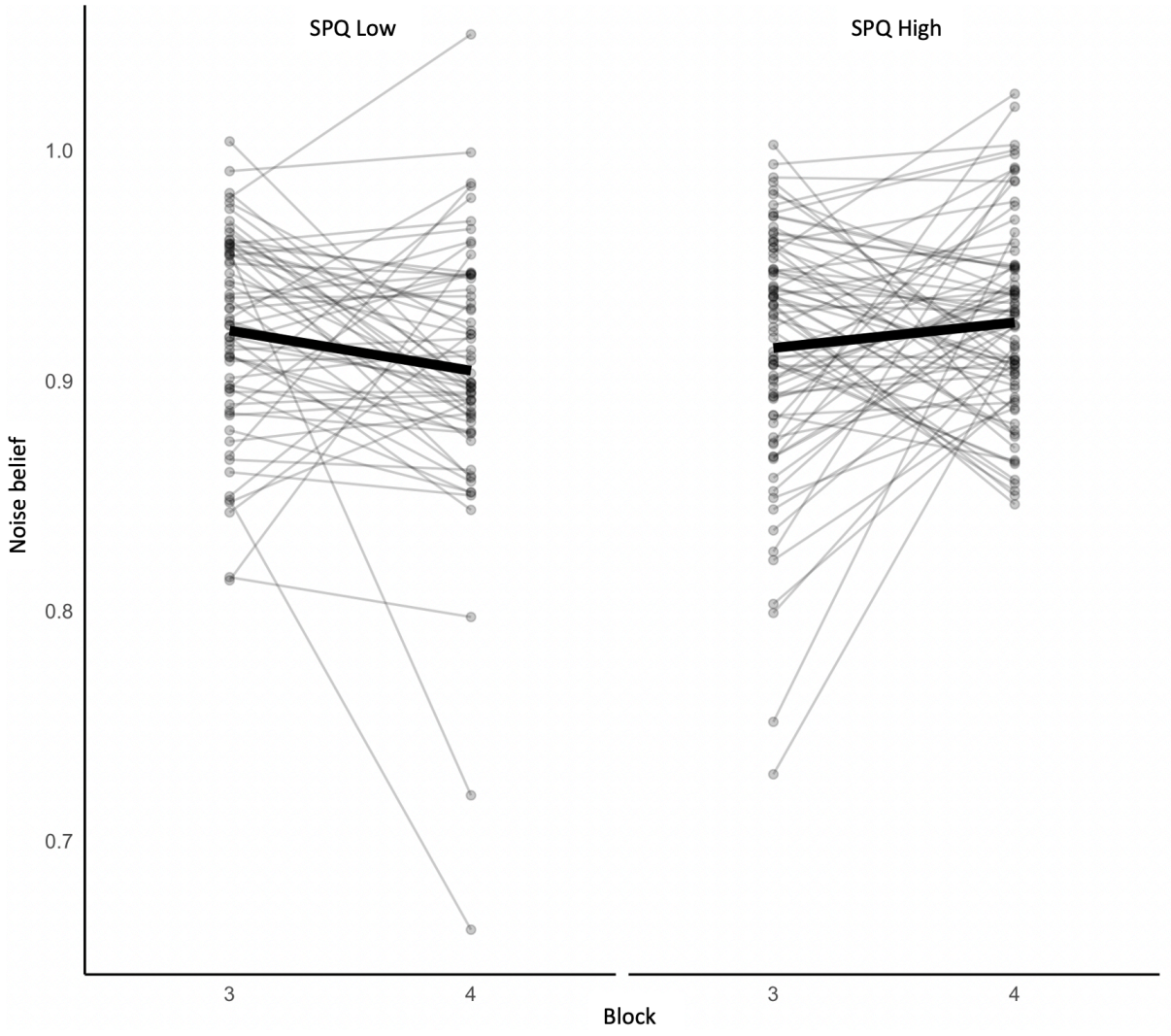


**Figure 6.7** *Plots showing $\beta_1$ value for each participant (dot) in blocks 3 (noise, low volatility), and 4 (high volatility, low noise), in high and low schizotypy groups. Values on the y axis represent individual estimates for $\beta_1$ . Each participant is connected by a continuous line (grey) between their $\beta_1$ in block 3 and 4 designed to show directionality. The bold, black line shows the mean $\beta_1$ value in blocks 3 and 4, for both high and low SPQ groups. Again. This is connected by a line, in this case bold and black, to show how the noise belief changed between these blocks. Here, the low SPQ scorers showed an overall decrease in be1 value between blocks 3 (M=0.92 ; SD=0.04) and block 4 (M=0.90; SD=0.06). On the other hand, those with elevated SPQ*

*symptoms showed an increase in SPQ scores from block 3 (M=0.95; SD=0.05) to block 4 (M=0.92; SD=0.04).*

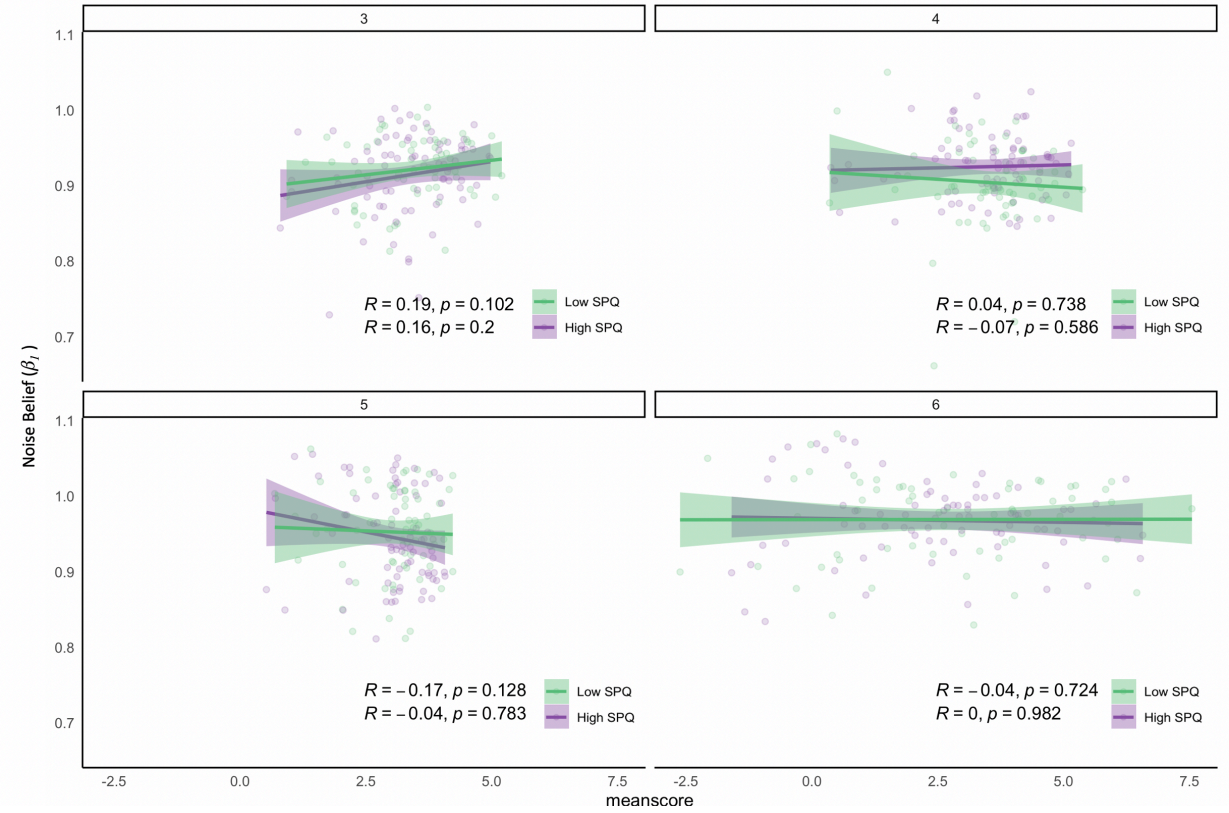


**Figure 6.8** *Plot showing the associations between mean scores for each block and participant, and noise belief ($\beta_1$) for the overall by block. High SPQ scoring groups are shown in purple. The corresponding statistic is presented alongside an indication of the group. Blocks are indicated in the top bar of the individual plot and include blocks 3 to 6.*

# 5 Discussion

The aim of this study was to investigate probabilistic learning under uncertainty in elevated schizotypy symptom groups, compared with controls. The experiment was conducted

using a novel task that drew from continuous "ground truth" probabilistic contingencies that were manipulated (via changes to the mean and standard deviation) to simulate noisy and volatile learning environments, independently and in combination. Trial wise parallel estimates of both the noise and volatility were subject to a novel and preliminary computational model that was able to capture learning about the variance and mean of the environments independently (HGF: JGET) (Mathys et al., 2014). Initial results indicate that individuals with elevated schizotypy personality traits did not adapt their behaviour according to the change in noise. While these results are in the preliminary stage, they may suggest that compared to low schizotypy subjects, individuals with elevated SPQ scores did not decrease their use of information about noise in their decision making, in accordance with its decrease in relevance for task performance. This difference was not associated with an over-estimation of the volatility, or differences in learning rate or raw data performance.

A common finding in the literature is that individuals with psychosis-spectrum disorder symptoms show noisier decision making, including increased choice-switching, in tasks where uncertainty is manipulated probabilistically, both in patient cohort studies and widescale population studies (Katthagen et al., 2020, Moutoussis et al., 2011; Croft et al., 2022; Culbreth et al., 2016a; Kaplan et al., 2016; Li et al., 2014; Murray et al., 2008; Schlagenhauf et al., 2014; Waltz et al., 2013). While this may indicate a degree of stochasticity in cognitive processes in those (at risk) of psychosis, it is unclear how informative this computational index of higher decision noise is with respect to specific cognitive mechanisms (Baker et al., 2019; Katthagen et al., 2022). Particularly given that these findings could represent unmodeled mechanisms such as socioeconomic status (Baker et al., 2019), IQ, or simply a difficulty in understanding, or paying attention to the task (Katthagen et al., 2022). This study reduced the cognitive burden of the task by providing information about the uncertainty of each condition via instructions before every

block, in the context of an overarching narrative. Results suggest that when individuals with elevated schizotypy are to some degree expecting, or informed of the type of uncertainty they are about to experience, then decision making under volatility is incongruously informed by the noise of the environment. In other words, elevated schizotypy groups incorporated their belief about the noise of the environment into their decision making when the noise (or variance) of the environment was not important. One interpretation of these exploratory findings is that by reducing the cognitive burden of the task, decision making stochasticity was superseded by a decision-making strategy incorporating superfluous information (about noise), when the world is volatile and not noisy. While this did not affect task performance it could potentially become a disadvantage in a more complex environment.

The ability to accurately estimate volatility Is affected in psychosis spectrum disorders (Cole et al., 2020; Deserno et al., 2020; Katthagen et al., 2020; Reed et al., 2020; Suthaharan et al., 2021). Aberrant prediction error processing in psychosis is commonly linked to volatility estimation via overweighting e.g., a small PE given undue weight leading to false inference (Fletcher & Frith, 2008). Increased focus on noise during conditions of volatility may indicate a related, potentially pre-morbid issue, such as a safety response to the confrontation of a learning environment in which a confident model of the world has been lost (Vinckier et al., 2015). For example, elevated ambiguity under volatility may cause an increase in explanation seeking and effort to identify regularities. As such, the response to a volatile environment for individuals with high levels of schizotypy may include opening themselves up to additional, but useless (and potentially problematic) information, to support their estimate. In turn, the rise in superfluous information would ultimately lead to increased opportunities to perceive illusory patterns and regularities when there are none. This could reduce the ability to stabilize the internal model and lead to a sense of change or a feeling of strangeness, as well as apophenia, hypermentalisation, and

jumping to conclusions (Broome et al., 2007; Fyfe et al., 2008; Whitson & Galinsky, 2008). While no differences were found in PE processing in this experiment, it is possible to hypothesise that overloading one's belief update with superfluous information could for example, dilute the effects of even a large prediction error signal. As such, while the overestimation of volatility in the environment would lead to seemingly random responses and choice switching (as every input is considered meaningful), overloaded and noisy inferences under volatility could lead to a feeling of uncertainty and a reluctance to believe that the inference properly explains the input resulting in increased exploration.

Contrary to our preliminary findings, research using binary based PLRTs commonly identify performance deficits relating to the noise (via choice-outcome probabilities) (Murray et al., 2008; Reddy et al., 2016; Weickert et al., 2010), and/or an overestimation of the likelihood for those probabilities to change (*volatility*) (Cole et al., 2020; Deserno et al., 2020; Schlagenhauf et al., 2014). As discussed, differences in findings may result from whether or not the task provides an intuition of uncertainty via narrative and instruction. However, population differences may also play a role in differences observed here. For example, research in the field of uncertainty estimation has focussed on delusions (Fromm et al., 2023), paranoia (Reed et al., 2020; Suthaharan et al., 2021), or hallucinations (Powers et al., 2017; Teufel et al., 2015), specifically. As such, there is the possibility that the findings relate specifically to elevated schizotypy. However, research has also shown incidences of intact probabilistic learning in psychosis (Kreis et al., 2022). A methodically similar task that also manipulated noise and volatility contingencies independently (albeit using binary inputs and responses), also showed no performance-based differences in individuals with schizophrenia, including no increased choice-switching under increased noise and/or volatility conditions, while simultaneously finding significant differences in computational parameters (Kreis et al., 2022). Similarly, a recent computational analysis of

abnormal belief updating (measured via a probability estimation bask) and psychosis experiences conducted from UK birth cohort records (n=3360) found limited evidence that belief updating was associated with psychotic symptomology at all (Croft et al., 2022). While it was somewhat surprising in this study to see a computational parameter difference, but no performance-based difference, there are several possible explanations. For example, given the nature of the population (subclinical) it may be that the unnecessary incorporation of information when learning under volatility is a very early mechanism, representative of attenuated symptoms common to schizotypy personality traits, such as the noticing of unusual connections. It must also be noted that performance metrics are higher order proxies for cognitive processes, that have been found to show limited reliability (Kreis et al., 2022). Computational modelling parameters on the other hand, are argued to be more able to capture the cognitive mechanism of interest (Karvelis et al., 2023), but require diligent adherence to modelling procedures and practices (Karvelis et al., 2023; Wilson & Collins, 2019).

### *5.1 Limitations and future directions*

One limitation relates to task differences in the presentation of volatility. While the task was aiming to simulate a volatile environment using mean changes at unexpected change points, there is the possibility that participants gleaned an understanding of the "context" of these changes i.e., an intuition for how frequent and/or when the changes would occur. This type of uncertainty is called structural uncertainty and refers to the uncertainty surrounding the number of discrete probabilistic relationship (Sandhu et al., 2023). Using a block design may increase the opportunity for participants to build expectations about the timing and frequency of changes i.e., rules which are rarely accounted for during learning task but that do guide decision making during the task by separating stable and changing periods into contexts (Lloyd & Leslie, 2013;

Sandhu et al., 2023). The ability to infer these higher order rues about the structure of the inputs may differ on an individual basis, and equally in how they relate to psychopathology. Here, while we tried to control for participants gleaning an idea about context in terms of change points by using jitter in the number of trials between stable and volatile blocks, it could be that there were unmeasured differences in the ability to gauge the structural uncertainty within the environment. Further analysis using latent cause models to account for whether participants can infer the presence of different contexts would be a route forward (Gershman et al., 2010; Gershman & Niv, 2012).

While behaviourally, beam widths (used in the calculation of noise belief) mimic the underlying variance as expected, in this novel task beam widths were inherently connected to reward i.e., to catch with the smallest beam possible. While this was to incentivise use of the beam as a representation of the underlying variance, behaviour with the beam could also incorporate a level of risk aversion e.g., to avoid losing money. When money could be lost (block 6), participants consistently used a wider beam overall, even when the variance was reduced. As such, the finding of increased use of noise belief could indicate a risk aversion strategy, rather than an indication of the belief about the underlying noise of the probability distribution. Beam widths, while most likely a combined proxy for both noise belief and risk aversion, did not differ between groups.

Individuals in this study were selected from an online population. This may be a less reliable route to garner accurate symptom responses, particularly in regard to questionnaires about psychosis symptoms. This is thought to be because people feel less able to admit to experiencing symptoms that imply a detachment from reality, and/or the symptoms being measured such as increased paranoia, could decrease the chances of the individual feeling confident in expressing symptoms. Future research using populations with diagnosed symptoms would support

investigation into whether the effect is still found. Similarly, research into clinical groups could investigate whether the incorporation of superfluous information during learning under volatility leads to a decrease in performance as symptom severity increases. Relatedly, while the task included partial information about the underlying contingencies, in an effort to reduce cognitive burden thought to potentially underlie noisy decision making in psychosis, other unmeasured variables may also be affecting the findings. For example, socioeconomic status was found to significantly relate to findings in psychosis groups (Baker et al., 2019). While this study used education and employment status as a proxy for cognitive ability, this could be vastly improved via the inclusion of IQ testing, or other cognitive tasks to compare results to. Future research should include alternative cognitive measures for comparison.

Finally, it should again be emphasised that due to the novelty of the task design and the computational modelling approach (currently unpublished JGET), the computational modelling was preliminary and requires repetition and scrutiny. For example, as the priors used for each block differed, it hampered our ability to directly compare between blocks and meant that the analysis for each block was limited by fewer trials than it would be if we were able to include the whole task (trial n=216). While the gold standard for computational modelling approaches has been outlines in recent research (Wilson & Collins, 2019), the parameter recovery step was also not accounted for in this study, leaving further room for improvement. Further analysis could also be done regarding analysis into the individuals who did not fit the model for each block. Finally, the effect size for the noise belief finding was small, indicating the need for replication.

## *5.2 Conclusions*

Statistical manipulations of probability distributions were used to simulate environments of uncertainty, including noise and volatility, in a novel learning task. Trial wise participant estimates of both the noise and volatility were analysed using a novel computational modelling approach (HGF (JGET)) to extract independent estimates of learning. Our preliminary findings suggest that increased decision noise found in elevated psychosis in the wider literature, cannot be replicated once participants are provided with an intuition of underlying contingency changes (uncertainty), alongside non-binary inputs and responses. Initial findings instead showed that during learning under a volatile environment with low, stable noise, elevated schizotypy groups disproportionally utilised information about the noise in their decision making, despite its relative redundancy. The tentative results add to evidence regarding a deficit in volatility estimation, potentially suggesting that at a pre-morbid stage of illness a lack of confidence in information processing under volatility could lead to increased exploration, and the incorporation of irrelevant information into belief updates.

## 6 Acknowledgements

I would like to thank Dr Teresa Katthagen for her work on the computational modelling, editing, and conceptual discussions. I would also like to acknowledge that Maite Arrabas collected the original Qualtrics data (n=1000) and provided the top and bottom 10% of SPQ scorers for this study.

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# 8 Appendix

**Table 6-4** *Showing the instructions and information given in the Space task for each screen.*

| Screen Name | description | Text prompt – |
|---|---|---|
| **Introduction** | Intro screen 1 | `It is your first mission with the Intergalactic Space Defenders. However, a near miss has left you marooned on a planet that deals with all the waste and rubbish from the surrounding planets!' |
| | Intro screen 2 | "Old spacecraft of all shapes and sizes are flown into orbit above you, one at a time. As they disintegrate, useful parts fall off them. Your job is to catch the parts so you can build a rocket and escape." |
| | Intro screen 3 | "Each spacecraft will be too high for you to see. To successfully capture the falling parts you will have to estimate two things:<br><br>1. The location of the passing spacecraft. This will help you estimate where the parts will be falling from. ii) The size of the passing spacecraft. For example, if the parts are falling from a large space craft, they are likely to be more spread out.<br><br>You will be given information about the incoming spacecraft at the start of each level that will help you to figure out the sizes and locations of the spacecraft." |
| | Intro screen 4 | "You have an electromagnetic ray to capture the falling parts and bring them in, so you can build the rocket. IMPORTANT: You only have a small amount of fuel, so you must use the least amount of power possible to bring the parts in (the smallest ray possible)." |
| | Intro screen 5 | You will get a HIGHER SCORE for catching the falling parts with a SMALLER ray - but remember you will get zero points if you miss it! |
| | Intro screen 6 | After seeing  where the last spacecraft piece fell, turn the ray ON by pressing UP and then press the RIGHT and LEFT arrows to position the electromagnet. Use the UP and DOWN arrows to increase and decrease its power.<br><br>Give it a try now!' |
| | Intro screen 7 | On a computer you can use the LEFT and RIGHT keyboard keys. Press enter, space or click to continue.' |
| **Block 1** | Practice round screen 1 | PRACTICE ROUND: You have 5 seconds to complete each turn. You must pass all 3 turns in the practice round to continue.<br><br>Turn the electromagnetic ray ON (red to green) by pressing UP, and then press the RIGHT and LEFT arrows to position the electromagnet. Use the UP and |

| | | |
|---|---|---|
| | | DOWN arrows to increase and decrease its power.<br><br>PRACTICE ROUND INFORMATION:<br><br>Number of incoming spacecraft: 1<br><br>Size of incoming spacecraft: Small<br><br>Location of incoming spacecraft: ONE location likely |
| | Practice round screen 2 | Good job! A quick reminder:<br><br>The Spacecraft will pass overhead one at a time - but may be different sizes, and in different locations. Information at the start of each level will help you to figure this out. |
| | Practice round screen 3 | "'Catch the parts that fall off the passing spacecraft using the smallest ray you feel is possible. This will earn you the most points. Every time you earn 500 points you get a bonus payment!. Do you want to repeat the tutorial? " |
| **Block 2** | Stable learning environment | Level 1 INFORMATION:<br><br>Number of incoming spacecraft: 1<br><br>Size of incoming spacecraft: No information<br><br>Location of incoming spacecraft: One location likely |
| **Block 3** | Learning when the SD changes | Level 2 INFORMATION:<br><br>Number of incoming spacecraft: 2<br><br>Size of incoming spacecraft: One large, one small. No information on the order they will pass.<br><br>Location of spacecraft: One location likely |
| **Block 4** | Learning when the mean changes | Level 3 INFORMATION:<br><br>Number of incoming spacecraft: Multiple<br><br>Size of incoming spacecraft: All around the same size<br><br>Location of incoming spacecraft: Multiple locations likely |
| **Block 5** | Learning with combined SD and mean changes | Level 4 INFORMATION<br><br>Number of incoming spacecraft: A large amount<br><br>Size of incoming spacecraft: All different sizes<br><br>Location of incoming spacecraft: Multiple locations likely |

| | | |
|---|---|---|
| **Block 6** | Learning with combined SD and mean changes<br>Round includes loses. | Level 5 INFORMATION:<br><br>Number of incoming spacecraft: A large amount<br><br>Size of incoming spacecraft: All different sizes<br><br>Location of incoming spacecraft: Multiple locations likely<br><br>IMPORTANT: If the falling spacecraft parts are not caught in this round you will LOOSE points, and potentially LOOSE the money you have earnt. BUT if you do catch the falling parts you will earn DOUBLE POINTS! Catch the parts in the smallest ray possible and earn 20 points each time! |

**Table 6-5** *Showing priors set for the HGF modelling by block.*

| **Parameter** | | **Block 3** *M(VAR)* | **Block 4** *M(VAR)* | **Blocks 5 & 6** *M(VAR)* |
|---|---|---|---|---|
| **κ (in logspace)** | **u** | 1 (0) | 1 (0) | 1 (0) |
| | **x** | 0 (0) | 1 (1) | 1 (1) |
| | **a** | 1 (1) | 0 (0) | 1 (1) |
| **$\omega_2$** | **u** | 0 (0) | 0 (0) | 0 (0) |
| | **x** | 0 (16) | 3 (16) | 3 (16) |
| | **a** | 0 (16) | 0 (0) | 3 (0) |
| **$\omega_3$ or θ** | **x** | 0 (0) | -8 (16) | -8 (0) |
| | **a** | 0 (0) | 0 (0) | -12 (0) |
| $\mu_2^0$ | **x** | 1 (0) | 1 (0) | 1 (0) |
| | **a** | -1 (0) | 0 (0) | 0 (0) |
| **$\sigma_1^0$ (in logspace)** | **x** | 0.1 (0) | 0.1 (0) | 0.1 (0) |
| | **a** | 1 (0) | 0.1 (0) | 0.1 (0) |
| **$\sigma_2^0$ (in logspace)** | **x** | 0 (0) | 0.01 (0) | 0.01 (0) |
| | **a** | 1 (0) | 0.01 (0) | 0.01 (0) |
| **β (in log-space)** | **a** | | 1 (16) | |

| | | |
|---|---|---|
| **ζ (in log-space)** | **x** | 10 (16) |
| | **a** | 0.01 (16) |

*Abbreviations: M (variance), variance equalling 0 means these parameters were fixed; u=input; x=mean learning, a=variance learning*

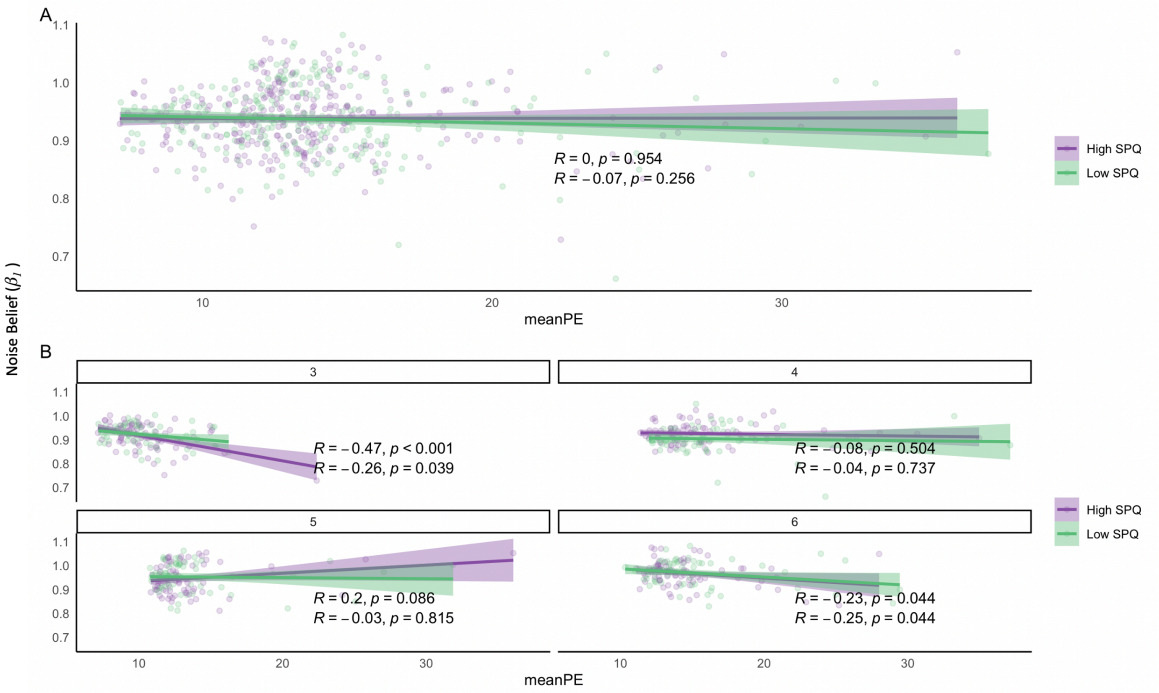


**Figure 6.9** *Showing the noise belief parameter associated with the mean PE over the whole task (A), and by block (3:6, B). Correlation Pearson statistic and r2 value is for each relationship is plotted on each figure. The top statistic refers the low SPQ group, and the bottom statistic refers to the High SPQ group for all plots.*

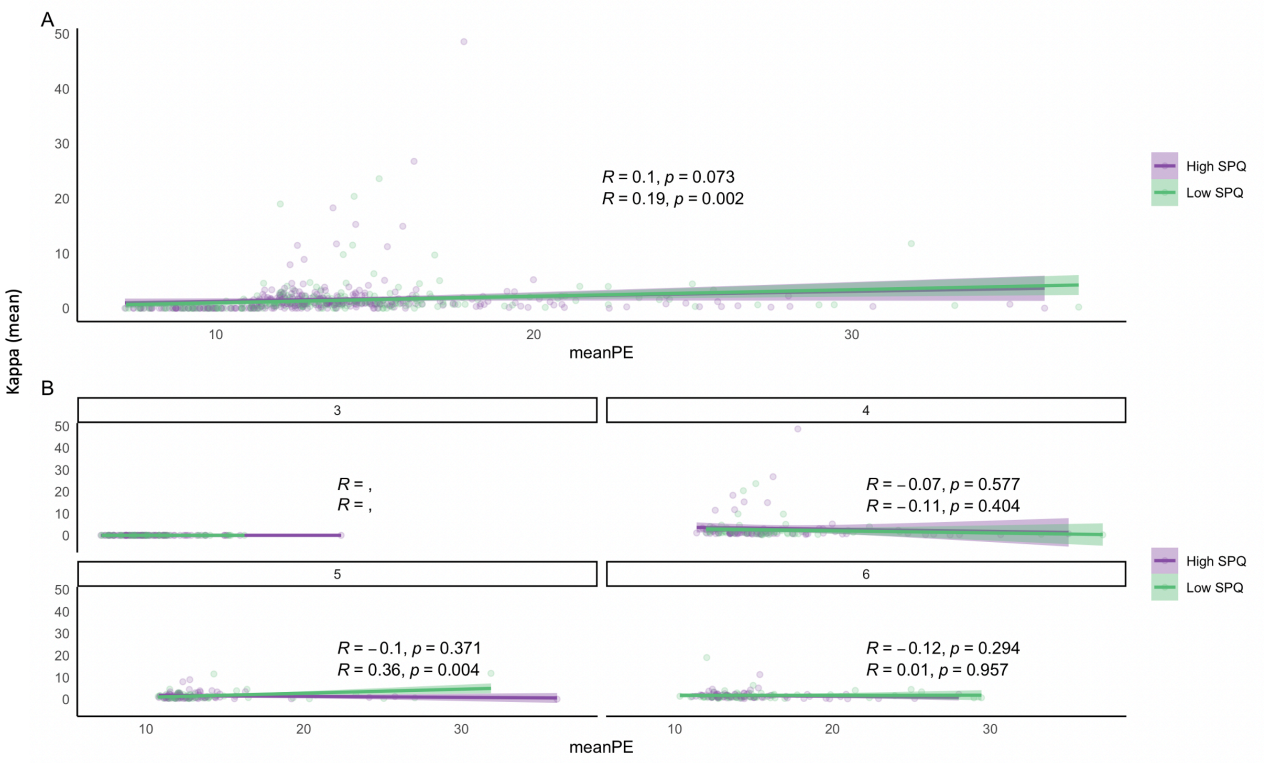


**Figure 6.10** *Showing the kappa for the mean (kax) parameter associated with the mean PE over the whole task (A), and by block (3:6, B). Correlation Pearson statistic and r2 value is for each relationship is plotted on each figure. The top statistic refers the low SPQ group, and the bottom statistic refers to the High SPQ group for all plots.*

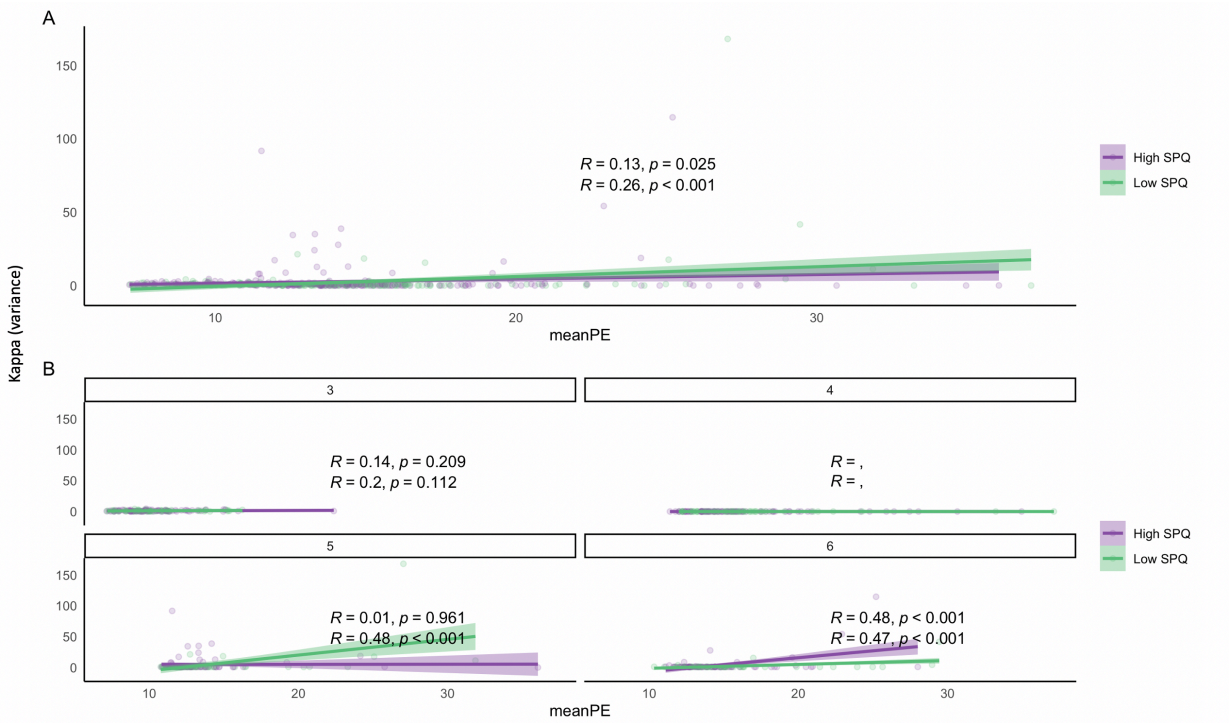


**Figure 6.11** *Showing the kappa for the variance (kaa) parameter associated with the mean PE over the whole task (A), and by block (3:6, B). Correlation Pearson statistic and r2 value is for each relationship is plotted on each figure. The top statistic refers the low SPQ group, and the bottom statistic refers to the High SPQ group for all plots.*

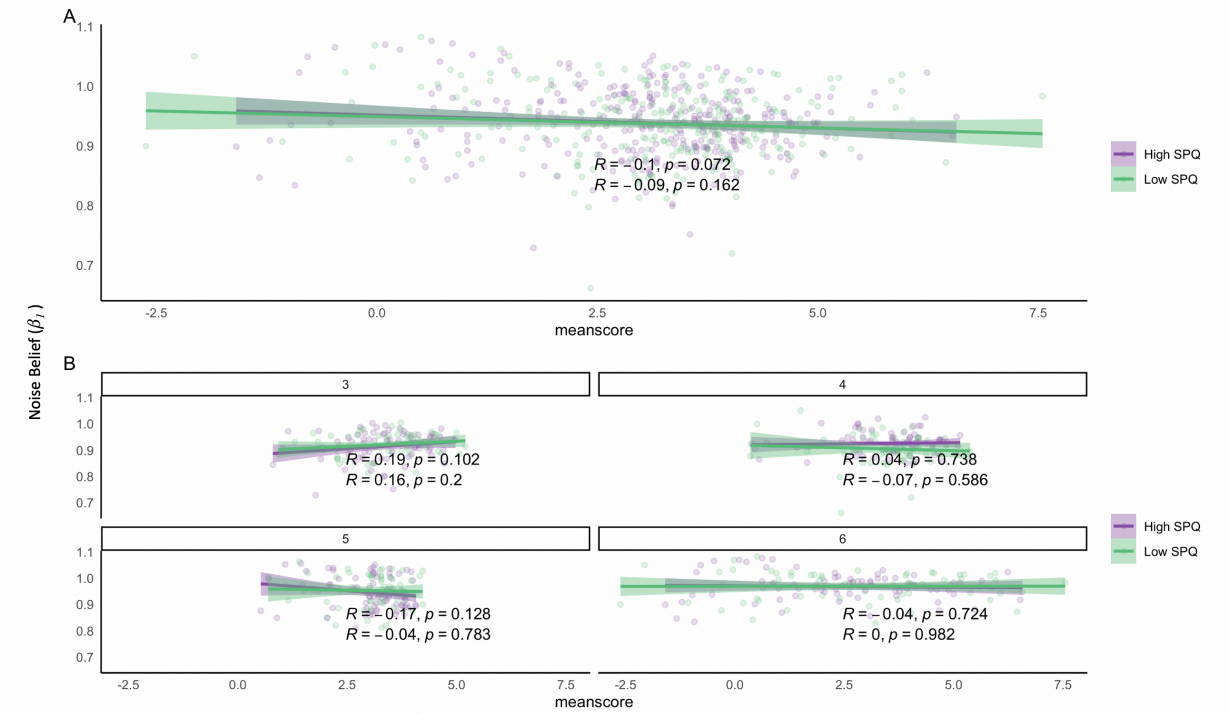


**Figure 6.12** *Showing the noise belief parameter associated with the mean score over the whole task (A), and by block (3:6, B). Correlation Pearson statistic and r2 value is for each relationship is plotted on each figure. The top statistic refers the low SPQ group, and the bottom statistic refers to the High SPQ group for all plots.*

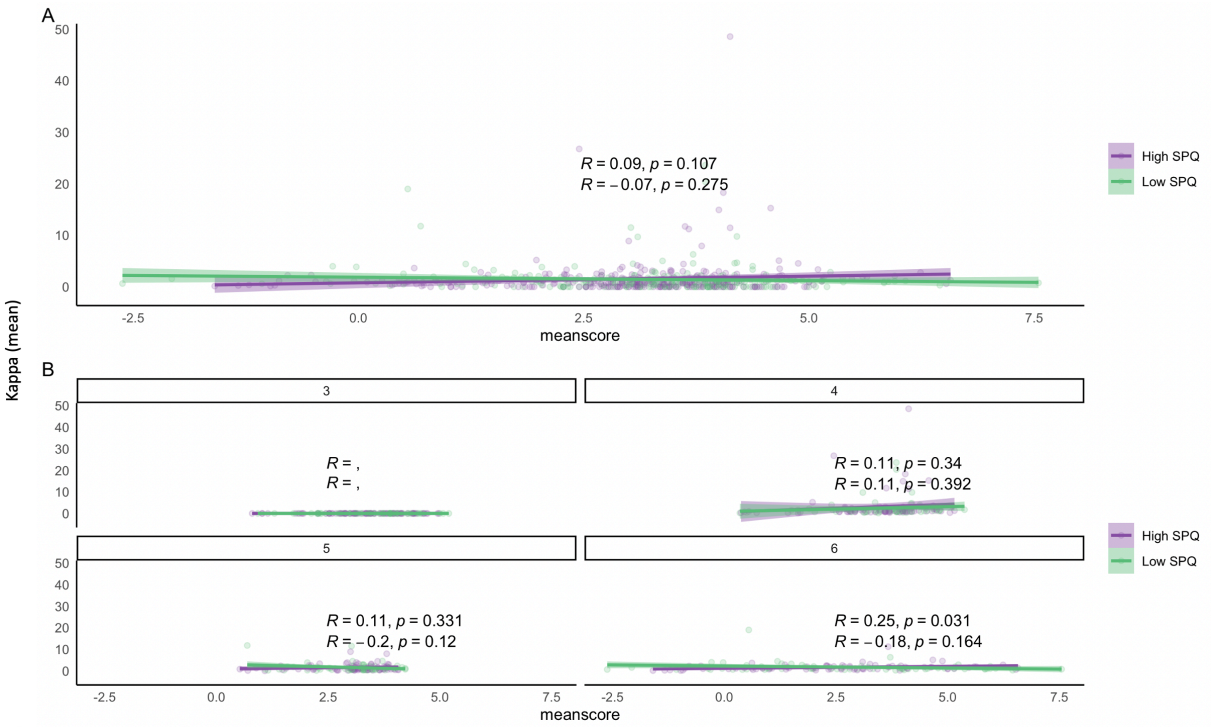


**Figure 6.13** *Showing kappa for the mean (kax) parameter associated with the mean score over the whole task (A), and by block (3:6, B). Correlation Pearson statistic and r2 value is for each relationship is plotted on each figure. The top statistic refers the low SPQ group, and the bottom statistic refers to the High SPQ group for all plots.*

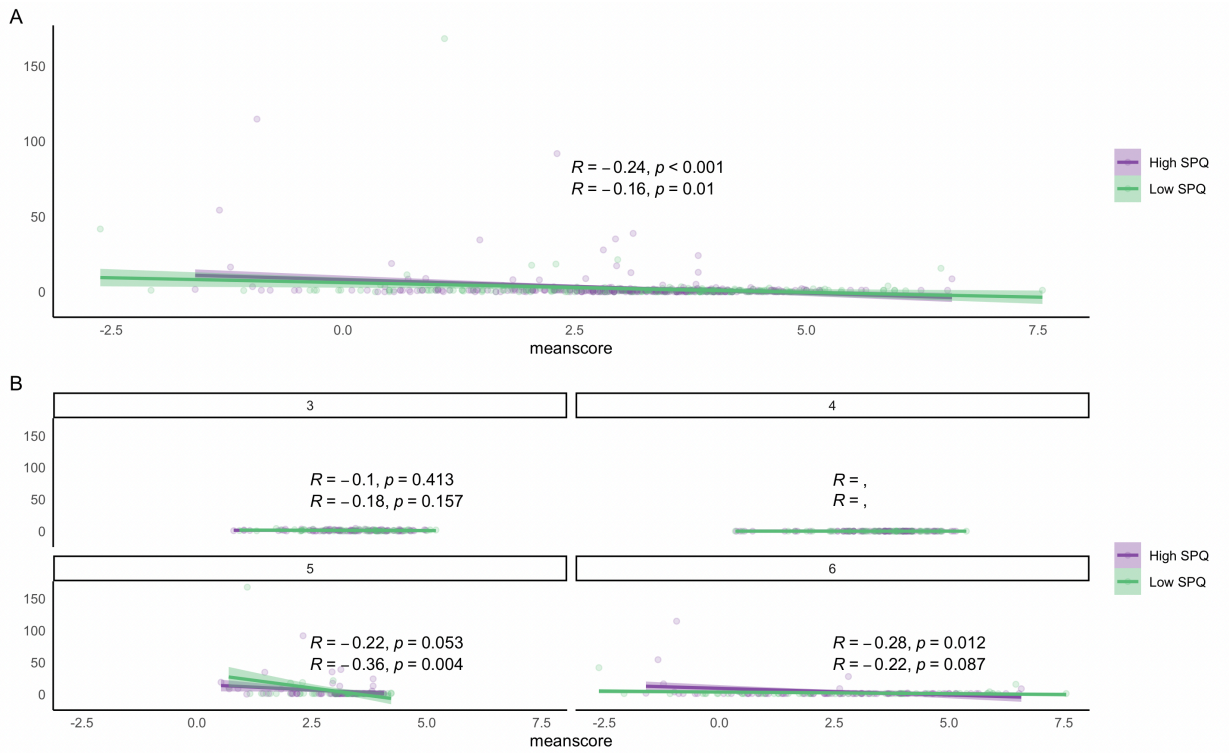


**Figure 6.14** *Showing the kappa for the variance (kaa) parameter associated with the mean score over the whole task (A), and by block (3:6, B). Correlation Pearson statistic and r2 value is for each relationship is plotted on each figure. The top statistic refers the low SPQ group, and the bottom statistic refers to the High SPQ group for all plots.*

# Chapter 7. General discussion, limitations, and future directions

## 1 A summary of the aims, and findings of the thesis

Learning involves adapting decisions in response to feedback, and as such, represents a fundamental survival skill. However, individuals experiencing poor mental health often show deficits in the cognitive processes involved in learning and decision making (LDM) (Lee, 2013). One aspect of LDM involves making inferences about information that is often partial and hidden. To make accurate inferences, the uncertainty ideally needs to be minimised. The precision, or certainty, is thought to dictate whether, and how much, our beliefs, and/or predictions, are updated as a result of the incoming information (input) (Pulcu & Browning, 2019). It is hypothesised that the ability to successfully process uncertainty i.e., to accurately recognise the type and amount, including the noisiness and the changeability (volatility) of information, may represent a key perturbed mechanism in LDM deficits across psychopathology. Computational modelling applied to LDM data from probabilistic (reversal) learning tasks (PRLT) are frequently used to parameterise individual estimates of uncertainty. This approach has revealed examples of individuals across the psychopathology spectrum mis-estimating

uncertainty in various ways (Adams et al., 2016; Huys et al., 2020; Katthagen et al., 2022; Pulcu & Browning, 2019; Sandhu et al., 2023; Soltani & Izquierdo, 2019).

While PRLT designs have been able to measure binary decisions in response to binary probabilistic inputs (e.g., 80:20 reward:no reward), some research has begun to capitalise on the benefits of sampling from continuous "ground truth" probability distributions (Nassar et al., 2010, 2012, 2021; Vaghi et al., 2017). This design not only provides a more ecologically valid learning environment i.e., a learning environment close to real life, but enables the manipulation and measurement of different types of uncertainty within the same experiment (Katthagen et al., 2022). This is important because it is the joint estimation of both the noise and the volatility that dictates the speed of learning i.e., the learning rate (Piray & Daw, 2021). Building on this premise, this thesis developed, validated, and implemented a novel task that manipulated different uncertainty environments (noise and volatility) using changes to underlying "ground truth" probability distributions. The task captured an individual's joint estimate of the noise (variance) and volatility (mean) of an underlying uncertain environment (probability distribution) in parallel, and on a trial wise basis. The overall aim of the thesis was to provide insight into whether the joint estimation of uncertainty is perturbed across individuals experiencing poor mental health. A secondary aim was to understand whether any differences shown by individuals with elevated psychopathological symptomology were unique to, or cut across, traditionally defined presentations of mental illness, potentially suggesting a more fundamental deficit, and ultimately, target for treatment.

***Chapter 2****: Systematic review.* The first step to achieving these aims was to carry out a systematic review of literature on the topic. This provided oversight into the field, and importantly formed the basis on which to design an experimental approach (Gibbs-Dean et al., 2023). The systematic

review was conducted into literature on belief updating in psychopathology (specifically depression, anxiety, and psychosis), using computational modelling approaches (patients/controls n=5371). To account for the heterogeneity in task design and modelling approaches found across the literature in this field (Katthagen et al., 2022; Pike & Robinson, 2022), studies included in the review were categorised according to several criteria, including task design (probabilistic, trial wise feedback), learning environment for testing (volatile or stable), and modelling approach (reinforcement learning, Bayesian learning models, of change point detection models). The review compared studies using extracted parameters from the computational models, such as learning rate, or temperature (beta).

The main findings of the review were that firstly, a deficit relating to the valence of feedback was predominantly found only in depression disorders (Cavanagh et al., 2019, Cooper et al., 2014). Specifically, in non-volatile learning environments, depression groups displayed both a difficulty in learning from positive feedback, as well as increased learning from negative feedback (Cavanagh et al., 2019, Cooper et al., 2014). However no studies using the same task or modelling approach found this effect in anxiety disorder (Cavanagh et al., 2019, Myers et al., 2013). While deficits in anxiety disorder did not appear to relate to the valence of feedback, symptoms did overlap with psychosis disorder in a difficulty in learning under volatility, both via overall learning rates and in the adaptation of learning rates to changes in volatility (Browning et al., 2015; Hein et al., 2021; Reed et al., 2020; Suthaharan et al., 2021). However, psychosis disorder was also associated with a tendency to overestimate their a priori belief about the volatility of the environment. Decision noise i.e., the temperature/beta parameters capturing an individuals' stochasticity in decision making, was also consistently higher in psychosis disorders, whereas no differences were noted between depression or anxiety groups when compared with healthy controls.

The review also highlighted how the measurement of learning under uncertainty would be improved via changes to commonly used experimental task design. Specifically, evidence suggested that use of continuous task inputs, drawn from "ground truth" probability distributions (Nassar et al., 2021; Vaghi et al., 2017), would support fine-tuned manipulation of uncertainty via the statistics underlying the probability distribution (mean, standard deviation). While limited research showed examples of this methodological approach in the measurement of volatility (Nassar et al., 2012, 2021) or noise, separately (Haarsma et al., 2020; Vaghi et al., 2017), a gap in the literature was apparent for a task design that was capable of measuring the joint estimation of both noise and volatility in a singular experiment (Piray & Daw, 2021). Inclusion of continuous responses was also highlighted as a means by which to enable direct access to important metrics of learning, such as prediction error (the difference between the participants estimate and the actual outcome), and learning rate (the speed of updating), without the need for complex modelling (Gibbs-Dean et al., 2023; Katthagen et al., 2022).

***Chapter 3****: Methods*. In response to findings from the systematic review, a novel learning task was developed that: i) sampled from continuous "ground truth" probability distributions, ii) tested different types of uncertainty in isolation and in combined conditions via manipulation of probability distributions, including volatility (changes to the mean) and noise (changes to the standard deviation), iii) captured the agents estimate of both the noise and volatility of the environment in a parallel and trial wise manner, and iv) increased ecological validity via a gamified format (Soltani & Izquierdo, 2019). To validate the novel learning task, large scale testing was required. As such, the research made use of recent advances in online experimental testing, using specifically designed platforms (Soltani & Izquierdo, 2019; Wise et al., 2023a). This enabled the research to capture large-scale population data that was robust to analysis and

replication. Two versions of the novel task were tested in two large-scale online general populations (n=555; n=167). Both versions were assessed on several criteria including: feasibility for online testing (via exclusions rates), measurements of construct validity, and ability to replicate previous findings (Berniker et al., 2010).

While version one of the task resulted in a large number of participant exclusions, and a question over the construct validity of the derived prediction errors, version two was successfully able to overcome these issues. Version 2 of the novel learning task included changes to the trial structure, as well as alterations to the task design to improve engagement. These changes reduced exclusion rates, and led to the hypothesised participant behaviours i.e., the integration of information across trials, as opposed to the over-use of novel information. This subsequently led to improved construct validity of prediction errors (PEs). Both versions of the task were able to replicate findings from the original task successfully (Berniker et al., 2010).

***Chapter 4****: Learning under uncertainty in Eating Disorder:* Post validation phase, the task was implemented in a clinical population of individuals diagnosed with an eating disorder (n=116) and compared to a healthy control group (n=67). It was hypothesised that a clinically defined eating disorder group would show inflexible updating in response to changes in volatility, in line with previous research showing inflexible learning strategies in binary learning tasks (Lopez et al., 2008; Roberts et al., 2007; Tchanturia et al., 2011). As the research was focussed on the adaptation of learning rates between blocks of uncertainty, this hypothesis was measured using the learning rate difference between blocks that simulated different types of uncertainty e.g., learning rates under volatility – learning rates under noise. Overall learning rates within blocks was also assessed, as well as performance metrics such as score, and catch success rate.

A small but significant effect provided evidence toward the stated hypothesis of decreased flexibility in adapting learning to increases in volatility. Here, ED groups showed less learning rate adaptation when the environment changed from high noise and low volatility, to high volatility and low noise. As a poorer performance for ED groups was also seen in high noise conditions, it was hypothesised that increased inflexibility in response to volatility may relate to a difficulty in learning about noise itself. However, future research is needed to investigate the potential of a downstream effect between poorer processing of noisy information, and the decrease in flexibility between noisy and volatile learning conditions.

***Chapter 5***: *Uncertainty estimation deficits across psychopathology.* Use of general population data collected online is argued to enable data to be gathered at a large enough scale for robust exploration and replication (Wise et al., 2023). Use of an online platform in this experiment enabled accessibility to a wide audience with natural variance in symptomology (n=580), thus allowing the exploration of psychiatric symptoms in less confounded populations i.e., without medication and chronic illness. In turn this approach provided insight into precipitating subclinical deficits to more serious of chronic illness (Gillan et al., 2016; Patzelt et al., n.d.; Rouault et al., 2018; Seow et al., 2020a; Soltani & Izquierdo, 2019; Wise et al., 2023b). Symptoms that were measured included depression, anxiety, and psychosis related symptoms such as paranoia, schizotypy, and delusionary ideation. This chapter was concerned with identification of any overlap between elevated symptoms and specific learning deficits. Overlap in cognitive deficit was hypothesised between elevated symptoms of anxiety and depression (Gagne et al., 2020; Pike & Robinson, 2022). It was hypothesised that overlap would be seen in conditions where punishments were introduced via i) decreased performances, ii) decreased overall learning rates, (Pike & Robinson, 2022). It was also hypothesised that elevated anxiety and depression would be associated with limited flexibility in adapting learning rates to increases

in volatility (Gagne et al., 2020). Individuals high in psychosis symptomology were hypothesised to show a broader deficit across both the adaptation of learning rates to changes in volatility, and in overall performance differences between conditions.

The results showed that while elevated psychosis and anxiety symptoms showed inflexible adaptation of learning rates to increases in volatility, elevated depression showed no adaptation difficulties. Overall learning rates followed a non-normative pattern for elevated psychosis, i.e., were increased during high noise and low volatility, and decreased during high volatility and low noise, potentially implying a more pervasive learning deficit in these groups. In contrast, elevated depression symptoms were associated with an overall performance benefit, that was increased further when the valence of the feedback changed to also include punishments. This was in contrast to elevated anxiety symptoms showed no relationship with changes to the feedback. Findings from the chapter overall highlight the importance of accounting for co-morbidity in experimental designs, given that cognitive deficits may describe aspects of multiple disorder types. Use of, for example, factor analysis, to reduce the dimensionality of symptom data, would provide a way to account for any shared variance in the symptom data. Computational modelling, using an approach that accounts for multiple types of uncertainty such as the hierarchical gaussian filter (HGF), would also provide a more in-depth assessment of learning profiles.

***Chapter 6***. *Belief updating in schizotypy.* Computational modelling, specifically the HGF, was applied to the following experiment, to access a more mechanistic level of learning deficit in association with symptoms. Here, selected individuals from the general population were used, specifically those that had scored at either a high (n=116) or low (n=67) level of a schizotypy measure. In response to PRLTs, individuals with psychosis have been repeatedly been shown to display increased decision noise, alongside increased a priori beliefs about environmental

volatility, as well as an increased trial wise volatility estimates (Katthagen et al., 2020, Moutoussis et al., 2011; Croft et al., 2022; Culbreth et al., 2016a; Kaplan et al., 2016; Murray et al., 2008; Schlagenhauf et al., 2014; Waltz et al., 2013). By studying a group shown to be predictive of ongoing psychosis (Fusar-Poli et al., 2017; Kwapil et al., 2013; Poulton et al., 2000). However, it is unclear how the processing of noise interacts with volatility estimation, and how noise is used in decision making. Given these findings, it was hypothesised that high schizotypy traits would be associated with high estimates of environmental volatility overall, and poorer performances.

Interestingly, results in fact showed no performance differences, or differences in estimates associated with beliefs about the volatility, between high and low schizotypy groups. Instead, a free parameter within the decision model of the HGF designed to capture how much individuals used their belief about the noise of the environment to inform their decision, was found to be significantly higher in high SPQ groups in block four (high volatility and low noise). Findings suggest that while learning mechanisms remained intact, individuals with increased schizotypy traits continued to incorporate their noise belief in decision making, once the noise in the environment had reduced (block three – block four). To our knowledge, this is the first study probing the computational mechanisms underlying the parallel, hierarchical learning about volatility, as well as noise, in relation to subclinical psychotic experiences. While these findings need to be replicated, it may be that a lack of confidence in a model of world when learning under volatility could lead these individuals to implement a type of safety strategy. In this case, the safety-type response included overloading themselves with superfluous information about the noise of the environment, when this was not relevant. In turn this could lead to ongoing issues in belief updating, as the environment becomes more complex, and/or symptom severity increases.

# 2 Interpretation and integration of results in relation to specific hypotheses

## *2.1 Anxiety and depression: a difference in uncertainty-based learning deficit*

Previous work investigating learning deficits in anxiety and depression disorders has indicated that both groups experience a particular difficulty in processing the valence of feedback. For example, both groups have been shown to display increased learning rates in response to punishments over reward (Pike & Robinson, 2022). Research has also shown that an internalising dimension of psychopathology (calculated by reducing dimensionality of scores from depression and anxiety symptom scales using factor analysis) is related to difficulties in adapting to changes in uncertainty, namely, volatility (Gagne et al., 2020). It was hypothesised that, in accordance with high levels of comorbidity found across anxiety and depression (Kessler et al., 2005), these symptom groups would also share similarities in cognitive deficits relating to learning, and specifically learning under uncertainty (Browning et al., 2015; Gagne et al., 2020; Pike & Robinson, 2022). As such, this thesis took several steps to assess the overlap between these groups via the systematic review of the literature in the field, and via experimental testing of individuals identified to be elevated in depression and anxiety symptomology using the novel learning task.

Findings from this thesis suggest there is in fact limited evidence for the assumption of overlap between anxiety and depression symptomology in this regard. For example, the systematic review showed that a deficit relating to the valence of feedback was predominantly found only in depression disorders (Cavanagh et al., 2019; Cooper et al., 2014; Gibbs-Dean et al., 2023). Experimental research using the novel task in an unselected general population study, showed evidence consistent with findings from the systematic review. For example, while elevated

depression symptoms were associated with a performance benefit across the entire task i.e., overall score, this was further increased when the feedback changed from reward only, to reward and punishment. This is in contrast to elevated anxiety symptomology, where no such relationship was identified.

Importantly, these findings contradict research that has been able to explain high rates of comorbidity between anxiety and depression symptoms via shared cognitive deficits (Pike & Robinson, 2022). For example, one systematic and meta-analytic review found that common to both groups was elevated punishment learning rates (Pike & Robinson, 2022). While the general population study was able to show a performance difference to the introduction of punishments, and overall higher learning rates, the study did not find increased learning rates to block six specifically. differences in findings here may relate to the fact that computational modelling was not applied to data from the novel task. Instead, a proxy for an averaged learning rate was used, which may have obscured effects. Additionally, Pike et al., (2022) used a simulation meta-analytic approach to infer meta-group differences from methodological heterogenous computational studies into anxiety and depression related learning deficits. The systematic review included in this thesis instead used a stringent approach to the categorisation of research to deal with complexities in experimental design and modelling, which may explain the difference in findings between the reviews. What was common to both reviews, however, was that the currently available research assessing learning under uncertainty in mental illness is difficult to assess and directly compare, due to heterogeneity in experimental design. Both reviews agreed that use of more homogeneous methodological approaches, and adherence to a gold standard of modelling (Wilson & Collins, 2019) would improve the ability to make concrete comparisons and advance the field.

There is also recent evidence that shows a degree of overlap between elevated depression and anxiety symptomology in terms of an inflexibility in learning rate adaption to volatility. Gagne et al., (2020), showed that an internalising symptom dimension (clustered anxiety and depression subclinical symptom scores) was related to lower learning rate differences between stable and volatile learning environments. These findings imply that once the covariance between symptom groups is accounted for, what is shared between anxiety and depression symptoms is in fact related to a level of inflexibility in updating when volatility is increased. As our study did not attempt to reduce the dimensionality of symptom data, we are unable to confirm this effect. Future research should consider using techniques to reduce the dimensionality of symptom data, such as confirmatory factor analysis, to provide further insight into ways in which comorbidly occurring mental health symptoms may overlap in relation to cognitive deficits (Gagne et al., 2020; Wise et al., 2023a).

While a lack of findings providing evidence for an overlap in cognitive deficit between anxiety and depression groups was somewhat surprising, the thesis' findings for elevated depression symptomology were broadly in line with computational modelling and behavioural findings from the wider literature. Here, research implicates depression related symptomology with differences in learning in response to valenced feedback specifically (Cavanagh et al., 2019; Cooper et al., 2014; Kumar et al., 2018; PLT-V: Dombrovski et al., 2019; Takano et al., 2019; kumar 2018; dombrovski 2019). Anhedonia, a difficulty experiencing pleasure and motivation, is often linked to aberrant reward processing in depression and may provide a pathway from cognitive deficit to symptom presentation (Eshel and Roiser, 2010, Pizzagalli et al., 2005, Pizzagalli et al., 2008). Specifically, it is argued that aberrant reward processing leads to failure in assessing, updating and/or maintaining the value of rewards, something which has been shown experimentally via research that links anhedonia to a reduction in effective valuation of rewarding outcomes (Huys

et al., 2013; Lawlor et al., 2020; Webb et al., 2015). Bayesian modelling studies add to evidence that depression may be inherently tied to a reward related learning deficit. Research here suggests that depression may be characterised by prior beliefs that are biased towards hypotheses that make loss of punishments more likely (Stankevicius et al., 2014), and/or an impaired ability to update an initial belief when presented with disconfirming evidence (Rupprechter et al., 2018). Overall, wider literature and research from this thesis appears to coalesce around the idea that depression is linked to a cognitive learning deficit specifically relating to the valence of feedback during learning. Similarly, findings for elevated anxiety, namely an inflexible learning style in response to increased volatility was also in line with the wider literature. For example, research in anxiety disorder shows evidence of an insensitivity and/or difficulty adapting to changing underlying contingencies specifically (Beltzer et al., 2019, Browning et al., 2015, Hernaus et al., 2018, Huang et al., 2017, Li et al., 2014). In these examples, this insensitivity led to suboptimal decision-making strategies when learning under volatility (Browning et al., 2015, Hernaus et al., 2018, Huang et al., 2017).

Overall, despite high rates of comorbidity between anxiety and depression symptoms, findings from this research appear to show that they are in fact distinct in terms of deficits associated with learning under uncertainty. Specifically, findings suggest that elevated depression symptomology may be associated with processing of the valence of feedback, whereas elevated anxiety appears to be associated with a deficit in adapting to volatility.

### *2.2 Inflexible and maladaptive learning in response to uncertainty: overlap across symptoms*

The vast majority of research in this field narrowly focuses on learning under volatility, operationalised by frequent or infrequent reversals (Behrens et al., 2007; Mathys et al., 2011; Piray & Daw, 2020, 2021). In accordance with a normative model of learning, higher learning rates are seen in high volatility environments. This was also found in data across this thesis (Chapter 3, 4, 5 and 6). Noise, or stochasticity, is usually not manipulated, and indeed often not manipulable between rewards that are usually binary (and the variance of binomial outcomes is determined only by the mean). Some research has begun to think about this. For example, Nassar et al. (2010, 2012, 2021), used an odd ball task design to simulate volatility, within different levels of (additive) noise). Here, and in accordance with a normative model of learning, learning rates decreased with increased noise. Again, data from this thesis also confirmed this effect, showing the on average learning rates were lower than high volatility conditions and/or stable conditions (Chapter 3, 4, 5 and 6). Given the interdependency of inferences about volatility and noise shown, experiments that have manipulated one type of uncertainty (usually volatility) in isolation and analysed the data with a model that attributes all dynamic learning rate effects to one of them, presents a general interpretational issue. For example, models that neglect the noise (stochasticity) of the environment could be misidentifying noise for volatility, and inappropriately modulating learning. This task sought to overcome these issues by testing learning in conditions of noise and volatility. Analysis tested i) learning rate difference between conditions and ii) learning rate adaptation between blocks. Experimental evidence from this thesis suggests that learning rate adaptation to volatility was significantly reduced in elevated trait anxiety and psychosis groups (Browning et al., 2015) (Chapter 5: General population study). A small effect was also found in the same regard for eating disorders, in a separate experiment (Chapter 4; Learning under uncertainty is eating disorders). Overall learning rates were shown to follow a non-normative learning pattern in psychosis (Chapter 5: General population study).

One theory underlining these findings suggests that deficits in estimating the noise could in fact be what underlies commonly reported misestimations of volatility (Piray & Daw, 2021). There are argued to be self-fulfilling consequences once for example, one type of uncertainty is neglected in some way e.g., misinterpreted, the other is overestimated (Piray & Daw, 2021). Here, its argued that a misestimation of noise leads to near ceiling misestimation of volatility, which damped further adaptation of learning rates to increases in volatility (Piray & Daw, 2021). As such, it may be the case that poor adaptation to volatility across these disorders and elevated symptoms, could be related to an initially poor estimation of the noise. Evidence of aberrant learning under noise was evidenced for ED groups via a poor performance, however no effects were found for learning rate. On the other hand, elevated schizotypy (unselected population) (Chapter 5: General population study) did display differences in their learning rates during noise and volatility – specifically via non-normative learning rates (high learning rates in noise, and lower learning rate in volatility). These findings show tentative evidence that for psychosis related disorders, a misestimation of the noise in the environment (block 3), could be leading to the misestimation of volatility/ceiling effects in high volatility (block 4), evidence by i) lower learning rates, and ii) less flexibility in adapting to increases in volatility.

Interestingly, while elevated trait anxiety and psychosis symptoms shared a clear inflexibility in ability to adapt learning rates to increases in volatility, overall learning rates were not affected in elevated trait anxiety. This may suggest that a more pervasive learning deficit in psychosis-related symptomology. This conclusion is also in line with findings from the systematic review included in this thesis. Here, higher order modelling in psychosis and anxiety groups showed a degree of separation in relation to aberrant uncertainty processing. For example, studies using the HGF have shown that while both groups showed aberrant beliefs about volatility itself psychosis

groups additionally show inappropriately high initial estimates of the environmental volatility (Cole et al., 2020; Hein et al., 2021; Reed et al., 2020; Suthaharan et al., 2021).

Importantly, learning rate and performance-based effects in psychosis related symptomology were not found in the final data chapter of the thesis (Chapter 6: Belief updating in schizotypy). Here, while the learning rates overall acted according to a normative account of learning, there were no group by block interactions for individuals identified to be high in schizotypy, compared to those identified to be low in these traits. While this was a smaller study, it was conducted with a population with supposedly more defined symptomology. As such, if the effect was related to psychosis specifically, it was more likely to have been found here. Further evidence is required to understand whether the effects seen in the general population study are in fact related to psychosis or were perhaps associated with a symptom dimension unaccounted for by the analysis. For example, while correlations between symptom scores were relatively low, there may have been important overlap between for example, psychosis and anxiety symptomology. Given that the study did not account for variance within the symptom data, this was not captured. This may explain why, when looking solely at schizotypy in chapter (Chapter 6: Belief updating in schizotypy), we don't see the effect.

While no learning rate differences were found between high and low schizotypy traits, this study had the benefit of higher order modelling. Specifically, a HGF model was applied to the data that had been specifically designed to capture learning about the mean and variance of the distribution independently. As such, we had a task that manipulated noise and volatility, metrics that captured noise and volatility, that were fed into a computational modelling approach that independently captured learning about noise and volatility. By comparing learning under conditions of isolated noise and volatility, something which has yet to be tested in the wider literature, we were able to

see that individuals high in schizotypy symptomology did something unusual. Here, High SPQ groups did not adjust their belief about the noise when transitioning from a learning environment that was noisy, to one that was volatile (and low in noise). While we would expect participants to decrease the noise belief during this transition, instead, high SPQ groups took on additional, essentially useless information (about the noise), in their decision making. While these findings need to be repeated, these findings do not appear to add to evidence of a compensatory trade-off. In this case, while the way in which noise was used in decision making differed and resulted in using their beliefs about the noise incongruously to the environment, it did not in turn lead to differences in volatility estimation. As the complexity of the environment and/or severity of symptoms increases, this effect may however, become more apparently. Further testing is required, but this study highlights the importance of capturing multiple dimensions of learning for efficient tracking of uncertainty estimation.

## 3 Methodological implications and considerations

Cognitive tasks can provide researchers with fundamentally important insights into cognition and psychiatric phenomena, in a non-invasive and relatively simple way (Zorowitz & Niv, 2023). When properly designed, cognitive tasks should be capable and sensitive enough to isolate and measure specific cognitive processes that may play a vital role in symptomology in psychopathology. Several factors affect the efficacy with which cognitive tasks in general can achieve their goals, including the reliability and validity of the task. The reliability of a task is particularly important to consider, as it represents a prerequisite to validity (Zorowitz & Niv, 2023). This is because an unreliable task measure will reflect measurement error, and therefore will not represent the construct of interest. Importantly, many studies have found that when the reliability of a cognitive task is actually measured and reported, task measures exhibit moderate

to low reliability (Frey et al., 2017; Hedge et al., 2018; Nitsch et al., 2022; Verdejo-Garcia et al., 2021; Zeynep Enkavi et al., 2019; Zorowitz & Niv, 2023). Reliability of a task primarily depends on performance variability across participants (Zorowitz & Niv, 2023).

In the case of the novel task used in this research, the task was tested in several large general population studies. The diversity of sampling used should increase the between participant variance, meaning the reliability was reasonably well assessed i.e., is unlikely to be specific to one group (Zorowitz & Niv, 2023). However, while online experimental paradigms enable wide scale testing and access to a broad spectrum of individuals, it has limited capacity for control of extraneous variables that may cause distraction or lack of attention. In turn, this may increase measurement error leading to a concomitant decrease in reliability. In an effort to at least partially overcome this, the task was gamified. Gamification of task designs is argued to diminish measurement error, due to the increase in participant engagement and motivation (Sailer et al., 2017; T et al., 2022; Verdejo-Garcia et al., 2021; Zorowitz & Niv, 2023). This in turn is suggested to overcome the boredom and fatigue that can reduce reliability of a task. One advantage of using this approach was that we were able to further decrease measurement error (and therefore increase reliability) by using a large number of trials per participants (n=219). For all cognitive tasks it is important to find a balance between engagement and task length. If increasing task length results in a lack of engagement, then reliability will of course be impacted negatively. Finally, a clear understanding of the task instructions is vital for task reliability (McLean et al., 2018; Zorowitz & Niv, 2023). While we found that version one of the task did not include clear enough instructions, the revised directives were reportedly much better understood. Use of practice trials further supported participants to reach a stead state of responding, that was not influenced by factors such as a lack of understanding or performance anxiety. In turn, this reduced

the noisiness of responses across task trials and increased reliability (McLean et al., 2018; Zorowitz & Niv, 2023).

# 4 Limitations and future directions

## *4.1 The online experimental paradigm and cognitive tasks*

This research capitalised on a novel experimental paradigm: using online testing of large populations to assess the strength of relationship between derived cognitive measures of learning, such as prediction error, learning rate (differences), and extracted parameters from computational modelling. The downsides to this method have been discussed previously in relation to the data quality i.e., a lack of control over participants' environments during testing. Other factors to consider in general include issues such as the increasing presence of bots on certain testing services that can further threaten validity (Burnette et al., 2022). To date, this experimental paradigm has primarily been used in cross-sectional experiments, which lack the ability to demonstrate convergent validity of measures and/or insight into correlation/causation relationships (Wise et al., 2023a). Given that online research enables access to large populations that enable robust exploration of data, future research should consider ways of overcoming and mitigating these negatives for example, via methods such as renewing focus of research toward alignment with incentives in online studies i.e., what actually incentivises individuals to partake and engage fully in testing (Wise & Dolan, 2020); to involve participants in the design of the experiment itself (Crocker et al., 2018); and to implement more attention-based checks (Donegan & Gillan, 2022).

The online experimental paradigm is only as strong as the cognitive tasks used for testing. This makes the testing of reliability and validity of cognitive tasks a vital step in the experimental process. Importantly, the reliability of a task is not absolute, but is impacted by, for example, the participants, and the context in which the task is administered. As such task reliability can vary as a function of age of the participant (e.g., adult/child), response modality (pc, tablet, phone), and importantly, testing location e.g., online or in a laboratory (Arnon, 2020; Cooper et al., 2017; Green et al., 2016; Paap & Oliver, 2016; Pronk et al., 2022; Rouder & Haaf, 2019; Zorowitz & Niv, 2023). One limitation of this research is that it did not provide evidence of the task performance in a laboratory setting, or in relation to other cognitive tasks. Additionally, while the research did illustrate the reliability and validity of the novel task to a degree, this could be further improved by use of metrics such as the intraclass correlations (ICC). While this is a limitation of this research, it is important to communicate the generality of this message to the field as a whole. It is currently common practice to change aspects of cognitive tasks before testing, to suit the question being posed. In most cases, the reliability of these amended tasks is not reported, but may have changed substantially (Hedge et al., 2018; Owens et al., 2021). This impacts the generalisability across findings and limits the ability to draw conclusions and signpost next steps for the field.

Finally, it is important to note that the online experimental paradigm, particularly using unselected populations (Wise et al., 2023), can only inform the field so far. A vital for the next step for research is an increased focus on treatment orientated work in relation to learning deficits. For example, parameters describing aspects of learning under uncertainty could be used to assess within subject capability to predict treatment response, relapse, or symptom development. (Moutoussis et al., 2018; Nair et al., 2020; Scholl & Klein-Flügge, 2018). Specific examples of this computational approach to treatment show promising results. Hauke et al.,

(2022) showed that parameters extracted from computational modelling applied to cognitive tasks in individuals diagnosed with schizophrenia were predictive of treatment response. These findings are particularly pertinent given recent research adding to evidence that model parameters such as learning rate are stable across time (Karvelis et al., 2023). Online methods may still be useful here in overcoming a primary issue of small sample size, that often goes hand in hand with patient experimental testing and treatment. Examples includes instances where academia and the digital health industry have collaborated to assess treatment response to cognitive behavioural therapy in relation to parameters describing aspects of cognition such as learning (Dercon et al., 2023; Lee, 2013). Other examples include the use of cognitive testing using smart phone applications (apps) and technological wearables, that when combined with a gamified format, would result in a useful way to gather measurements at repeated time points, and in parallel with biometric data.

### *4.2 Symptom measurement*

This research was interested not only in the measurement of cognitive learning deficits in mental illness, but whether it was possible for these deficits to explain high rates of comorbidity across traditional symptom categories. To achieve this, the research used a cognitive learning task across a large scale unselected general population, that had natural variation in symptomology. The severity of the symptoms found in this population were then analysed in relation to performance outcomes, and learning metrics. One limitation to this approach is that individual members of the population with elevated symptomology on one symptom scale may, and in fact are quite likely, to exhibit other elevated symptomology from a different scale. Correlation analysis was computed prior to analysis, showing no relationship over .60, which while indicating a relationship, is an acceptable level for analysis (Akoglu, 2018). However, this

shared symptom variance remains problematic for the interpretation of findings. Reducing the dimensionality of symptom data would be one way to overcome this issue. For example, factor analysis, or other latent modelling approaches. By clustering the symptom groups, symptom dimensions can be formed that represent more realistic groups of symptoms found in the population. These symptom dimensions can then be related to learning parameters, and performance metrics (Wise). This specific approach is commonly used in subclinical or unselected general populations, and has recently been outlined in a paper by Wise et al., (2023). The paper demonstrates its use across a number of cognitive domains including information seeking (Kelly & Sharot, 2021), foraging (Fan et al., 2022), mental effort avoidance (Patzelt et al., 2019; Scholl et al., 2022), choice stochasticity (Suzuki et al., 2019), error-related negativity (Seow et al., 2020b), and the interrelation of symptom dimensions (Petitet et al., 2021.). While reducing symptoms from unselected groups may be a useful tool for future analysis, it is important to note that this is based on a (reasonably well established) assumption that i) symptoms follow a liner progression from subclinical to clinical; and ii) that the data provided for e.g., factor analysis, is representative of the wider population. This latter point is important because latent modelling can only explain the structure of the data it has been given, and thus greatly depend on the characteristics of the sample being studied (Wise et al., 2023a). As such, the robustness and reliability of emergent, latent factors found using these techniques needs to be established. As would any association between identified dimensions and cognitive measures (Hoven et al., 2023; Patzelt et al., 2019; Wise et al., 2023a).

### *4.3 Behavioural analysis and computational modelling*

One important advantage to computational modelling is that it allows trial wise analysis, i.e., the extraction of valuable information from trial level variability. This is particularly

important when measuring learning. One methodological consideration of this research is that where computational modelling was not applied, data was averaged across blocks to account for the multivariate and trial wise nature of learning data. Importantly, information may have been lost via the averaging of performance measures, and learning rates. Future research could look towards building on directly accessible measures of learning (like those found in the novel task) and develop a way in which trial wise estimates could be directly compared. Linear mixed models that account for the variance attributed to each individual may be a route forward here (Browning et al., 2023).

Notably, metrics within learning tasks remain a relatively distant proxy of actual underlying cognitive processes. Generative computational modelling has been hailed as one route by which researchers can navigate this issue, and garner a closer look at mechanisms reflecting cognitive processes of interest. This is because generative modelling explicitly specifies the underlying cognitive process, as such extracted parameters expected to be much closer to the theoretical constructs of interest. In turn it is thought that this should increase ability to capture individual differences in these cognitive differences. However, it is important to note that recent computational research has been shown to report poor to moderate reliabilities of parameter estimates (Karvelis et al., 2023), that in some cases were in fact less reliable than conventional summary statistics (Pike et al., 2022, Shahar et al., 2019, Smith et al., 2021, Loosen et al., 2022, Waltmann et al., 2022, Hitchcock et al., 2022), and in others showed a moderate, but not substantial, improvement (Price et al., 2019, Mkrtchian et al., 2023, in Psychiatry Network Research Consortium, N., 2018, Chung et al., 2017, Weigard et al., 2021).

The reliability of an experiment can be greatly compromised if parameter estimation is compromised. One of the clearest factors affecting the reliability is the approach used for model

fitting (Waltmann et al., 2022). While recent guidelines have been published outlining the gold standard for computational modelling (Wilson & Collins, 2019), a limitation of the computational modelling computed in this research is that several of the steps were not followed, including parameter recovery. In the same way that mixed models account for uncertainty at different levels, hierarchical model fitting with empirical Bayes i.e., where individual level parameter estimates are informed by group statistics and vice versa, offer a route by which research can access improved parameter estimates (Huys et al., 2011, 2012; Katahira, 2016; Wiecki et al., 2013). Additionally, the optimisation of task design via changes to e.g., trial number, outcome probabilities etc., in the improvement of reliability and subsequently validity, can be systematically improved via model simulations and parameter recovery. For example, in the latter instance, the strength of relationship between the true and recovered model parameters indicates how reliable parameters would be if the assumed model was indeed a good approximation of the true cognitive process. In this way, low parameter recoverability is likely to relate to low reliability.

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# Chapter 8. Conclusions

In conclusion, successful inference about uncertain outcomes during learning depends on the ability to accurately estimate characteristics of the environment such as its' statistical uncertainty i.e., its likelihood of change (volatility), and how noisy (or stochastic) it is. The primary aim of this work was to shed light on whether a cognitive deficit in estimating uncertainty during learning and decision-making (LDM) could represent an underlying biobehavioral mechanism commonly perturbed across multiple symptoms of mental illness. To achieve this, a combination of approaches were taken. These included a systematic review, and clinical and general population experiments, using a novel online task. Given that the vast majority of research in the field has focussed on how the brain tracks volatility of the environment specifically, a novel task was developed and validated that was able to provide information about how volatility *and* noise were jointly learnt about. Analysis of the task data included a computational modelling approach using an extended version of the Hierarchical Gaussian Filter, that was able to independently capture learning about the variance (i.e., noise) and mean (i.e., volatility).

By comparing learning rates between noisy/stochastic and volatile environments, this thesis showed that as predicted, the majority of individuals conformed to a normative account of learning i.e., displayed on average higher learning rates under volatility compared to noise and/or stable environments. Similarly, the majority of individuals adapted their learning appropriately

to changes in uncertainty, showing appropriate learning rate adaptation to increases in volatility. However, elevated anxiety and psychosis related symptoms, as well as eating disorder patients, displayed significantly lower learning rate increases in response to volatility. One theory is that individuals could be mistaking the type of uncertainty in the environment (e.g., high noise for volatility) (Piray & Daw, 2021). However, from these data, this did not appear to be the case for elevated trait anxiety or eating disorder patients. Here, overall learning rates did not differ between these blocks, suggesting that while they showed a degree of inflexibility in their adaptation to increases in volatility, this did not affect (or was not currently significant enough to affect) their ability to recognise the types of uncertainty being tested.

For elevated psychosis related symptoms, on the other hand, the inability to flexibly adapt learning rates to volatility occurred in tandem with a non-normative presentation of learning rates in isolated volatility and noise conditions. In this case, elevated psychosis-related symptomology was associated with learning rates and performance errors that decreased during volatility compared to noise conditions. This may be an indication of a "trade-off" effect that would be expected if, for example, the agent had indeed mistaken noisy (stochastic) inputs, for a meaningful changes. As such, one would expect higher learning rates under noise (as it is perceived as volatility), leading to subsequent ceiling effects in response to volatility. This would also affect how much adaptation would need to occur in response to increases in volatility. Future research implementing a similar methodological approach is required to probe these findings further. As such, while findings indicated that some degree of overlap may exist between symptoms, psychosis-related symptomology may be uniquely associated with a more pervasive learning deficit in relation to uncertainty estimation. This experimental finding was broadly mirrored in the systematic review of the literature, where anxiety and psychosis disorders were shown to overlap regarding a deficit associated with the estimation of volatility specifically, but

a more pervasive deficit in psychosis disorder was seen via increases in decision noise, and an over-estimation of a priori volatility estimates.

These findings were not directly replicated in a population selected to be high and low in schizotypy personality traits (SPQ). However, a novel computational modelling approach did identify a difference between these groups. Here results suggested that during the transition between high noise and volatility (low noise) conditions, elevated schizotypy groups continued to disproportionately incorporate information about noise into their decision making. In contrast, the low schizotypy group decreased their use of the belief about the noise in line with a decrease in the noise. As such, while elevated schizotypy groups did not seem to believe that the environment was *more* noisy i.e., learning was intact, they still continued to incongruously use knowledge about the noise in their decision making, when it was no longer useful. This overloading of superfluous information may be related to symptoms found in more severe presentations of psychosis, such as feeling of strangeness, as well as apophenia, hypermentalisation, and jumping to conclusions, via a reduced ability to stabilize an internal model of the world (Broome et al., 2007; Fyfe et al., 2008; Whitson & Galinsky, 2008).

Interestingly, individuals who showed elevated depression related symptoms showed an overall performance benefit (including increased learning rates) in the novel task, that was further increased by the presence of punishments. This valence dependent finding was not found for any other symptom category, including anxiety. The lack of overlap between anxiety and depression symptoms and disorders was surprising given the extent of comorbidity usually found between them (Kessler et al., 2005). However, the dissociation between anxiety and depression was also found in the systematic review. Here, findings showed that when the literature is organised to account for high levels of methodological heterogeneity, depression disorder uniquely related to

increased learning in response to negative feedback, whereas anxiety disorders were related to difficulties in learning about volatility specifically (Gibbs-Dean et al., 2023; Chapter 2).

In summary, through systematic review, experiments, and computational modelling, this research found both overlapping and distinct uncertainty estimation deficits across different mental disorders and symptom presentations. Consistency was observed between the systematic review and experimental findings, revealing specific deficits associated with valenced feedback in depression, and volatility-related deficits in anxiety and psychosis. These findings suggest tentative evidence that the adaptation of learning to increases in volatility could represent a shared mechanism across symptoms, and highlights the need for further research. However, while these findings do not concretely establish whether or not specific uncertainty estimation deficits can define multiple symptoms in mental illness, the findings from the thesis do strongly highlight the need to account in their experimental design for multiple aspects of uncertainty during learning. Learning rates are jointly determined by the comparison between volatility and noise, or moment to moment stochasticity. The novel task used in this thesis, alongside the analysis, was able to provide evidence to this point, and highlights the need for future work to incorporate such an approach. By considering the problem of joint estimation, the mutual interdependence of inferences about volatility and noise can be established and enrich findings. Other limitations should be addressed in future research, including assessing and reporting task reliability and validity, adhering to gold standard measures when conducting computational modelling, and exploring treatment-oriented approaches for understanding learning deficits and treatment response in mental illness. Ultimately, the most important purpose of research in this area is to cultivate more effective treatments. Developing a deeper understanding of cognitive processing in mental illness, such as uncertainty estimation, is a vital route towards this goal.

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