



INVESTIGATING THE INFLUENCE OF MOOD BIAS ON REWARD PERCEPTION AND HOW THIS RELATES TO MOOD INSTABILITY

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DECLARATION

I, Ilinca Ureche-Angelescu confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

ABSTRACT

Mood influences our life satisfaction and affects our daily functioning, determining how we perceive risks and rewards and guiding our decisions. While neuroscience has demonstrated how outcomes affect mood, it has not fully explored the bidirectional relationship between mood and outcomes. This thesis aims to address that gap by understanding 1) if mood biases how valuable outcomes seem 2) if this bias differs across contexts and 3) how this can lead to mood instability and bipolar spectrum disorders.

The thesis begins by reviewing the literature on mood research in cognitive neuroscience. It then describes the development of an innovative smartphone app, "The Happiness Project", highlighting how it can be used to democratise research access and collect large datasets. In a large general population study (over 4000 participants) using the app, results show mood can bias the perceived value of rewards, even in non-monetary contexts. This effect is more pronounced in individuals with greater trait mood instability. The thesis then examines the influence of mood bias in social contexts using a novel task where participants received rewards in the form of feedback from others. Results show negative mood can bias people's expectations of reward, but it does not seem to impact the value of social rewards. Finally, the thesis focuses on an app-based clinical study comparing mood bias between individuals with bipolar disorder and controls. The results show a clear mood bias on reward valuation in the bipolar group, absent in the control group. Additionally, the magnitude of mood bias increases with the severity of manic symptoms, suggesting its relevance in maintaining bipolar spectrum disorder symptoms. The thesis concludes by discussing the various contexts in which mood influences reward valuation, offering insights into the spectrum of mood instability, ranging from the general population to bipolar disorder.

IMPACT STATEMENT

The commencement of my PhD journey in February 2020 coincided with the outbreak of the COVID-19 pandemic, which has undeniably highlighted the importance of mental well-being.

During the first two years of this PhD, I worked on developing *The Happiness Project* smartphone app together with my laboratory team. The app contains gamified psychological experiments, mood surveys and questionnaires, as well as many fun features for participants to enjoy (e.g. world ranking scoreboard, rewards, and customisable characters). By harnessing the power of smartphone-based tools, we have gained access to a much larger and more diverse participant group than possible with laboratory-based research studies. The app brought the research laboratory to everyone's pocket. It democratised access to cognitive neuroscience research by making it easily accessible for anyone, anywhere in the world.

Through the development of the gamified app, we have successfully bridged the gap between scientific research and the wider community, involving a much larger and more diverse group of participants. It fostered mutual learning: we were able to collect behavioural data that furthered our understanding of mood and its influence on learning and behaviour, while our participants learned about the science of mood. This cutting-edge methodology has facilitated dense data collection, allowing for a more comprehensive examination of mood, learning and decision-making. It also provides the scaffold for future longitudinal studies that can examine causal relationships between mood biases and mood disorders.

The integration of computational modelling approaches and smartphone-based tools in this thesis has yielded promising results. It showed that mood biases reward valuation in individuals with symptoms of mood instability as well as those diagnosed with bipolar disorder and this bias correlated with manic symptom severity. These findings have the potential to serve as cognitive markers for mood instability, aiding in

the clinical diagnosis of bipolar spectrum disorders. Additionally, they offer valuable insights for developing targeted therapeutic interventions, including talk therapies and drug studies, thereby paving the way for more effective and tailored treatment approaches.

Moving forward, the continued exploration of mood biases, utilising computational modelling and smartphone-based tools holds immense promise. By leveraging the power of technology, we can deepen our understanding of the intricate mechanisms underlying mood regulation, develop innovative interventions that can be delivered directly to participants via their phones, and ultimately enhance mental well-being on a broader scale.

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CHAPTER 1. General Introduction

We've all had those days. You wake up you feel like today just isn't your day. You turn on your phone to see an email from the journal where you submitted a paper last month. The paper was rejected with no explanations. Not surprisingly, it puts you in a bad mood. You leave the house and get to the office only to discover that the coffee machine is broken. You will need to go to the new coffee place down the street to get your morning flat white. "URGH! Yet another thing not going well today" you think as you stand in the queue to order. You get your coffee and go back to the office. It's an average flat white, a bit too hot. You think it's terrible and you won't have coffee from there again.

Let's think of the opposite example. You wake up rested after a good night's sleep. You turn on your phone to see an email from the journal where you submitted a paper last month. The paper was accepted without revisions. Suddenly, you are in such a good mood. You leave the house and get to the office only to discover that the coffee machine is broken. You will need to go to the new coffee place down the street to get your morning flat white. "Finally! A chance to try out this place!" you think as you stand in the queue to order. You get your coffee and go back to your office. It's an average flat white, a bit too hot. You sip it slowly to enjoy the roasted coffee aromas. You will likely return there for your afternoon coffee.

What does being in a good or bad mood really mean? And how can mood change your perception of the world, when in reality things remain the same? How can your mood affect the decision you make today and as well as future decisions?

1 Definition of affect, mood, emotion and feeling

The terms affect, mood, emotion and feeling are often used interchangeably in research and clinical practice (Alpert & Rosen, 1990; Beedie et al., 2005). This is also true for colloquial language, for example the same positive event can elicit the following reactions “I am very happy about it” – emotion; “This made me feel amazing” – feeling; “It’s put me in a great mood” – mood. However, while this oversimplification may work for our day-to-day lives, it does not translate well to scientific research. The terms affect, mood, emotion and feeling are conceptually distinct. They each operate over different time scales, ranging from seconds to months. The distinction is essential for conceptual clarity in research, as well as for the development therapeutic interventions.

Affect is an umbrella term, both mood and emotion being considered affective states (Frijda, 1994). Affect covers a broad range of feelings and is often used to describe valence, in terms of positive affect or negative affect.

Operating on the shortest time scale, *emotion* is the immediate response to a specific event, action, or object (Handayani et al., 2015). Emotions carry information about the environment and are reflected in facial expressions. They describe bodily sensations and environmental contexts (Barrett, 2016). Emotions have a causal event, are intense, automatic responses, short in duration, and have behavioural implications (Scherer, 2005). Examples of basic emotions include anger, sadness, happiness, fear, disgust, surprise, contempt and neutral (Mignault & Chaudhuri, 2003).

The term *feeling* relates more to the conscious subjective experience of emotion. The word feeling is used to describe physical sensations though experience or perception. One way to distinguish between feelings and emotions is that emotions relate to internal or external states and the bodily changes that accompany them, while feelings relate to the perception of bodily changes. Feelings are conscious subjective experiences resulting from a physical or emotional experience (Damasio, 1999;

Damasio, 1994). Emotions and feelings are responses to discrete events. Their role is to guide action selection, by providing salient summaries of bodily sensations and environmental contexts (Barrett, 2016).

Operating on a longer time scale than emotion, *mood*, integrates the effects of events over time (Kensinger & Ford, 2020). It is often described as a longer lasting affective state with a time course of hours, days or even weeks. Mood acts like a running average of previous experiences and outcomes (Walsh et al., 2013). It has a non-intentional property, as it does not relate to specific discrete events (Beedie et al., 2005) and is not necessarily causally linked to the environment (Hartig et al., 1999). Moods consist of more global, undirected, and mostly unconscious background sensations that are more stable than emotions (Lochner, 2016). Mood states can be conceptualised as hedonic summaries of recent life events as well as indexes of one's progress or prospects in life (Robinson, 2000). Mood is frequently described as a latent state, an unobservable variable that causes changes in behaviour and emotion.

This thesis will explore the role of mood in learning and decision-making, across social and non-social domains, in individuals with and without mood disorders.

2 Why is mood important?

Throughout human evolution, mood served as an adaptive mechanism, guiding our behaviours and our responses to environmental stimuli (Kringelbach & Berridge, 2017; Nesse, 1990). Positive mood states, such as happiness, joy, or contentment, have been linked to increased resilience, resourcefulness, and social bonding, all of which provided advantages in our ancestral environments (Fredrickson, 2004; Hill & Dunbar, 2003). Positive emotions likely served as adaptive mechanisms that facilitated cooperation, group cohesion, and successful navigation of social environments in our ancestral past. The ability to experience positive moods provided an evolutionary advantage, enabling individuals to build social networks, form alliances, and maintain

cooperative relationships (Hill & Dunbar, 2003). When in a positive mood, individuals tend to exhibit greater curiosity and motivation to explore new environments, increasing the likelihood of discovering new and valuable resources (Raghunathan & Trope, 2002; Tamir et al., 2007).

Conversely, negative mood states, such as fear, sadness, or anxiety, served as signals that alerted individuals to potential threats and dangers in the environment (LeDoux, 2012; Nesse, 1990). These negative emotions triggered physiological responses that mobilized individuals to respond to threats, either by avoiding them or taking necessary actions for survival (e.g. fight or flight response). In this sense, negative mood states have adaptive functions by promoting self-preservation and ensuring the continuity of our species. Negative moods can serve as cues to avoid risky or energetically costly behaviours (Kahneman & Tversky, 1979; Weiss et al., 2015). They promote cautious decision-making and attention to potential threats, guiding individuals away from unproductive or hazardous resource options (Isen, 2000; Mellers et al., 1997). In situations where resources are scarce or competition is high, negative mood states may increase vigilance and focus (Nettle, 2006; Weiss et al., 2015).

The same mechanisms that once promoted survival and reproductive success can also contribute to the development of mood disorders when dysregulated (Clark & Watson, 1988; Etkin et al., 2010; Hasler et al., 2004; Kendler et al., 2004). Mood disorders arise from the interplay between genetic predispositions and environmental factors that disrupt the delicate balance of mood regulation mechanisms (Caspi et al., 2003; Monroe & Harkness, 2005). While the evolutionary foundations of mood provide insights into the origins of these disorders, it is important to also consider the complex interplay between evolutionary adaptations and contemporary stressors (Keller et al., 2007; Nesse, 2015). Modern challenges, such as social isolation, chronic stress, and disrupted circadian rhythms, can significantly impact homeostasis of mood, exacerbating vulnerability to mood disorders (Slavich, 2016; Walker et al., 2020).

Understanding the role of mood in human functioning is crucial for promoting mental health and well-being. By recognizing the influence of mood on cognitive processes, emotions, social interactions, and overall well-being, interventions can be designed to enhance positive mood states, mitigate negative mood states, and ultimately improve

individuals' functioning and quality of life. Furthermore, by understanding the adaptive functions of mood and the specific dysregulations that contribute to mood disorders, researchers and clinicians can develop tailored interventions to restore the delicate balance of mood regulation systems and enhance overall well-being (Clark & Beck, 2010; Cuijpers et al., 2010).

3 The spectrum of mood (disorders)

From the 1980s, until the publication of the Diagnostic and Statistical Manual of Mental Disorders, fifth edition [DSM-5; (APA, 2013)], psychiatric disorders were classified and thought of as falling into one or more distinct categories. However, this categorical approach failed to account for the considerable heterogeneity and overlapping symptomatology observed in clinical practice. The shift toward a dimensional perspective in the DSM-5 acknowledged the growing evidence supporting a continuum model, wherein psychiatric disorders are viewed as existing on a spectrum rather than rigidly defined categories. This recognizes that individuals may exhibit varying degrees of symptoms and impairment, blurring the boundaries between different disorders. Research findings from genetics, neurobiology, and psychopathology have increasingly supported the notion of shared underlying mechanisms and transdiagnostic features among psychiatric conditions (Caspi et al., 2003; Clark & Beck, 2010; Hasler et al., 2004; Keller et al., 2007). Embracing this continuum perspective holds promise for advancing our understanding of the complex nature of psychiatric disorders and facilitating more personalized and targeted approaches to diagnosis and treatment.

The duration of emotional states is important for distinguishing between normal mood fluctuations and prolonged, clinically meaningful experiences. Understanding these durations helps to identify thresholds separating typical mood variations from more persistent mood disorders. For example, it allows for the distinction between transient mood swings and enduring states of distress characteristic of severe mood disorders. Evaluating the duration of emotional states holds critical importance in clinical evaluations, and serves one of the key criteria listed in the DSM-5.

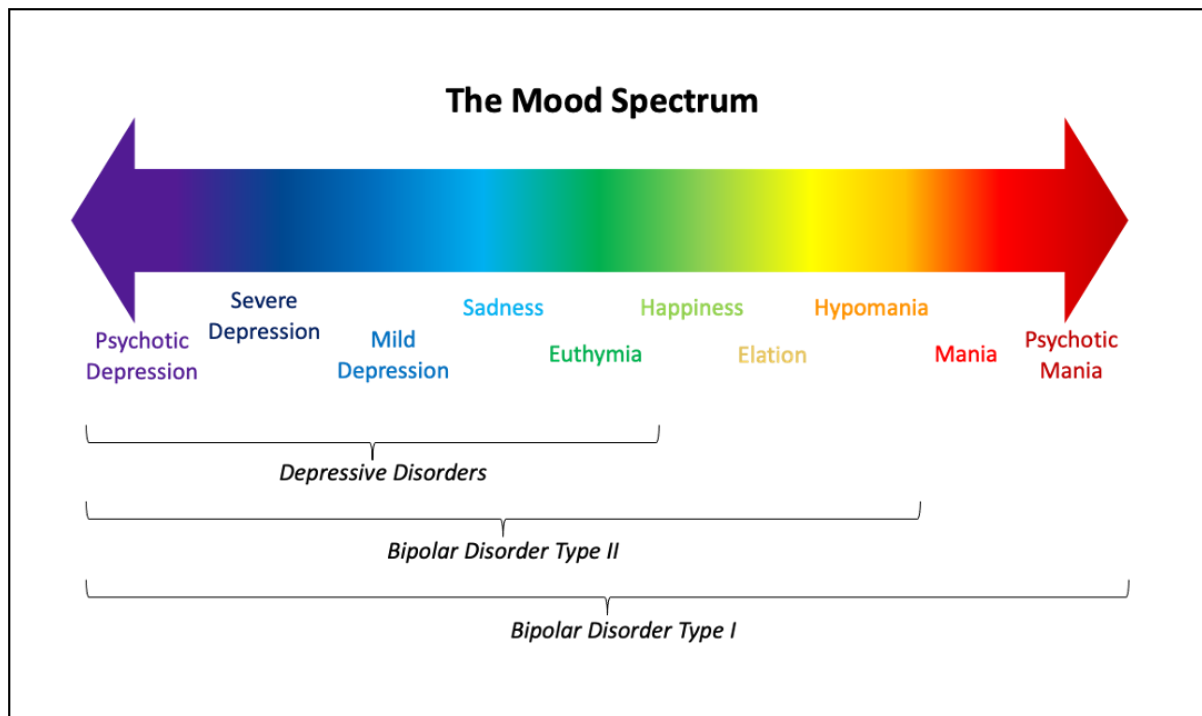


Figure 1. A visual representation of the human mood spectrum including mood disorders.

Towards the centre of the spectrum, are non-clinical mood variations that are part of normal human experience. These fluctuations involve temporary shifts in emotional states, such as feeling joyful, content, or momentarily sad. Non-clinical mood encompasses the ebb and flow of emotions that individuals encounter in response to daily life events, interactions, and personal circumstances.

Mood disorders, depicted in the extreme ends of the spectrum (Figure 1), are pervasive and enduring emotional states that profoundly affect behaviour across multiple domains. Mood disorders are characterized by significant disruptions in emotional functioning and range from severe depressive episodes to states of mania with psychosis. However, in the case of bipolar disorder, symptoms of mania and depression can co-occur, manifesting as overarousal, agitation, irritability and/or anxiety. This complicates the linear dimensional perspective and indicates that an orthogonal or multi-dimensional approach might be more appropriate for understanding the mood spectrum.

4 How does mood affect behaviour?

The relationship between mood and behaviour is reciprocal and bidirectional. Mood is a consequence of cognitive appraisals of one's subjective experiences (Kuppens et al., 2010; Larsen, 2000; Russell, 2003; Smith & Ellsworth, 1985). It is a running average of recent experiences in the individual's life. Or in other words, how one perceives life events will alter their mood. On the other hand, mood itself can alter cognitive processes and influence the appraisal of future experiences (Neville et al., 2020; Tamir & Robinson, 2007). Mood is, therefore, a consequence of a person's recent actions as well as a predictor of their future actions (Bonsall et al., 2015; Broome et al., 2015; Koval et al., 2013).

Mood can bias people to think or act irrationally. For example, happy people think positive events are more likely and negative events are less likely to happen to them, while sad individuals believe the opposite is true (Wright & Bower, 1992). People gamble more on a sunny day or after the unexpected victory of their favourite sports team (Bassi et al., 2013; Edmans et al., 2007; Otto et al., 2016), although there is no objective reason to believe the weather improves gambling odds. These findings have been extended to show mood enhancement favours risk-taking (Arkes et al., 1988; Isen & Patrick, 1983; Schulreich et al., 2014). Manic patients tend to ignore the potential negative consequences of their actions which can lead to risky decision-making, while depressed patients tend to neglect positive consequences (APA, 2013; Beck, 2008; Huys et al., 2015) maintaining the depressive cycle. Thus, examining the relationship between mood and behaviour is crucial for better understanding our own actions and biases, as well as the psychopathology of mood disorders.

5 How is mood studied experimentally?

Understanding mood and its impact on psychological processes has been a key focus of research in psychology and neuroscience. However, mood is a multifaceted

construct that encompasses different experiential dimensions, including momentary mood states, event-related mood fluctuations, and long-term mood patterns. Studying mood involves employing various measurement approaches, including questionnaires, surveys, and direct inquiries, as well as manipulating mood through mood inductions.

5.1 Measuring Mood

To capture the complexities of mood, researchers employ different measures that assess both momentary and long-term mood experiences. Momentary mood states, which reflect transient emotional states experienced in specific situations or contexts, can be assessed using tools such as mood scales or visual analogue scales that require participants to rate their current mood intensity or valence (Rutledge et al., 2014; Stone & Shiffman, 2002; Watson et al., 1988). These will include questions like “How happy are you right now, in this moment?”.

Longer-term mood patterns, on the other hand, are often assessed using self-report measures such as questionnaires or surveys that inquire about overall mood experiences over a specific time period, such as weeks or months (Watson et al., 1988). Examples of commonly used measures include the Positive and Negative Affect Schedule [PANAS; (Watson et al., 1988)] or the Hospital Anxiety and Depression Scale [HADS; (Bjelland et al., 2002)]. These measures provide valuable insights into individuals' subjective experiences of mood over the past predefined period (usually one or two weeks) and allow for the examination of mood fluctuations and stability over time.

Measuring trait mood involves assessing individuals' enduring and stable patterns of mood experiences over time (Teilegen, 2019). These measures capture long-term mood tendencies or baseline mood state, which tend to be stable over time. They provide valuable insights into individuals' characteristic emotional states and overall mood profile. Commonly used measures for assessing trait mood include self-report questionnaires such as the State and Trait Anxiety Scale [STAI; (Spielberger, 1983)] which assesses individual differences in trait anxiety, or the Hypomanic Personality

Scale [HPS; (Eckblad & Chapman, 1986)] which assesses the presence of hypomanic traits characterized by elevated and changeable moods, racing thoughts and irritability.

5.1.1 Experience Sampling Methods (ESM)

While the questionnaires described above provide measures of mood and psychopathology that are universally agreed-upon by researchers, these measures can only be used with certain periodicity (days or weeks), and thus cannot measure the dynamic changes in mood that occur over shorter timescales. Furthermore, they rely on retrospective self-reports which can be limited or altered by recall bias (De Vries et al., 2021). To this end, experience sampling methods (or ecological momentary assessment) can be used to capture the time series of an individual's mood in real time. It is similar to trying to understand a person's mood by taking a photograph of them each day compared to taking multiple photographs every hour.

Originally, these assessments required the use of a set timer that 'beeped' at variable intervals throughout the day, reminding participants to fill in a daily booklet (Shiffman et al., 2008). With technological advancements and increased access to smartphones connected to the internet, these methods have now been refined into user-friendly apps, increasing the popularity of EMS as a tool of clinical interest. Participants in research studies now have the convenience of using smartphone apps on their personal devices to regularly report their current affective state and activities. Through repeated sampling prompted by push notifications, a time series of evolving affective states can be generated, allowing exploration of their relationship with day-to-day activities. Although this thesis does not directly analyse ESM measures, the use of these methods in combination with experimental tasks motivated the development of *The Happiness Project* app (more in Chapter 2).

5.2 Manipulating Mood

In addition to measuring mood, researchers employ mood manipulation techniques to induce certain mood states in controlled experimental settings. Mood inductions involve exposing participants to specific stimuli or activities designed to elicit desired

mood states (Gross & Levenson, 1995). These techniques aim to evoke specific mood states, such as happiness, sadness, or anxiety, allowing researchers to examine the effects of manipulated mood on various psychological processes.

Commonly used mood induction methods include audio-visual stimuli like short movie clips, guided imagery, recall of personal experiences, jokes, pictures of facial expressions, surprise wins or losses on lotteries, or cognitive manipulations (Joseph et al., 2020). For instance, film clips or music can effectively evoke emotional responses and induce transient mood states (Gerrards-Hesse et al., 1994; Zajonc, 1980). Guided imagery and recall of autobiographical events, on the other hand, have been found to be effective in inducing more sustained and complex mood states (Westermann et al., 1996).

The efficacy of mood induction techniques depends on various factors, including the individual's gender and age, their susceptibility to mood induction, the specific technique used, and the desired mood state (Joseph et al., 2020). Some individuals are also more responsive to certain induction techniques than others. For example, women have been shown to be more sensitive to negative mood inductions than men (Joseph et al., 2020).

5.3 Experimental Paradigms

Once mood is manipulated and/or measured, researchers can investigate its influence on a wide range of psychological processes. Experimental paradigms are designed to examine how mood impacts cognition, emotion regulation, decision-making, social interactions, and other relevant domains. For example, studies have examined the effects of induced positive mood on creativity (Kok & Fredrickson, 2013), the influence of negative mood on attentional biases (Mathews & MacLeod, 2005), and the role of mood in risk-taking behaviour (Lerner & Keltner, 2001). These paradigms provide valuable insights into the mechanisms through which mood influences psychological functioning and contribute to our understanding of the complex interplay between mood and other cognitive and affective processes.

6 The computational modelling approach

The relationship between mood and behaviour is complex and poses large conceptual and data-analytic challenges (Huys et al., 2021). The field of computational psychiatry is well suited for overcoming these challenges, given that it uses powerful computational tools applied to multiple types of data and conceptual frameworks (models) to improve understanding of these dynamical processes (Hauser et al., 2022). Modelling analyses can be used to explore moment-to-moment dynamics, rather than relying on classic statistics such as means or standard deviations. This is particularly important when researching processes such as learning and decision-making where the goal is to explain dynamic changes in affective and behavioural states during the experiment. These dynamic interactions would be impossible to capture with cruder measures like average performance which only provide a snapshot of the participant's performance. Computational modelling is temporally rich and explores variability over time, obtaining more information from a given dataset, including subtle effects that are often lost in collapsed mean accuracy or response times (White et al., 2010). Furthermore, computational models can provide explanations which might otherwise be too complex to specify and test. For example, trait anxiety is associated with reduced learning rate adaptability, a model parameter which describes the ability to update beliefs in response to new experiences (Browning et al., 2015b). Specifying and identifying this without a computational modelling approach would be very difficult (Robinson & Chase, 2017). Computational modelling provides a framework within which to summarize existing knowledge, offers a powerful means of detecting and explaining individual variability, allows competing hypotheses to be compared, and facilitates the interpretation of complex data.

6.1 Reinforcement learning models

Reinforcement learning (RL) has been widely used to study learning and decision-making, and more recently, mood. It provides a well-established computational framework, which intersects multiple fields including computational neuroscience (Doll

et al., 2012; Niv, 2009; Schultz, 2006; Sutton & Barto, 1998) and neuroeconomics (Glimcher & Fehr, 2013; Hasler, 2012; Sharp et al., 2012). Reinforcement learning is a computational approach to understanding how agents learn to make decisions in a complex and uncertain world. RL models are based on the idea that animals and humans learn to associate actions with outcomes and that they are more likely to repeat actions that lead to positive outcomes and less likely to repeat actions that lead to negative outcomes. This parallels our day-to-day lives, where we learn from the consequences of our actions, motivated by rewards, and avoiding punishments. Based on these principles, reinforcement learning models can provide measures of behaviour that offer insight into optimal behaviour (Mnih et al., 2015) as well as pathologies seen in clinical settings (Huys et al., 2016a).

The reinforcement learning framework offers a valuable approach to studying affective processes because of its ability to capture the dynamic interplay between actions, outcomes, and subjective experiences. Affective processes play a central role in RL models by modulating the value and salience of different outcomes, influencing decision-making and learning (Sutton & Barto, 2018).

In the context of psychopathology, RL models have proven to be particularly insightful in elucidating the mechanisms underlying maladaptive behaviours and mental health disorders. These models enabled the investigation of reward processing abnormalities, impaired learning from rewards, and decision-making biases in individuals with depression, bipolar disorder, anxiety, and addiction (Admon & Pizzagalli, 2015; Eldar & Niv, 2015; Huys et al., 2016b; Lawson et al., 2013; Maia & Frank, 2011; Pizzagalli et al., 2008; Voon et al., 2015). By incorporating affective components into RL models, researchers can simulate and investigate the alterations in reward-related processes that contribute to the development and maintenance of mood disorders, offering valuable insights for developing targeted interventions and treatments.

6.2 Reward prediction errors (RPEs)

Fundamental to reinforcement learning and decision making is the notion of reward prediction errors (Mellers et al., 1997; Schultz et al., 1997). Reward prediction errors

(RPEs) are the difference between expectation and reality, quantifying the difference between the predicted reward (EV) and the actual reward received. RPEs are encoded in the brain by dopaminergic neurons from the midbrain and processed by areas such as the anterior cingulate cortex (Hauser et al., 2014; Kennerley et al., 2011), the ventral striatum (Daw et al., 2011; Rutledge et al., 2010), and ventromedial prefrontal cortex (Hauser et al., 2015; Kennerley et al., 2011). These dopaminergic neurons increase their firing in response to an event that was better than expected, such as finding out that you will be getting a free dessert with your meal (positive RPE); and suppress their firing after an event was worse than expected, such as dropping that free desert on the floor shortly afterwards (negative RPE) (Schultz et al., 1997).

Large RPEs have been shown to induce positive or negative moods (Blain & Rutledge, 2020; Eldar & Niv, 2015), influence learning (Eldar & Niv, 2015; Gold et al., 2019), and even bias memory (Jang et al., 2019; Rouhani et al., 2018; Rouhani et al., 2020). For instance, Blain and Rutledge (2020) conducted a series of experiments examining the impact of RPEs on mood states, revealing that the size and direction of prediction errors play a pivotal role in shaping subjective emotional experiences. Larger RPEs triggered a larger mood change in the same direction (i.e. +RPE led to increased happiness, -RPE led to decreased happiness). Eldar and Niv's work (2015) demonstrated how large prediction errors significantly influence learning processes, with their research emphasizing the role of prediction errors in updating expectations and guiding behaviour in the direction of positive RPEs and away from negative RPEs. Gold et al (2019) argued that the enjoyment people feel when listening to music can be modelled based on the musical prediction errors. They showed that one of the reward centres of the brain, the nucleus accumbens tracked musical RPEs, and the amount of activity related to the reported feeling of pleasure.

In the realm of memory, Jang et al. (2019) and Rouhani et al. (2018, 2020) investigated how prediction errors contribute to memory formation, creating boundaries and making events more memorable if associated with a higher prediction error. Finally, Villano et al. (2020) showed, in a naturalistic setting measuring expectations, emotions and outcomes in students before and after receiving exam results that the temporal dynamics of real-world emotion are more strongly linked to prediction errors than outcomes.

Together with dopamine, the neurotransmitter serotonin is also involved how the brain processes rewards. Serotonin receptors, particularly 5-HT1B and 5-HT2C subtypes, densely populate key reward-related brain regions, modulating dopamine release in all three major dopaminergic pathways. Several serotonin receptor subtypes (5-HT1A, 5-HT1B, 5-HT2A, 5-HT3 and 5-HT4) act to facilitate DA release, while the 5-HT2C receptor can inhibit DA release (Alex & Pehek, 2007). This interaction influences the perception and processing of rewarding stimuli. Studies using neuroimaging techniques demonstrate changes in serotonin levels during tasks involving reward anticipation (Miyazaki et al., 2014), while pharmacological manipulations through SSRIs or serotonin agonists showcase significant alterations in reward sensitivity, decision-making, and responses to rewards (Higgins & Fletcher, 2003) highlighting the complex intertwine of serotonergic and dopaminergic transmission in reward processing.

7 Computational models of affect

Several different computational models of affect have been proposed. However, each focuses on a different construct (i.e. momentary mood, emotion, affect). One way of distinguishing between these constructs is by noting the timescale they operate on, which ranges from momentary measurements of mood to measurements of long-term life satisfaction.

7.1 Happiness Model

At the briefest end of the temporal scale is the Happiness Model defined by Rutledge and colleagues (Rutledge et al., 2014) which states that momentary mood is influenced by events going better or worse than expected. Here, momentary mood (or momentary happiness) was measured with the question “How happy are you at this moment?” asked every few trials. The authors argue that life satisfaction is a temporal integration

of momentary mood over a longer time scale (Kahneman et al., 2004). In this model, momentary mood is explained by the combined influence of recent reward expectations and the prediction errors generated by those expectations. Mood increases when outcomes are better than expected (positive RPEs) and decreases when outcomes are worse than expected (negative RPEs). Several studies have found that mood is modulated by past prediction errors both in lab-based experiments (Otto et al., 2016; Rutledge et al., 2015) and real-world emotions of students following exam results (Villano et al., 2020). These findings have been replicated in a large smartphone-based experiment and shown to have underpinning in the striatum (Rutledge et al., 2014), a target area for dopamine neurons that represent RPEs (Hare et al., 2008; Knutson & Gibbs, 2007; Niv et al., 2012; Schultz et al., 1997).

One real-life example of this theory is the finding that pessimism was associated with the fewest depression symptoms in a group of participants experiencing a downwards spiral in health (Chipperfield et al., 2019). In this study, a group of elderly participants were followed for over 18 years, with the goal of understanding how expectations of one's health predict the development of depressive symptoms. They found that realistic pessimism (when the expectation and the reality were that health will decrease) was a protective factor, reducing the rates of depression as well as the risk of death in participants who shared this view. At the opposite end, unrealistic optimism (when the expectation was that there will be no health decline, when in reality there will be) was associated with the highest rates of depressive symptoms and an 313% increase in the risk of death. Thus, being realistically pessimistic would mean that one's view is not very different from reality and thus fewer negative RPEs arise that could trigger depression. On the other hand, being unrealistically optimistic in the face of a downward health spiral leads to large negative surprises that can then lead to depressive symptoms.

7.1.1 Limitations

While the Happiness Model has been shown to explain momentary mood in some contexts, such as risk taking, in other contexts mood may track different processes. For example, in a different reinforcement learning task (Blain & Rutledge, 2020), mood was not modulated reward prediction errors (learning irrelevant information) and

instead tracked the difference between outcome and the estimated probability of winning (learning relevant information). Consistent with previous work (Rutledge et al., 2017; Rutledge et al., 2014; Rutledge et al., 2015) potential rewards were a key determinant of behaviour. However, rewards were not a determinant of mood in this study, in contrast to previous results in risky decision tasks (Rutledge et al., 2017; Rutledge et al., 2014; Rutledge et al., 2015) suggesting that how we learn about our environment may be more important for how we feel than the rewards we actually receive. In a social task, momentary mood was best explained by outcomes, RPEs and the rewards received by other players, although these were irrelevant to the participant (Rutledge et al., 2016). In addition, a recent study has shown that when accounting for reward size, momentary mood was only influenced by negative prediction errors. This effect was only seen in free-choice trials when counterfactual information was absent. The authors concluded that reward prediction errors may not be the primary factor driving momentary mood (Forbes & Bennett, 2023).

Another criticism of the Happiness Model is that it does explain the effect of mood on learning and decision-making (Kuppens et al., 2010; Larsen, 2000; Russell, 2003; Smith & Ellsworth, 1985). In the model, momentary mood is explained by recent unexpected outcomes, but there is no quantification of the effect current mood has on how future outcomes are perceived.

7.2 Mood as Momentum

It is not only surprising outcomes that bias mood, but mood also biases the perception of future outcomes. A recent theory posits that mood serves as an indicator of reward momentum within an environment (Bennett et al., 2022; Eldar & Niv, 2015; Eldar et al., 2016; Kao et al., 2022). Mood reflects the moving average of recent prediction errors and tracks whether an environment is getting better or worse (Eldar & Niv, 2015; Eldar et al., 2016). Mood therefore facilitates learning, by guiding the individual towards more rewarding environments and away from barren or negative environments.

According to the Mood as Momentum model, a positive mood can impact behaviour by enhancing the perceived value of rewards, leading to increased value updates following unexpected rewards. Conversely, negative mood leads to a perceived

reduction of value of rewards. Furthermore, the amount of bias mood exerted on reward perception has been shown to correlate with risk of developing bipolar disorder (Eldar & Niv, 2015).

To test this, the authors designed an experiment in which participants learned about the reward value of three slot machines during a learning block. This was followed by a wheel of fortune draw in which participants either won or lost \$7, serving as a positive/negative mood induction procedure. Participants then completed a second and third learning block, each containing 3 slot machines with different reward probabilities matching those in the first block. Finally, in the test block participants were asked to choose between slot machines learned about before and after the wheel of fortune draw (Figure 2). Momentary mood was evaluated by asking participants to rate their momentary happiness three times per block.

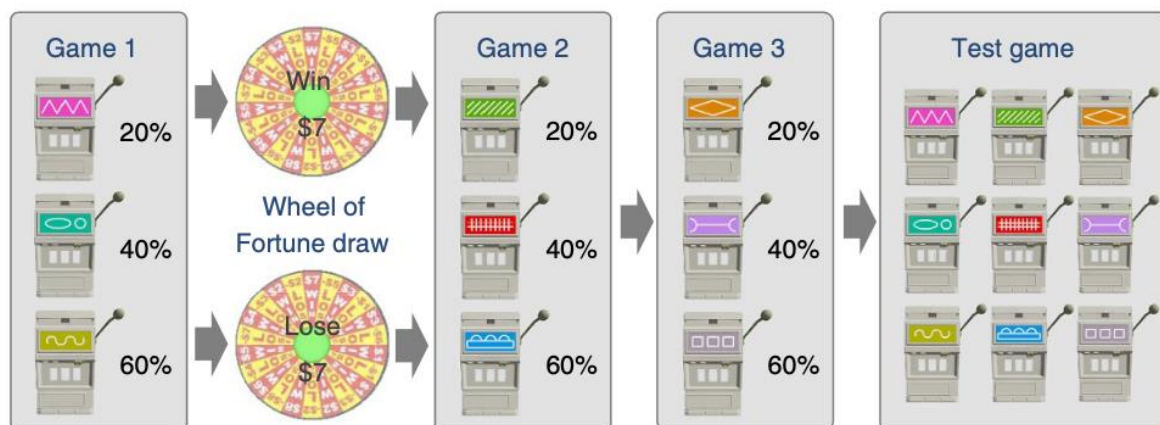


Figure 2. Task design of the slot machine game, from Eldar and Niv (2015).

Results showed that a large unexpected outcome (wheel of fortune draw) affected the emotional state of participants who reported less stable mood in their day-to-day lives (measured with the Hypomanic Personality Scale questionnaire) and biased their reward perception in the same direction. If participants won the draw, they were in a better mood and preferred the slot machines learned about after the draw. If they lost the draw, they were in a worse mood and preferred the slot machines learned about before the wheel of fortune. In contrast, participants with more stable mood showed no

influence of unexpected outcomes (and their associated mood changes) and valuation of future rewards.

The authors then formalised the interaction between emotional state and reward perception in a reinforcement learning model. The model successfully explained trial-to-trial choices of participants with high mood instability traits, indicating that both the effect of outcomes on mood and the effect of mood on outcomes played a role in determining the behaviour of this participant group. In participants with low mood instability, outcomes affected mood, but mood did not alter the perception of outcomes.

Mood increases learning efficiency only when the emotional reactions are appropriate in intensity and duration. Positive and negative moods maximise learning by persisting until expectations are fully updated and match the changes in rewards in the environment. Afterwards, mood returns to a baseline level, specific to each individual (Brickman et al., 1978; Lykken & Tellegen, 1996). However, this homeostasis relies on appropriate updating of expectations, via balanced learning processes. Losing this balance can lead to psychopathology.

Eldar et al. (2016) and later Mason et al. (2017) showed that this model can be used to better understand mood instability, as well as bipolar disorder. Specifically, positive surprises lead to a more positive mood which in turn biases perception of outcomes to be perceived as better than they are, increasing the frequency and magnitude of future positive surprises (Figure 3 blue). This causes the development of unrealistically positive expectations. When reality inevitably contradicts these expectations, large negative surprises arise which then lower mood and start a negative cycle (Figure 3 red). This in turn negatively biases perception of future outcomes until expectations become overly low and positive surprises arise leading to a positive cycle. These oscillatory dynamics are argued to map onto the manic (positive cycle) and depressed (negative cycle) episodes of bipolar disorder.

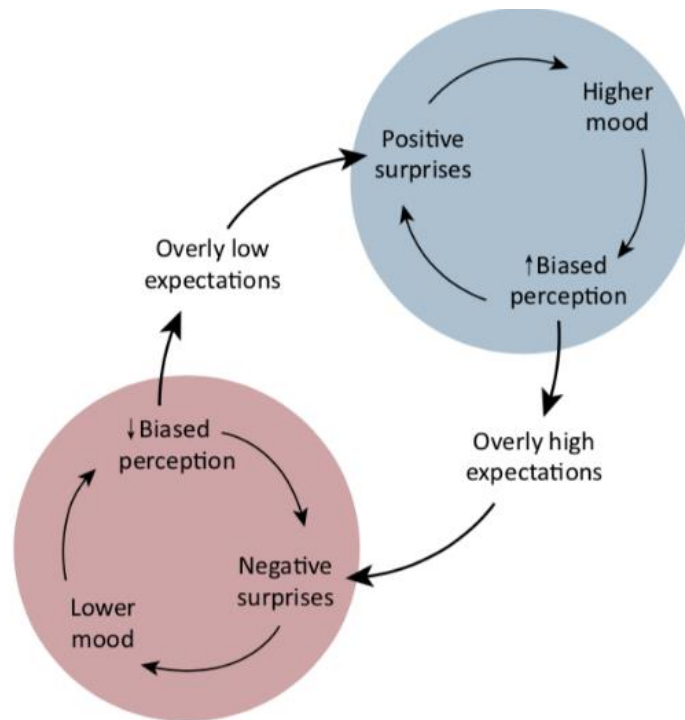


Figure 3. Mood as Momentum model explaining mood instability, adapted from Eldar et al. (2016)

7.2.1 Limitations

There are a few limitations that need to be considered in the case of the Mood as Momentum model and its ability to explain mood instability and bipolar disorder symptoms. Firstly, in the original experiment, the authors did not account for the amount of mood change experienced by participants. It could be that mood bias was solely driven by large mood changes following the mood induction procedure, which was higher in participants with hypomanic traits.

Secondly, the Mood as Momentum model has not been tested empirically in participants diagnosed with mood disorders. Instead, it was tested in participants from the general population some of whom scored higher on a measure of hypomanic traits (Eldar & Niv, 2015) or based on simulations of artificial data (Mason et al., 2017) to show it could explain bipolar mood cycles. More research is needed to empirically validate this model and confirm its ability to capture mood dynamics in clinical

populations as well as to confirm a causal relationship between the bias of mood on reward valuation and the development or maintenance of mood symptoms.

7.3 Mood as Integrated Advantage

Bennett and colleagues (Bennett et al., 2022) attempted to unify previous work on mood under one theory, giving rise to the Mood as Integrated Advantage model. They claimed that while RPE models account for expectation and surprise effects on mood, they do not take into account contextual effects, such as counterfactual information, how typical the action is or action/ inaction asymmetry. This account conceptualises mood on a longer time frame than previous models.

The Mood as Integrated Advantage model proposes that mood is a weighted average (or leaky integral) of the advantage of actions taken previously. Thus, if one's estimates of the advantage of their previously taken actions is positive, then their mood will increase, while if the advantage of their actions was negative, mood will decrease. The role of mood is to track and guide behaviour towards the most optimal actions in any given environment, similarly to the view of the Mood as Momentum model.

7.3.1 The counterfactual effect

Indeed, mood is not only influenced by the outcome of the actions taken, but also by the outcome of the unchosen actions also known as counterfactual information, which can lead to feelings of regret or envy (Coricelli & Rustichini, 2010; Gleicher et al., 1990; Johnson, 1986; Landman, 1987; Mandel, 2003; Markman et al., 1993; McMullen & Markman, 2002; McMullen et al., 1995; Roese, 1994; Rutledge et al., 2016). For example, imagine you are given the choice between two gift cards of unknown value to you (gift card A is worth £20 and gift card B is worth £100). If you choose gift card A you now have £20 more than you had before, which should make you happier. However, if you find out that choosing gift card B would have meant receiving £100, you might now feel regret for not having chosen this option instead.

The direction of the counterfactual effect on mood relies upon the direction of the comparison: comparing the attained outcome to a better one (upward counterfactuals)

will lead to negative mood, while comparing the attained outcome to a worse one (downward counterfactual) will lead to a positive mood (Markman et al., 1993). This effect is modulated by how mutable or controllable an event is (e.g., weather is immutable, while choosing a restaurant is mutable (Wells & Gavanski, 1989). Counterfactual effects cannot be captured by RPE models because they rely on comparison between possible action outcomes, while RPEs are defined only with respect to the chosen action. However, the counterfactual effect is only present if the individual has information about the outcomes of the unchosen option. If counterfactual information is not available to the individual, it does not impact mood (Epstude & Roese, 2011).

7.3.2 The action typicality effect

Affective responses are stronger following actions that are unusual or exceptional, also known as the action typicality effect (Feldman & Albarracín, 2017; Kahneman & Miller, 1986; Kahneman et al., 1982; Kutscher & Feldman, 2019; Miller & McFarland, 1986). The classic example of this effect was offered by Kahneman and Miller (1986), replicated by Kutscher and Feldman (2019), who presented subjects with two hypothetical scenarios involving an individual who had a car accident driving home from work. In one scenario the accident occurred while the driver was following his regular route home, while in the other scenario the accident occurred on a route that the driver took very rarely. When asked in which scenario would the driver be more upset about the accident, a large majority of subjects chose the atypical route scenario. The action typicality effect is difficult to explain with RPE models of mood, because RPEs are calculated without taking into account the typicality of the chosen action.

7.3.3 The action/ inaction asymmetry

The action/ inaction asymmetry describes the fact that outcomes following an overt action influence mood more strongly than outcomes following inaction (Feldman & Albarracín, 2017; Gilovich & Medvec, 1994, 1995; Gleicher et al., 1990; Kahneman & Miller, 1986; Kahneman et al., 1982; Landman, 1987; Zeelenberg et al., 2002). Kahneman and Miller (1986) showed this effect by asking participants who would be more unhappy: an investor who lost \$1,200 because they did not sell their stock

holdings in company A to buy stock in company B when they had the chance or another investor who lost \$1,200 because they sold their stock in company A for stock in company B. Despite equal monetary losses, most subjects believed that the second investor, who acted, would feel greater regret than the first, who lost money by inaction. Similarly to the counterfactual and action-typicality effects, the action/ inaction effect is not accounted for by RPE models of mood because an objective quantification of action/inaction symmetry is difficult to achieve.

7.3.4 Limitations

The mood as integrated advantage model is a new theory brought forward by Bennett et al. (2022) only last year. It builds on previous work and increases its complexity by adding several other effects to the model. Model complexity is a double-edged sword in computational research as it allows for a more nuanced understanding of complex phenomena, but it also increases the risk of overfitting the data and sacrificing generalisability (Friston et al., 2003). Furthermore, the mood as integrated advantage model is currently supported by limited empirical evidence. To assess this model, it would be necessary to employ experiments that account for all the additional effects encompassed by the model. This artificial complexity may in fact reduce the generalisability of this model to real-world situations. It is exceptionally rare that real life choices would include this breadth of additional information associated with current choice and the unchosen options.

7.4 Reinforcement Learning in mood disorders

Reinforcement learning (RL) models have proven invaluable in the investigation of mood disorders, offering unique perspectives, and uncovering intricate mechanisms underlying these conditions. These models have extended our understanding beyond mere mood ratings or task outcomes, allowing for deeper insights into the complex nature of mood disorders (Kao et al., 2022). For example, contrary to earlier beliefs, studies using RL paradigms have demonstrated that depressed individuals did not exhibit performance deficits on risk-taking tasks (Rutledge et al., 2017) or reinforcement learning tasks (Blain & Rutledge, 2020).

RL studies have found that individuals with depression exhibited lower momentary mood ratings with increasing severity of depressive symptoms, but did not differ from controls in how reward prediction errors impacted mood (Rutledge et al., 2017). Furthermore, depressive symptoms had a greater impact on momentary mood in volatile environments compared to stable environments (Blain & Rutledge, 2020), suggesting that individuals with depression may be more sensitive to changes in their environment. In an ultimatum game, non-depressed participants tended to reject offers if their emotional experience was more negative than expected (i.e. negative emotional prediction error), while this was not the case for depressed individuals (Heffner et al., 2021). In other words, while depressed individuals do not seem to use emotional prediction errors to guide their behaviour, they do act based on reward prediction errors in the same way as non-depressed controls (Heffner et al., 2021; Rutledge et al., 2017). Learning processes have also been shown to differ in depression in certain contexts, depressed individuals showing higher learning rates (i.e. learning faster) for punishments and lower learning rates for rewards (Pike & Robinson, 2022). However, there is considerable heterogeneity across studies investigating this. Nevertheless, RL models have provided valuable insights into the altered reward processing mechanisms underlying depression, highlighting the importance of investigating how reward-related learning interacts with mood dysregulation in this population.

Anxiety, on the other hand, has been associated with increased risk aversion (Maner et al., 2007) but not loss aversion (Charpentier et al., 2017). Chronic worry was also associated with greater punishment avoidance (Sharp et al., 2022). Participants with high trait anxiety showed impairments in the ability to adjust expectations of rewards between stable and volatile environments, while those with low trait anxiety matched updating of their outcome predictions to the volatility of the current environment (Browning et al., 2015a). This suggests that individuals with high trait anxiety may be more likely to persevere on negative information, and they may have difficulty learning to adapt their behaviour to changing conditions, while those with low trait anxiety are more flexible in their learning and adapt better to changing environments. Anxious individuals also had difficulty learning the causal structure of adverse environments (Browning et al., 2015a). This can lead unexpected negative outcomes being perceived as less predictable and less avoidable, which can lead to poor decision making (e.g. unnecessary avoidance) and the maintenance of anxiety symptoms.

Stress has also been shown to affect decision making processes including outcome valuation, learning, and risk taking, both in the lab and in real life (Morgado et al., 2015; Porcelli & Delgado, 2017).

In the case of mood instability, RL models have shown that individuals with high trait mood instability had stronger neural response to large unexpected rewards and weaker neural responses to large unexpected losses (Eldar & Niv, 2015). In an RL task, individuals with high trait mood instability showed a stronger bias of their current mood on the perception of rewards (i.e. larger mood bias parameter), which led to biased decision making. Computer simulations of different mood bias parameter values ran by Mason et al. (2017) have shown that a larger mood bias can cause expectations and mood to oscillate, similar to bipolar mood episodes.

Overall, RL models provide a promising framework for understanding mood disorders. RL models can be used to study the cognitive and neural mechanisms underlying mood disorders, and they can be used to develop new targetter treatments for mood disorders.

7.5 Types of rewards used in RL studies

Most studies presented until now that investigate mood have one experimental design feature in common: they use monetary outcomes to reward participants or to elicit mood changes. This is experimental choice is made for several reasons. Monetary rewards provide a tangible and universally understood incentive that is easily quantifiable and comparable across individuals and contexts (Haber & Knutson, 2010; Pessiglione et al., 2006). They offer a clear and objective measure of value and can be easily manipulated to investigate different reward magnitudes or probabilities. Monetary rewards have been found to elicit robust neural responses in brain regions associated with reward processing, such as the ventral striatum and prefrontal cortex (Knutson et al., 2001; Knutson et al., 2000). These neural responses can be measured using neuroimaging techniques, providing valuable insights into the underlying mechanisms of reward-based learning and decision-making.

However, in day-to-day life, individuals encounter a variety of rewards beyond monetary incentives. These non-monetary rewards play a crucial role in shaping mood

and behaviour. For example, intrinsic rewards, such as engaging in enjoyable activities (e.g. hobbies) or experiencing a sense of accomplishment (e.g. receiving your doctoral degree), have been shown to impact mood alongside extrinsic rewards (Chew et al., 2021).

Music is one the greatest human pleasures and listening to music often impacts how we feel (Juslin & Västfjäll, 2008; Koelsch, 2014). Research suggests that this due to the anticipation of the next sound which generates positive prediction errors when what is heard is better than expected (Salimpoor et al., 2015), or when the music deviated substantially from what the listener had expected (Gold et al., 2019).

In a naturalistic experimental design Villano et al. (2020) showed that the mood of students receiving exam results depended on both the outcome grade received and the prediction error (i.e. how much the actual grade differed from the expected grade). Students reported higher mood when they received a result much better than expected and lower mood when the result was worse than expected, consistent with the Happiness Model (Rutledge et al., 2014).

Social rewards such as approval, praise, and affiliation have also been shown to have powerful influences on mood and behaviour (Lieberman, 2007; Ruff & Fehr, 2014). Extending the happiness model described above, Rutledge et al. (2016) showed that, in social contexts, momentary mood not only tracked the rewards and reward prediction errors the individual experienced, but also tracked the rewards received by an unknown social partner. Both advantageous unequal outcomes (i.e. individual has more) and disadvantageous unequal outcomes (i.e. individual has less) reduced self-reported momentary mood. Furthermore, momentary self-esteem, measured with the question “how good do you feel about yourself right now?”, has been shown to fluctuate in response prediction errors about how much others will like or dislike the individual (Will et al., 2017). The authors showed that learning from social feedback relied on the same learning mechanisms seen in non-social reward learning at both an algorithmic (i.e., driven by prediction error) and neural level (i.e., the striatum, anterior cingulate cortex and prefrontal cortex (Will et al., 2017)).

This overlap between processing of social and monetary rewards has been explained by the idea of a common neural network (Ait Oumeziane et al., 2017; Flores et al.,

2015; Ruff & Fehr, 2014) which translates different types of rewards to a common currency (Montague & Berns, 2002). The theory is based on the observation that the same reward structures in the brain (i.e. striatum and prefrontal cortex) are activated by social and non-social rewards in similar ways (Cooper et al., 2013; Davey et al., 2009; Gunther Moor et al., 2010; Guyer et al., 2012; Izuma et al., 2008; Lin et al., 2012; Meshi et al., 2013; Morelli et al., 2014; Olino et al., 2015; Powers et al., 2013; Saxe & Haushofer, 2008; Zink et al., 2008). This common currency helps the individual to make decisions that maximise rewards (Montague & Berns, 2002) and could explain why some people participate in prosocial action while foregoing monetary gains (Bateson et al., 2006; Haley & Fessler, 2005; Kurzban et al., 2007).

Understanding the role of non-monetary rewards in shaping behaviour is essential for a comprehensive understanding of mood and decision-making. By considering the broader range of rewards that individuals encounter in their daily lives and incorporating them into reinforcement learning models, researchers can provide insights into how individuals function in real-world contexts.

8 Neuroscience needs an update

The field of neuroscience, including clinical neuroscience, has faced significant challenges in terms of underpowered studies and difficulties with replication and meta-analyses (Button et al., 2013; Marek et al., 2020; Müller et al., 2017; Widge et al., 2019). Effect sizes have often been small and dependent on comparisons between disorder and healthy control groups, rather than being specific to diagnostic categories (Bickel et al., 2012; Davidson & Heinrichs, 2003; Hoogman et al., 2019; Lipszyc & Schachar, 2010; Voon et al., 2015). Additionally, the complex interplay of various genetic and environmental factors, such as childhood adversity, stress, diet, exercise, and social isolation, further complicates our understanding of mental health (Chekroud et al., 2018; Fluharty et al., 2016; Ford & Kamerow, 1989; Jané-Llopis & Matytsina, 2006; Kelly et al., 2015; Kessler et al., 1997; Lorant et al., 2003; O'Neil et al., 2014; Paykel et al., 2000; Weitzman, 2004).

To overcome these challenges and develop robust neurocognitive models of mental illness, new methods are needed that can provide richer, multivariate datasets and larger samples (Gillan & Rutledge, 2021). One of the most promising approaches is utilizing smartphones as a tool for conducting research in neuroscience. Smartphones offer several advantages, including the ability to use experience sampling methods (ESM) to collect data in real-time, allowing researchers to capture individuals' experiences and behaviours in their natural environments (Rutledge et al., 2017). They have the potential to enhance research in computational psychiatry by bridging the gap between behavioural models and subjective experiences, as they relate to real-world emotions and psychiatric symptoms (Kao et al., 2022).

With smartphone-based studies, taking part in research studies becomes easy and accessible to a larger and more diverse population that would otherwise struggle to get to the lab, whether due to scheduling conflicts, disabilities, or caregiving responsibilities. Removing the constraints of physical proximity as well as the need for a computer, these studies attract a broader participant pool, contributing to more representative and varied data. The ownership of smartphones is pervasive globally, with over 64% of the world's population owning one. In regions like America and Western Europe, the prevalence of smartphone users reaches over 80% of the population and these numbers are growing with each year (source <https://www.statista.com/forecasts/1143723/smartphone-users-in-the-world>, accessed 15 Dec 2023).

Furthermore, researchers can collect data on mood, cognition, physiological indicators, and various environmental factors on a large scale and over extended periods of time, enabling longitudinal designs (Gillan & Rutledge, 2021; Hitchcock et al., 2022). Shifting away from cross-sectional research to longitudinal research is important to be able to develop predictive models, as opposed to descriptive ones (Isaac et al., 2020). This will allow more direct translations to clinical practice, aiding diagnosis, measuring the effectiveness of treatments, and developing new targeted interventions. Moreover, smartphone-based studies offer the potential for real-time monitoring and delivery of personalised treatment interventions, in a cost-effective, accessible manner.

Smartphones offer incredible potential for research, but they come with their own set of challenges compared to lab-based studies. One significant disadvantage is the lack of control over the research environment. In a lab setting, researchers have control over variables like noise, distractions, and the overall setting, ensuring a standardized environment for all participants. With smartphones, the research environment varies widely as it's the participant's natural setting, introducing potential inconsistencies that can impact data quality.

Moreover, data integrity and validity can be more challenging with smartphone-based research. The reliability of data collected remotely via smartphones might be affected by various factors such as participant compliance, honesty, or the accuracy of self-reported information. In a lab setting, researchers can oversee data collection, providing additional feedback or instructions to participants if needed. Issues regarding data privacy and security are more pronounced with smartphone-based research, as the data might traverse through various networks and devices, potentially posing risks to the confidentiality of information.

Lastly, participant engagement and adherence to study protocols might be lower in smartphone-based research compared to lab settings. In a lab, participants are more likely to adhere to the researcher's instructions and are within a controlled environment, whereas remote participation might lead to lower commitment or adherence to the study requirements due to various distractions and priorities in their natural environment. It is therefore crucial for researchers to proactively address these limitations in the study design and set-up phase, so they can increase the quality, reliability, and privacy of data gathered.

Smartphone-based research, despite its challenges, stands as a transformative and invaluable tool in behavioural studies. Its capacity to reach diverse populations, capture real-time data in natural settings, and engage participants in their daily lives opens new avenues for understanding human behaviour in unparalleled depth and breadth. By leveraging the ubiquity and convenience of smartphones, researchers can gain insights that were previously inaccessible, enriching our understanding of behaviour and paving the way for more inclusive, dynamic, and ecologically valid research.

9 Thesis aims

This PhD thesis aims to fill crucial gaps in the existing literature by providing a comprehensive exploration of the influence of mood on reward processing in diverse contexts, including social and non-social rewards domains. By employing a combination of behavioural analyses and computational modelling techniques applied to large datasets, this thesis aims to enhance our understanding of how mood can bias the valuation of rewards. Additionally, it seeks to examine, for the first time, whether mood bias exists on a spectrum, by recruiting a large and diverse sample comprising individuals with varying levels of mood instability or hypomanic traits, as well as individuals diagnosed with bipolar disorder.

The main research questions that this thesis will explore are:

1. How can smartphone-based experiments be used to study mood bias on reward valuation?

Chapter 2 will detail the development of a novel research method of quantifying mood bias, without the use of monetary rewards. The new experimental paradigm forms part of a new research app.

2. Does mood bias non-social reward valuation? Is there a link between mood bias and mood instability?

Chapter 3 will replicate and extend the previous work of Eldar and Niv (2015) by investigating mood bias on non-monetary rewards. By recruiting a very large sample of participants from the general population, the study will examine the relationship between mood bias and mood instability, aiming to provide a more comprehensive understanding of how fluctuations in mood may influence the valuation of non-monetary rewards across a diverse and representative group of individuals. By using a computational modelling approach, this study seeks to uncover nuanced insights into the intricate dynamics between mood, reward processing, and mood instability within the broader context of non-monetary incentives.

3. Does mood bias on reward valuation extend to social contexts?

Chapter 4 will explore, for the first time, if mood biases social reward valuation, using a novel experiment specifically designed for this study.

4. How does mood bias manifest in individuals diagnosed with bipolar disorder compared to healthy controls? (Chapter 5)

Chapter 5 will expand on the work presented in Chapter 3 and experimentally test the predictions made by Mason (2017) and Eldar and Niv (2015) that mood bias is increased in individuals with a diagnosis of bipolar disorder, relating to the development of manic and depressive symptoms.

The findings from this thesis aim to significantly enhance our understanding of the underlying cognitive mechanisms of mood-related disorders, thereby contributing valuable insights to both theoretical frameworks and clinical applications in mental health research and intervention.

CHAPTER 2. App development

Smartphones have become ubiquitous tools in people's daily lives, and they have significant potential to be used to collect data about people's behaviours, experiences, and activities. The proliferation of applications (apps) has further amplified this potential, providing each user with a platform to engage with various functionalities tailored to their specific needs and preferences. As individuals increasingly integrate smartphones into their routines, the use of apps offers a unique opportunity to capture real-time and contextually rich data. These apps can be designed to facilitate seamless data collection across diverse domains, from health and well-being to social interactions and calendar planning. However, with so many different apps competing for the user's attention, it is crucial to be aware of the challenges associated with engagement, usability, and data quality. In this saturated app landscape, users may experience decision fatigue and may be less inclined to actively participate or provide accurate data. Therefore, maintaining a delicate balance between creating compelling and user-friendly interfaces, ensuring data privacy and security, and employing effective strategies to sustain user engagement becomes paramount. Addressing these challenges is essential to optimize the acceptability and effectiveness of smartphone applications designed for data capture, ultimately maximizing their potential impact in research.

One key factor that affects the acceptability of smartphone apps is their perceived usability (Ahmad et al., 2018). Usability refers to the ease with which people can learn to use an app and how quickly they can complete tasks. Apps that are easy to use are more likely to be used by people, and this is particularly important for apps that collect data. If people find an app difficult to use, they are less likely to use it consistently, or they may even give up using it altogether.

Another important factor that affects the acceptability of smartphone apps is their perceived usefulness (Akdim et al., 2022; Hsiao et al., 2016). Usefulness refers to the degree to which people believe that an app can help them achieve their goals. If people

believe that an app can help them improve their health, track their progress towards a goal, or simply have a more enjoyable experience, they are more likely to use it.

When creating a research app, there are a number of design principles that can be applied to make it more acceptable and effective in data capture. The most important one is taking user-centred design approach for crafting interfaces that prioritize user experience and engagement (McCurdie et al., 2012). This is an evidence-based approach to design informed by understanding the target user group, their needs and wants and how they will use the app in their daily lives. In parallel, there is a need to consider the ethical implications of using smartphone apps to collect data. Users should be told about the purpose of the app and how their data will be used. They should also be given the option to opt out of data collection, and their data should be stored securely, as per General Data Protection Regulation (GDPR) guidelines.

Gamification in app design integrates game elements and mechanics into non-game contexts to enhance user engagement and motivation. By incorporating features such as points, badges, leader boards, and challenges, apps can tap into intrinsic human motivations, fostering a sense of accomplishment and competition (Deterding et al., 2011). The application of game-like elements serves as a powerful tool to increase user participation, influence behaviour, and promote user loyalty (Hamari et al., 2014). Leveraging principles from behavioural psychology and game theory, gamification not only transforms user interactions into enjoyable experiences but also encourages sustained app usage by creating a dynamic and rewarding environment. Successful implementation of gamification principles requires a deep understanding of the target audience, aligning game mechanics with app objectives, and maintaining a balance to prevent potential pitfalls such as user burnout or disengagement (Zichermann & Cunningham, 2011). Ultimately, gamification in app design holds the potential to amplify user involvement and contribute to the overall success and effectiveness of mobile applications, reaching a larger audience base and engaging users to interact with the app more.

In neuroscience research, the key advantage of creating a smartphone-based infrastructure is that it can increase the amount of data gathered on any one person, enabling us to integrate across many levels of analysis. It democratizes access to research studies and brings the lab to anyone's pocket. It allows collection of any data

types, from quantitative task data to written journal entries. Furthermore, by using larger participant samples, we can assess how generalizable theories and models are, recognise and take into account population variety, support multivariate studies, and provide the algorithms necessary to combine complex datasets. This infrastructure is thus crucial if neuroscience wants to move away from cross-sectional techniques and towards time-series data that can help us understand causality and develop predictive models (Gillan & Rutledge, 2021). While this approach is limited to people who own a smartphone, in 2021, mobile users worldwide topped seven billion, accounting for 91.54% of the world's population (Wei, 2023).

Over the course of the first two and a half years of this PhD, the co-development of the “Happiness Project” app has been a major part of my work. This chapter aims to describe the app and features I created.

1 The Happiness Project overview

The Happiness Project app is freely downloadable on the iOS and Android stores. Users have the option of agreeing to share their data and take part in research or use the app without sharing their data. All data collected is anonymised or pseudonymised. The app included four gamified psychological experiments (referred to as *games*) and several customisable surveys. One of the games was *The Wheel of Fortune* game which will be described below and used as the main experimental task in Chapters 3 and 5.

1.1 General app features

One of the main scientific objectives of the entire project was to create longitudinal datasets, so it was crucial to motivate users to play each game multiple times and to engage with the app frequently over time. To achieve this, we focused on two main aspects: (1) designing a smooth user experience journey throughout the app and (2)

motivating users with fun features, prompts and rewards. We expected reward-type features to give users a dopamine boost (Schultz, 2002) that would increase their happiness and engagement with the app.

Focusing on creating a smooth user experience through the app, we simplified each screen a user sees before reaching the main home screen. We minimised the number of demographic questions we asked users before they reached the games and opted instead to move some of the questions into specific surveys that are accessed later. We wanted the users to reach the games as quickly as possible after installing the app, as this is the moment when they are most excited and curious to explore the app.

To motivate users and increase repeated plays, we developed several features described in detail below. For all features we implemented, I worked closely with the team of full-stack developers to ensure that functionalities were coded in such a way that the research team maintained the ability to personalise any text or images shown at any time with minimal changes to the source files (i.e., jsons).

1.1.1 Interactive ‘About Section’

The interactive About section feature provided players with more information about the app's science and team (Figure 4). This feature helped to build trust between players and the app's creators and provided players with a sense of community. Most of the users who freely chose to download and install the app were people interested in being citizen scientists or people who had a particular interest in the neuroscience of happiness. Therefore, many were interested in learning more about the science behind the games and surveys on the app. The About section provided more information about the aims of this research, the team who created the app and those interested could follow a link to the lab webpage which has more info and resources.

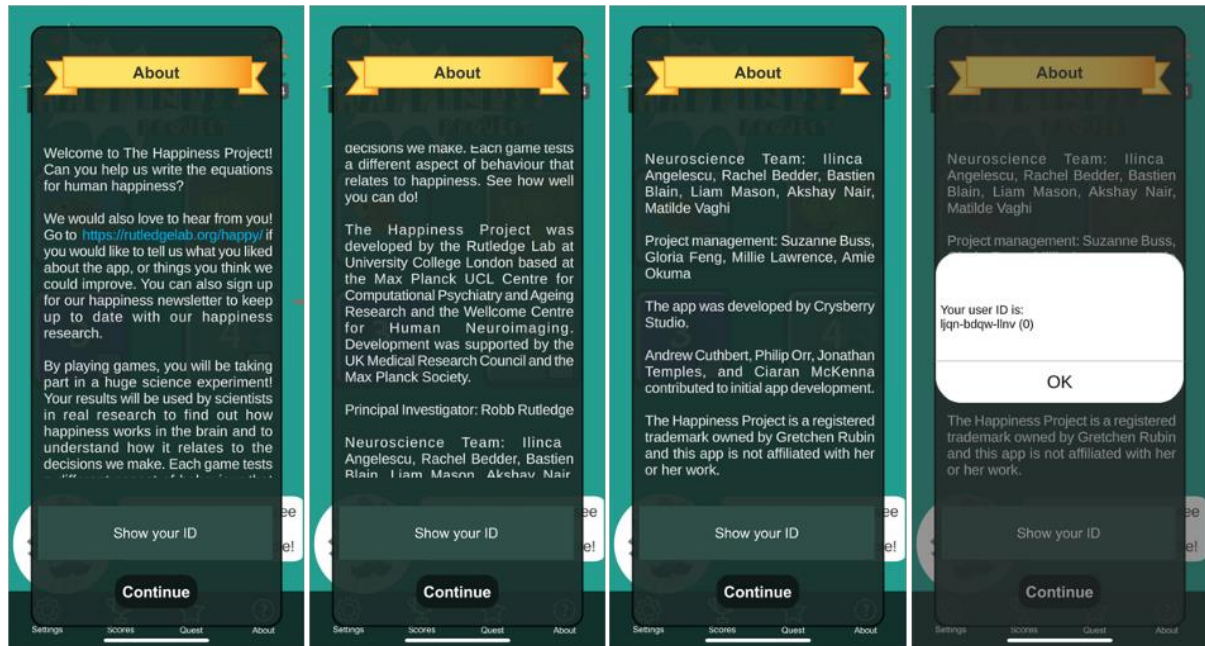


Figure 4. The Happiness Project: About Section

1.1.2 Tick System

We incorporated a tick system to indicate game completion by adding a green tick to the game icon on the home screen when the user completed it (Figure 5). It displayed as a short animation of a pulsating green tick that appeared in the corner of the game icon that had been completed. This feature helped players to visualize their progress and encouraged them to keep playing until they completed all the games on the screen (which then unlocked a quest). After all the games on the home screen are completed a new home screen appeared with the icons unticked. The tick system feature was also useful for participants taking part in research studies to keep track of the games and/or surveys they completed each day.



Figure 5. The Happiness Project: Tick system

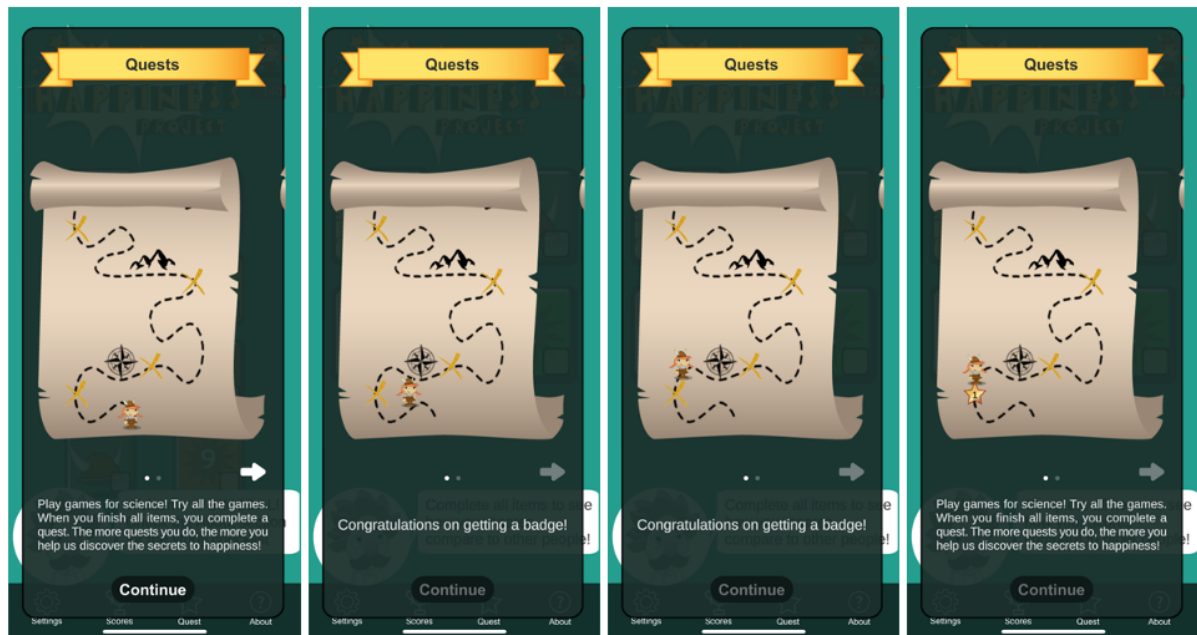
1.1.3 Quest Map and Badges

To promote player engagement, we designed a quest map feature that would allow players to track their progress in the game. When a player completed all the games visible on the home screen, they progressed to the next point on the quest map, as seen in Figure 6A. This was displayed as an animation of the character which moves to the next checkpoint. Progression in the quest also unlocked a badge, which was an image of an animal and fun facts about it, as shown in Figure 6B. After each badge, the user returns to a new home screen.

From start until completion of badge 1 users play two of the four games (randomly chosen) and complete two surveys. Badge 2 required the completion of the other two games and two new surveys. After receiving Badge 2, the user saw all four games and two new surveys on the home screen. The games remained on the home screen with each new badge completed and a mix of new and previously seen surveys appeared.

The feature of “unlocking” new games and surveys was designed to captivate users and motivate them to play more to unlock more games and surveys.

A.



B.

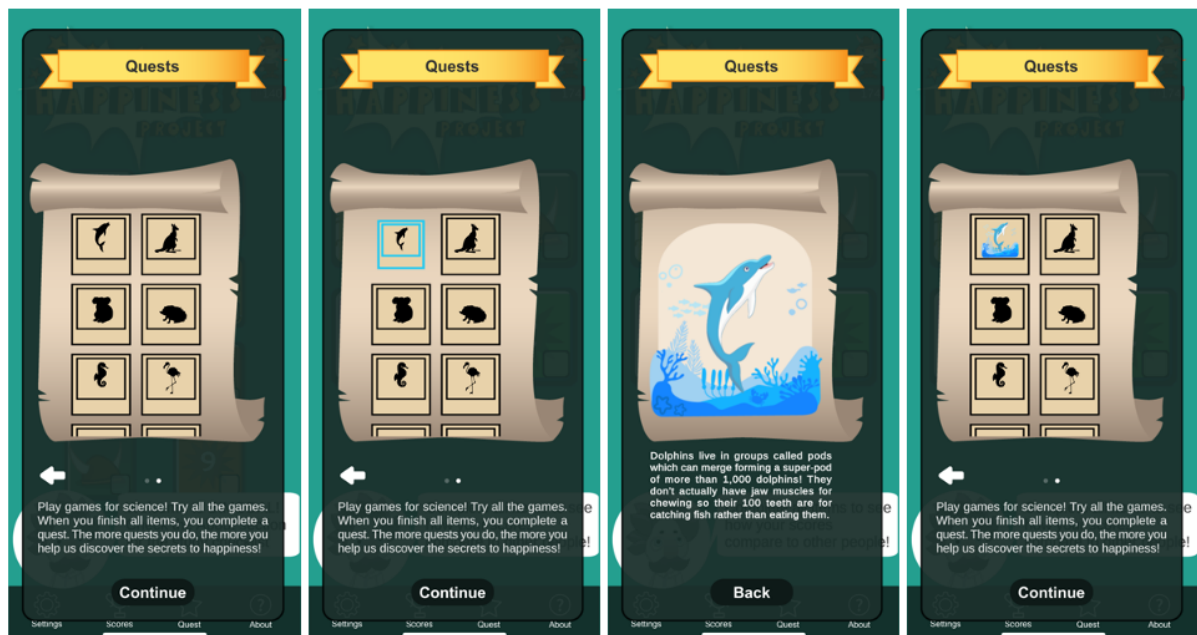


Figure 6. The Happiness Project: Quest map features. A) When players complete all games on the home screen they progress in their quest and B) unlock an animal picture and fun facts.

The quest map also helped players visualize their progress and provided a sense of accomplishment. The quest map feature was valuable in motivating players to continue using the app regularly. It also allowed the research team to run longitudinal studies with clear and simple goals for participants that were easy to remember over time (e.g. complete 1 badge per day or 5 badges per week).

1.1.4 Personal Best Chart and World Ranking

The personal best chart feature was designed to promote competition and motivate users to try to beat their top scores. Players could also see their progress relative to others in the form of a percentile ranking, which helped to foster a sense of community and allowed players to see how they stacked up against other players (Figure 7). The percentile ranking was colour coded to make it more intuitive: green – 80% to 100%, yellow – 50 to 79%, and red – under 49%. These features were particularly effective in promoting competition among players and motivating them to improve their scores. It increased player engagement with the same games over extended periods of time.

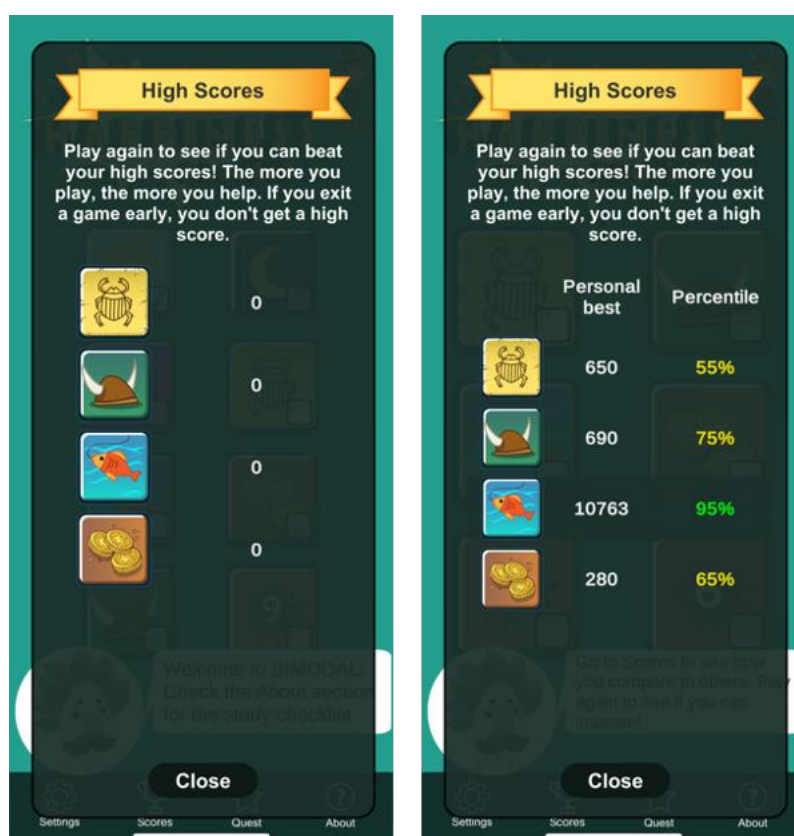


Figure 7. The Happiness Project: High Score Chart and World Ranking

1.1.5 Dynamic Einstein Messages

We incorporated dynamic messages to serve as instructions, prompts, reminders, encouragements, and more. These messages were designed to be motivational and engaging, while also providing guidance and support to players. All messages were easily customisable and set to be triggered at any time, either automatically by the app, or launch following certain user actions or manually by the researchers. Einstein was the little scientist character shown in the bottom left corner in Figure 8.

Einstein messages automatically duplicated the text of push notifications the user received (Figure 8). They were implemented after receiving user feedback during our pilot studies that players forgot what they needed to do if the notifications disappeared. Einstein messaging ensured the user can access the notification text even if they tapped the notification and it disappeared (when tapping on a notification the app home screen is automatically opened), serving as helpful reminders of activities participants needed to complete when taking part in studies.



Figure 8. The Happiness Project: Einstein messages examples

1.1.6 Notification System

1.1.6.1 *Customizable Push Notification System*

The customizable push notification system feature allowed researchers to customize the notifications to suit any schedule. The researcher had control over the text of the notification, the users it was pushed to, the time of day and date and the frequency of repeated notifications (e.g. daily at 14:00 and 18:00). This feature helped to keep players engaged by ensuring that they received relevant notifications at the right time reminding them to complete specific games (if they were part of research studies) or encouraging them to explore the app more (all other general users).

1.1.6.2 *Smart Automatic Push Notification*

We designed a smart in-game push notification to remind players when a survey was available to complete. As part of some of the research studies we ran on the app, we developed two paired surveys: *the before survey* – asking participants to rate how they predict an activity will go and *the after survey* – asking participants to rate how the activity went. The notification for completing *the before survey* was pre-set by the researchers. When participants completed the before survey, they were asked to input the time their chosen activity will end. That time was then used by the app to push a notification that *the after survey* was unlocked and could be completed. The survey was locked until this notification was delivered. This feature increased the ecological validity of our research designs, by allowing for flexible notifications to be set directly by the participant and by ensuring that the timing of the paired survey was tailored to each person, for each situation.

1.1.7 Summary

Overall, the general app features that we developed played a crucial role in promoting player engagement, and increased the percentage of repeated plays and time spent

on the app. These features helped to ensure that the app was engaging, user-friendly, and enjoyable to use. The customisable notifications and messages allowed for the design of research studies with good ecological validity, set in participants' normal daily lives. Moreover, the app features and reward principles highlighted in this section can be applied to other app development contexts to enhance player engagement and promote cognitive and emotional well-being.

1.2 *The Wheel of Fortune game*

In this section, I will discuss the various features that we developed specifically for the Wheel of Fortune (WoF) game. These features were developed and implemented to enhance user experience in the game and promote replayability. Each feature will be described, including the rationale for its development, a brief overview of its functionality, and its implications for users.

The WoF game was originally developed by Eldar and Niv (2015) to measure the biasing effect of mood on learning and decision-making, in a reinforcement learning paradigm. It builds upon classic probabilistic learning experiments where participants choose between two or more options to get a reward, and learning over time which one is the more rewarding stimulus. By including a mood induction procedure half-way through the game which increases or decreases participants' mood, researchers can compare learning in a neutral mood state (in the first block) versus a learning in a happier/ unhappier mood state (in the second block). Using computational modelling to analyse the results of this task, parameters of interest can be quantified for each participant, such as learning rate, mood bias, choice stochasticity, and many others that help paint a detailed picture of participants' choices. I chose the WoF task because it is an elegant redesign of a classic RL paradigm, it was shown to be sensitive enough to quantify mood bias in a small participant group, and it lends itself to the fitting of RL computational models which give us a more fine-grained understanding of how mood can impact learning and decision-making.

1.2.1 Skippable illustrated instructions

The WoF game begins with illustrated instructions slides that describe how the user should play the game. We included images of our game mascot, the pharaoh character who is a guide for users throughout the game. We added a the "Skip Instructions" button that converted to a "Start Game" button on the last slide (Figure 9). The rationale for this feature was to provide clear and concise instructions that were easy to follow, reducing the time users spent trying to figure out how to play the game and implicitly the noise in our dataset. This feature was also intended to be aesthetically pleasing and convey the game story, adding to the overall user experience.

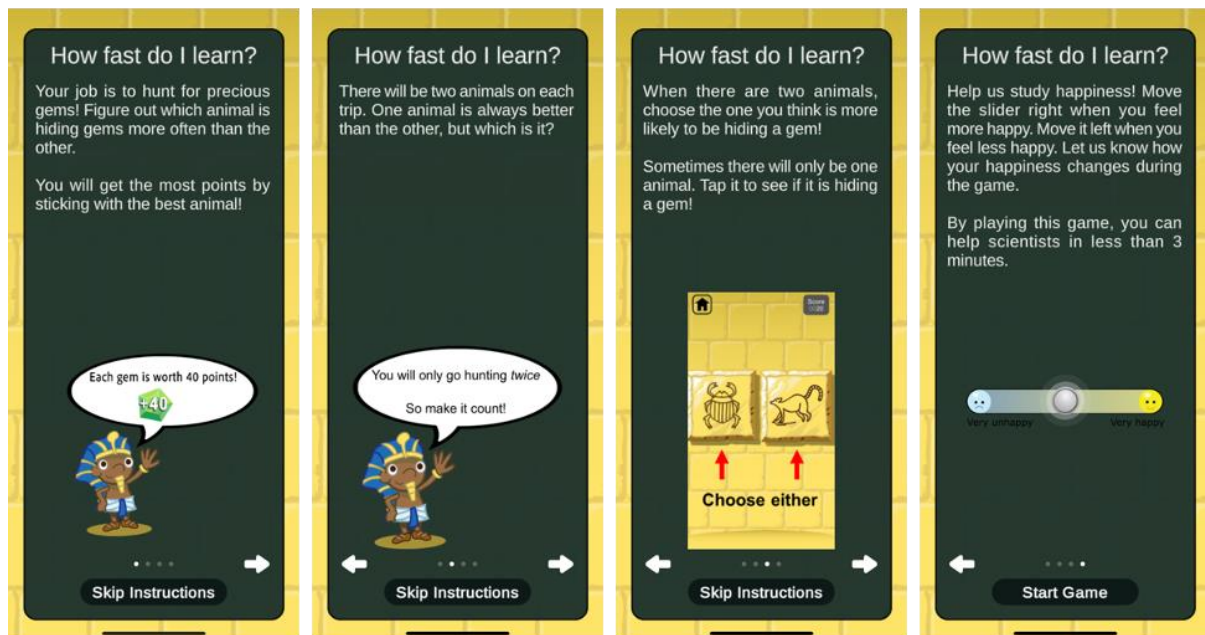


Figure 9. Wheel of Fortune game: Screenshots of the game instructions pages

1.2.2 Dynamic display of stimuli

At the start of each game, a dynamic display showed icons of the four animals which users would learn about in the game (Figure 10). These were selected by the app at the start of each game from a set of 48 animal icons. The selection logic involved an automatic creation of a shuffled list of all the available animals, for each user, and selecting four at a time for each game. When all 48 were used, the list would get

reshuffled. The rationale for this feature was to give users an idea of what they would be learning in each game. This feature also added an element of surprise and excitement, as users never knew which animals they would be learning about until the start of each game.



Figure 10. Wheel of Fortune game: Dynamic stimuli display

1.2.3 Pop-up happiness ratings

Each game in the Happiness Project app included pop-up happiness ratings that automatically recorded the slider rating and progressed to the next screen, removing a redundant continue button. The rationale for this feature was to make the transitions between screens faster and more seamless, reducing user frustration.

1.2.4 Wheel of Fortune interactive animation

Perhaps the most important feature in the WoF game was the Wheel of Fortune spin, as it served as the mood induction component of the game. Several qualitative and

quantitative pilot studies indicated that the wheel spin part of the game was not clear and overall, the design was not very convincing to users. Therefore, several changes were made to improve the animation, including user-controlled wheel spin speed.

If users tapped faster, the wheel would spin faster and slow down if they stopped tapping. This gave the illusion of higher control, as the wheel outcome was predetermined at the start of each game. A wheel speedometer was added to show the speed range possible and further drive this point of user control. A release button was added to allow users to first adjust the speed before releasing. A backup feature was also included to ensure that users who did not want to engage with the feature or were unsure how it worked could still progress through the game. If a user did not tap the wheel or release button at all, it would start an automatic spin after 3 seconds.

We also added two pulsating red arrows pointing towards the release button when wheel spin time was running out, to further visually show users that they should press the release button (Figure 11). After releasing, to be more convincing, the wheel spin decreased in speed quickly and slowed down slowly over 2.5 seconds until it eventually landed on an outcome. The landing positions were predefined to be close to the edges of each value to increase suspense and generate a stronger emotional reaction. Overall, these changes made the wheel spin more engaging, fun, and easier to use and generated stronger mood induction effects than the simplified previous versions.

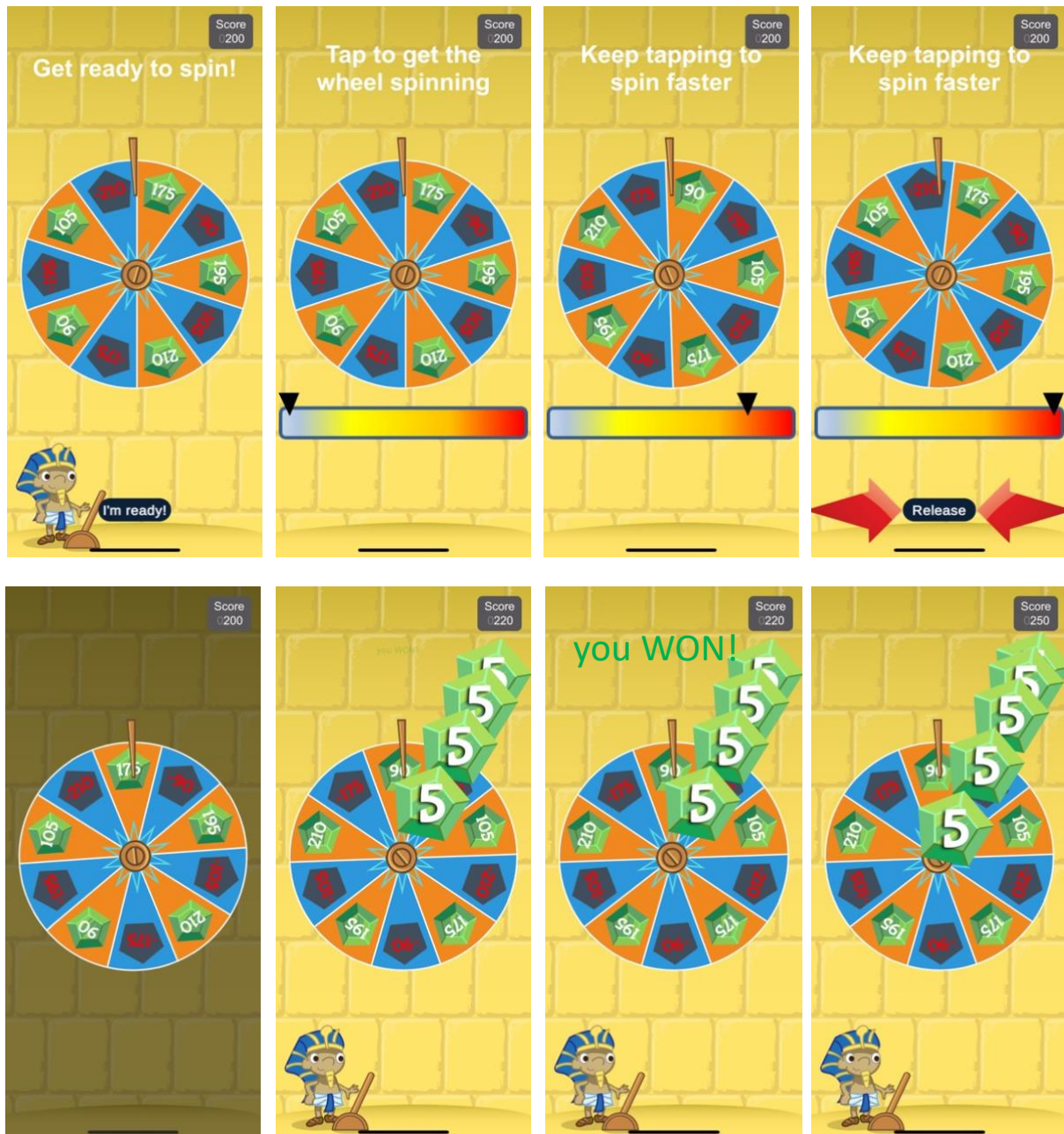


Figure 11. Wheel of Fortune game: The Wheel of Fortune spin.

1.2.5 Bonus gems

During the game, the app offered a bonus gems reward on three random test choices predefined at the start of the game. The user did not know which responses would be rewarded. The bonus reward was displayed in a pharaoh speech bubble and automatically updated depending on the user's number of correct choices (Figure 12A).

The rationale for this feature was to provide users with an added incentive to do well, motivating them to learn and to respond correctly on the test.

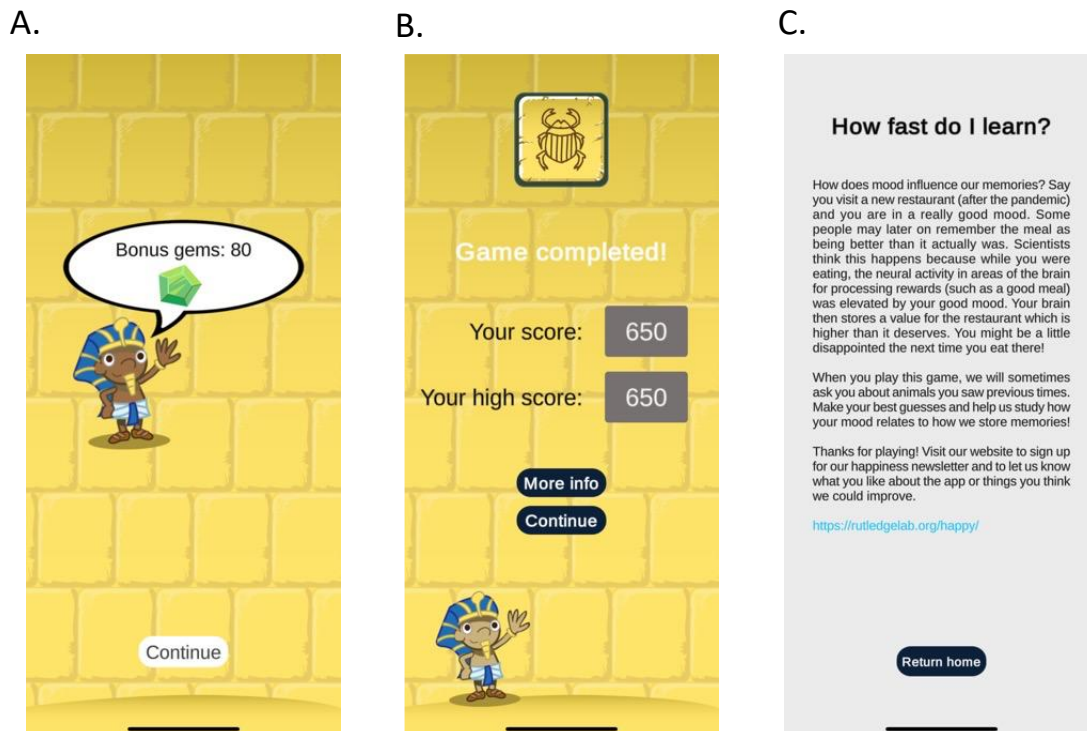


Figure 12. Game end screens including the A) Bonus games screen, B) High score screen and C) Information screen activated by pressing the ‘more info’ button.

1.2.6 Game end screen

At the end of each game, the current game score and high score were displayed, motivating users to play again to beat their own high score, as shown above in Figure 12B. On this screen we added a ‘More info’ button leading to lay explanations of the science behind the game without giving too much away (Figure 12C). We also included a clickable link to the app website. These features were motivated by several users telling us they are interested in learning more about the science behind the game.

1.2.7 Summary

The Wheel of Fortune game features were designed and developed following extensive user experience pilots which gave us insights into how users were playing the game and what issues they encountered. Quantitative as well as qualitative feedback showed us that several pressure points existed in the game. These included: the game feeling too long, confusing instructions, redundant actions (like clicking submit following a happiness rating, when there is no other action to take), and a not-very-convincing wheel of fortune spin. All these issues led to increased user frustration, incomplete game plays, small mood induction effects and random choices due to users not understanding how the game worked. We addressed each of these issues, by redesigning the instructions slides and adding a skip button, removing redundancies in rating submissions, making transition times between screens as short as possible, and redesigning the wheel spin to give users a higher sense of controllability. Following these changes, feedback improved significantly, with users reporting higher levels of engagement and enjoyment playing the WoF game as well as showing better learning, stronger mood changes and more accurate test choices, suggesting that our redesigns were successful.

CHAPTER 3. Assessing the impact of mood on reward valuation with a new gamified smartphone task “The Wheel of Fortune”

Abstract

Mood is an important determinant of well-being, affecting many areas of daily functioning (Robinson, 2000). Research using reinforcement learning models has shown that the interaction between mood and learning may be bidirectional: experiences affect mood (Kuppens et al., 2010), and mood can influence the appraisal of experiences (Eldar & Niv, 2015; Tamir & Robinson, 2007). The degree to which mood biased experiences was linked to symptoms of mood instability (Eldar & Niv, 2015). It remains unknown whether this effect is replicable and robust in non-experimental laboratory conditions. In a large sample of the general population (N=4629), I evaluated a new smartphone-based gamified task “*The Wheel of Fortune*” that aims to quantify the extent that mood biases the perception of reward. The task was an adaptation of previous work (Eldar & Niv, 2015), redesigned to be shorter, more enjoyable, and accessible anytime anywhere on any smartphone. The task was well understood by participants and successful in inducing positive and negative moods. It showed mood biased learning, with participants preferring the block they were happier in. This effect was found to be directly related to the degree to which mood was influenced by mood induction and was more pronounced in participants exhibiting symptoms of mood instability. Computational modelling was used to further examine the effect of mood on reward perception. The game is quick, portable, and it allows for the collection of large datasets while minimising participant burden. The *Wheel of Fortune* task showed potential as a brief cognitive probe for measuring a bias of mood on learning.

1 Introduction

Mood plays a crucial role in our overall well-being and has a significant impact on various aspects of our daily functioning. It serves as a powerful determinant of our motivation and influences our pursuit of goals. It can shape our perceptions, decision-making processes, and behavioural responses in everyday life (Robinson, 2000). Mood and behaviour are interdependent and reciprocally influence one another. Mood is a consequence of cognitive appraisals of one's subjective experiences (Kuppens et al., 2010; Larsen, 2000; Russell, 2003; Smith & Ellsworth, 1985) or in other words, how one perceives life events can determine their mood. On the other hand, mood itself can bias cognitive processes and influence the appraisal of future experiences (Neville et al., 2020; Tamir & Robinson, 2007). As a result, mood can be conceptualised as a reflection of an individual's past actions as well as a predictor of their future actions (Bonsall et al., 2015; Broome et al., 2015; Koval et al., 2013).

Research has shown that individuals in a positive mood state tend to have a bias towards approaching rewards and making more optimistic decisions, while individuals in a negative mood state tend to have a bias towards avoiding rewards and making more pessimistic decisions (Forgas, 1995; Isen & Daubman, 1984; Verkuil et al., 2010). Mood enhancement has been shown to favour risk-taking (Arkes et al., 1988; Isen & Patrick, 1983; Schulreich et al., 2014). Similarly, ecological studies have demonstrated that people gamble more on a sunny day or after an unexpected victory of their favourite sports team (Bassi et al., 2013; Edmans et al., 2007; Otto et al., 2016). This can lead to a self-perpetuating cycle, where an individual's current mood state influences their decisions and actions (e.g. avoidance due to depression or anxiety), further reinforcing their mood state (Mkrtchian et al., 2017; Paulus & Yu, 2012).

Mood biases can also affect how an individual learns from rewards and punishments. Individuals in a positive mood state tend to learn more effectively from positive reinforcement (Zillmann, 1988), while individuals in a negative mood state tend to learn more effectively from negative reinforcement (Eldar et al., 2016; Forgas, 1995; Isen & Daubman, 1984; Oishi et al., 1999). Individuals in a negative mood state were more

likely to make negative predictions about future events and avoid potential rewards. This effect was stronger in participants with a history of depression, and it has been suggested that a biased approach to rewards may be a cognitive mechanism that maintains depressive symptoms (Oishi et al., 1999; Pulcu et al., 2014), in line with Beck's cognitive model of depression (Beck, 2002). Other research has shown that manic patients tend to not learn from the potential negative consequences of their actions which can lead to risky decision-making (Murphy et al., 2001; Ramírez-Martín et al., 2020), while depressed patients tend to not learn from positive consequences (Beck, 2008; Huys et al., 2015) maintaining the depressive cycle. Examining the relationship between mood, learning and behaviour is therefore important for better understanding healthy behaviour and the psychopathology of mood disorders.

Reinforcement learning (RL) has been widely used to study mood, learning, and decision-making. In RL, an agent learns about the world based on associations between actions and rewards or punishments it encounters (Kaelbling & Kaelbling, 1996; Sutton & Barto, 2018). In real life, humans learn about the world in similar ways, being motivated by rewards and avoiding punishments. Thus, reinforcement learning models can provide behavioural parameters that offer insight into both optimal behaviour (Mnih et al., 2015) and dysfunction and pathology (Huys et al., 2016b).

Fundamental to reinforcement learning is the notion of reward prediction errors [RPEs, (Berns et al., 2001; Schultz et al., 1997)]. RPEs are the difference between the predicted outcome and the actual outcome received. Large RPEs have been shown to induce positive or negative mood changes (Eldar & Niv, 2015), influence learning (Eldar & Niv, 2015; Gold et al., 2019), and even bias memory (Rouhani & Niv, 2019; Rouhani et al., 2018; Rouhani et al., 2020; Schultz et al., 1997). Momentary mood (i.e., how people feel at a given moment in time) has been shown to be influenced not by how well things are going (in terms of rewards) but by whether they are going better or worse than expected (Rutledge et al., 2014). Mood increases when rewards are better than expected (positive RPEs) and decreases following rewards that are worse than expected (negative RPEs) (Mellers et al., 1997; Shepperd & McNulty, 2002). Several other studies have found that mood is modulated by past prediction errors, both in lab-based experiments (Otto et al., 2016; Rutledge et al., 2015), large smartphone studies (Rutledge et al., 2014), and real-world emotions (Villano et al., 2020).

Eldar and Niv (2015) argued that it is not only surprising outcomes that bias mood, but mood also biases the perception of outcomes, and this relates to mood instability. The “Mood as Momentum” theory posited the role of mood is to track the rate of change of reward availability in the environment (Eldar et al., 2016). According to this theory, a high mood (either positive or negative) biases the perception of outcomes in the direction of the current mood, which then makes outcomes appear as better (or worse) than they actually are, leading to further increases (or decreases) in mood and maintaining the cycle of high (or low) mood.

To test this theory, the authors designed an experiment in which participants learned about the reward value of three slot machines during a learning block. This was followed by a mood induction procedure in the form of a wheel of fortune draw in which participants either won or lost \$7. Participants then completed a subsequent learning block, with new stimuli matched in reward probabilities to those in the first block. Finally, in the test block participants were asked to choose between slot machines learned about before and after the mood induction (Figure 2). Results showed that the large, unexpected outcome (Wheel of Fortune draw) affected the emotional state, increasing mood after wins and decreasing it after losses. Furthermore, mood biased reward valuation in the participants with a predisposition to mood instability (measured with the Hypomanic Personality Scale questionnaire). If participants won the draw, they were in a better mood and preferred the slot machines learned about after the draw. If they lost the draw, they were in a worse mood and preferred the slot machines learned about before the draw. In contrast, participants prone to more stable moods showed no influence of unexpected outcomes (and their associated mood) on the valuation of future rewards. The interaction between mood and reward perception was formalised with a reinforcement learning model that included a mood bias parameter which biased reward perception in line with current mood. The mood bias model explained the choices of participants with mood instability, while a standard value-based learning model (Rescorla & Wagner, 1972) better explained the choices of participants without mood instability. The authors concluded that the interaction between emotional state and reward perception may underlie mood instability. Mason et al. (2017) took these findings further and showed that the mood bias parameter from this model can generate patterns of mood symptoms seen in bipolar disorder (i.e. manic, depressive, and mixed episodes). While a moderate mood bias of reward valuation can serve an

adaptive role for the individual, strong mood biases can lead to cycles of elevated or depressed mood.

The original experiment by Eldar and Niv (2015) has several limitations that should be acknowledged. First, sample size was relatively small, and lacked diversity, with all participants being recruited from Princeton University, all being young highly educated adults aged 18-33. This may limit the generalizability of these findings to a larger, more diverse population. Many studies do not withstand replication attempts on a large scale (Rutledge et al. 2017) or with meta-analyses (Müller et al. 2017, Widge et al. 2019). When they do, the effect sizes tend to be small (Marek et al. 2020) and are primarily driven by comparisons between clinical groups and healthy controls (Davidson & Heinrichs 2003, Hoogman et al. 2019). Second, the study was conducted in a controlled laboratory setting and it remains unknown if these effects would survive in non-experimental conditions. Finally, it remains unknown whether the observed mood bias on reward perception effect was stronger in participants with mood instability because the mood induction had a stronger effect on them.

The present study aimed to replicate and extend previous work by Eldar and Niv (2015), by measuring the mood bias on reward perception in a large sample of participants from the general population. For this purpose, we developed a new, gamified version of the original task. Our game was designed as part of a freely available smartphone app (*The Happiness Project*) and could be used remotely, at any time, with minimal burden on participants. It allowed thousands of people from all corners of the world to play it, there was no limit to the number of plays available, or the times of day when people can access the app. The game was significantly shorter in duration, taking under 3.5 minutes to complete (about 10% of the previous task duration) and did not require researcher instructions.

The first aim of the current study was to evaluate if the *Wheel of Fortune* task was a successful redesign of the original task (H1 and H2). The second aim was to investigate the relationship between mood bias and mood instability in a large sample of the general population (H3). Finally, computational modelling was used to test the bidirectional relationship between mood and reward and how this related to mood instability (H4 and H5). I hypothesised the following:

H1. Participants will correctly learn which stimulus was more rewarding in each of the short learning blocks, evidenced by their choices during the learning blocks and at test.

H2. The mood manipulation will be successful in increasing momentary mood (after wins) and decreasing momentary mood (after losses).

H3. When presented with options that were learned under different mood states (i.e. pre versus post mood induction), participants with high trait mood instability will prefer the block they were happier in during learning.

H4. The winning computational model will include a bidirectional effect of mood on rewards (i.e. rewards bias mood and mood biases rewards).

H5. The computationally derived mood bias parameter will be higher in people with high mood instability (indicating greater impact of mood bias on reward perception) and lower in those with lower mood instability.

2 Methods

2.1 App design

The Happiness Project was developed as a smartphone app which features short, gamified cognitive tasks. The original release (4th January 2021) featured four games based on laboratory experiments. The app was (and still is) free and available to download for iOS and Android devices from: <https://rutledgelab.org/>. For more information about the app, please see Chapter 2: App development.

The app home screen first showed players two randomly selected games out of the four available. If players played both games, they unlocked the other two games. If

they completed all 4 games, they unlocked the first questionnaire, then the second and so forth until all questionnaires are unlocked.

2.2 Participants & Procedure

Participants freely downloaded the app from either Google Play or the Apple App Store, after hearing about it in news outlets. After downloading the app, participants were presented with a choice of sharing their data by selecting the option “take part in a scientific experiment” or not sharing data and simply playing the games for fun. The app was designed to collect anonymised data, complying with European data protection laws. There were no participant inclusion/ exclusion criteria defined, as the study aimed to include a large and diverse sample of the general population. Data from participants who indicated they were under 16 years old were excluded from the study as we could not obtain consent from their guardians.

Data included in this analysis were collected between the 4th of January 2021 and 15th of June 2021 and included a total of 4629 participants who agreed to share data. There was no reimbursement for taking part. The Research Ethics Committee of University College London approved this study.

2.3 The Wheel of Fortune (‘WoF’) game

The data presented in this study are from the *Wheel of Fortune* game, see Figure 1 below. The design of the game was based on the task developed by Eldar and Niv (2015). The goal of the game was to collect as many gems as possible by learning which stimulus (or animal) was better.

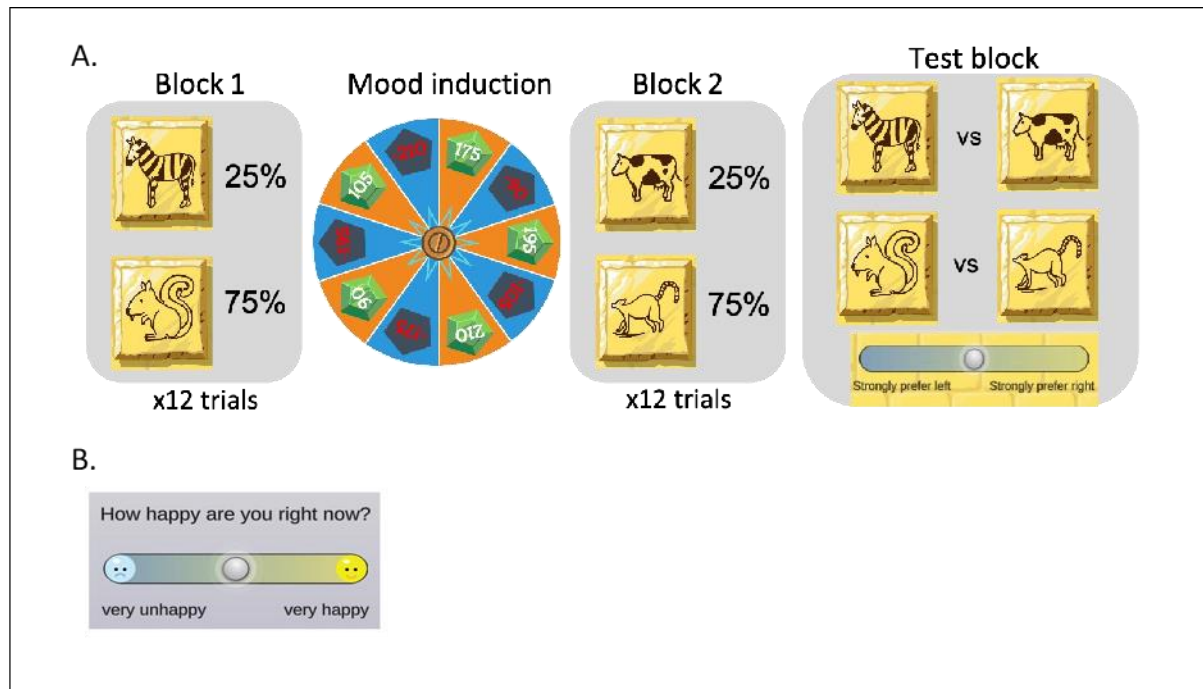


Figure 1. Wheel of Fortune game design. A. Participants learned by trial and error about two stimuli in each block, one associated with rewards 75% of the time and the other 25% of the time. Between the learning blocks positive or negative mood was induced by spinning a wheel of fortune. Finally, in the test block trials participants were asked to choose which animal they preferred (left or right) by binary choice and slider rating. B. Momentary mood ratings appeared on the screen every 3-4 trials.

2.3.1 Learning blocks

The game included two learning blocks, in which participants learned by trial and error which of the two stimuli presented was rewarded more often. In each learning block one gave a reward 25% of the time, while the other gave a reward 75% of the time (see Figure 1). The reward was always 40 gems which were added to their total gems and displayed on screen throughout the game. The gems did not have any real monetary value. There were 12 trials in each learning block, 8 free choices between the two stimuli and 4 forced choices (only one stimulus was presented and participants were 'forced' to select it), to ensure sampling of all stimuli.

2.3.2 Mood induction procedure

In between the learning blocks, there was a mood induction manipulation in the form of a wheel of fortune. Participants spun the wheel as fast as they wanted by tapping on the screen. The wheel then slowly stopped on one of the 10 possible outcomes and the total number of gems was updated accordingly (Figure 1). The outcomes were 90, 105, 175, 195, 210, equal for wins and losses.

2.3.3 Test blocks

The test block asked participants to select which animal was best out of the two presented ("Which animal was best? Go with your gut!"). Participants made binary choices as well as slider ratings to indicate their degree of preference for one animal or the other (Figure 1). Comparisons included animals learned in the current game as well as animals learned in previous plays. Test trials comparisons within block (i.e. high vs low reward animals learned in block 1 and block 2, respectively) served as a learning test when probing the current play and as a memory test when probing previous plays. Comparisons of equally rewarding animals learned in pre- and post-mood induction blocks (low vs low and high vs high reward animals) quantified the effect of mood bias on reward perception.

2.3.4 Momentary mood ratings

Momentary mood was sampled three times throughout each learning block by asking participants to indicate how happy they were feeling at that moment by moving the slider from 'very unhappy' to 'very happy' (Figure 1B.). The slider was always displayed in the neutral position (at 0.5 on a scale from 0 to 1). The position of mood ratings within the blocks was jittered, ratings appearing every 3-4 trials and never after a forced-choice trial.

Mood change was defined as the difference between the average mood rating in block 2 (ratings 4-6) and the average mood in block 1 (ratings 1-3), such that a positive mood change score meant participants were happier in block 2 and a negative score meant they were happier in block 1.

2.4 Questionnaires

The app also included the following questionnaires: a trait measure of proneness to strong and changeable moods, related to predisposition to bipolar spectrum disorders - the Hypomanic Personality Scale [HPS, (Eckblad & Chapman, 1986)]; a measure of severity of depression symptoms - Patient Health Questionnaire [PHQ-8, (Kroenke et al., 2001)]; a measure of severity of anxiety symptoms - Generalised Anxiety Disorder Scale [GAD-7, (Spitzer et al., 2006)]; and the behavioural subscale from the Apathy and Motivation Index [bAMI, (Y.-S. Ang et al., 2017)].

The HPS short version was used for brevity, as it strongly correlates to the original 48 item version [$r = 0.92$, $p < .001$, (Sperry et al., 2015)]. The questionnaire was developed to assess tendencies towards subsyndromal manic symptoms as well as personality traits thought to be related to bipolar disorder and shown to have high reliability (15-week test–retest reliability = 0.81; $\alpha = 0.87$, (Eckblad & Chapman, 1986)). Research shows that over a 13-year follow-up period, 73% of persons at high risk for mania as defined by the HPS developed diagnosable symptoms of bipolar spectrum disorder (Kwapil et al., 2000). Furthermore, numerous psychosocial variables, predictive of the trajectory of mania within bipolar disorder, exhibit strong correlations with risk indicators for mania (Alloy et al., 2008; Jones et al., 2006).

The PHQ-8 was used to measure depression severity as it was shown to be a simple, effective, and reliable tool for this purpose. The PHQ has a high test-retest reliability coefficient of 0.74 and internal consistency Cronbach's α of 0.89, and correlates ($r = 0.61$, $p < .001$) with other depression measures such as the Hamilton Depression Scale (Sun et al., 2020).

The GAD-7 was selected to measure anxiety, having been used to detect symptoms of anxiety disorders in various settings and across diverse populations, beyond its original use in primary-care settings. It has an excellent internal consistency coefficient Cronbach's α of 0.895, and good convergent validity (Dhira et al., 2021).

The Apathy-Motivation Index (AMI) is a brief self-report index of apathy and motivation. In the current study the Behavioural Activation subscale (bAMI) was used to measure tendency to self-initiate goal-directed behaviour. The test-retest reliability coefficient for the bAMI was 0.84, and it strongly correlated with other apathy measures, confirming good construct validity (Y. S. Ang et al., 2017).

Questionnaires were introduced on the app as items to be completed in a staged manner after playing the games. The first questionnaire to unlock was the PHQ, followed by the GAD, bAMI, and finally, HPS which was our primary measure of interest. Due to this design, only a subsample of participants completed the HPS questionnaire.

2.5 Planned statistical analyses

All analyses were performed using MATLAB (Version, 2020). All averages were reported as mean \pm standard deviation (SD) in text and tables, and as mean \pm standard error of the mean (SEM) in figures. Parametric tests were used when data were normally distributed, otherwise non-parametric tests were used. The significance threshold was defined as $p = 0.05$.

2.5.1 H1. Participants will correctly learn which stimulus was more rewarding in each of the short learning blocks, evidenced by their choices during the learning blocks and at test.

During each learning block, participants made choices between the two animals presented on the screen and got rewarded with gems - the more rewarding animal gave out gems 75% of the time (later referred to as the high probability of reward animal or high prob animal) and less rewarding animal gave out gems 25% of the time (low probability or low prob animal). Learning curves were calculated as the average percentage of participants who selected the more rewarding option, during each of the 8 free-choice trials. Forced-choice trials were excluded from this analysis as they did not represent a measure of learning or choice. Initially, an equal proportion of

participants (50%) were expected to choose the more rewarding and less rewarding options in the game. Over the course of the blocks, performance was expected to improve as participants learned which option was more rewarding. By the end of each block, the average participant performance was expected to surpass chance level. To evaluate differences in learning between blocks, t-tests were used.

Learning was probed in the test trials by asking participants to choose between the more and less rewarding animals they learned about in each block. Responses were coded as correct if participants chose the more rewarding animal or incorrect if they chose the least rewarding one, then averaged across participants (to compute each person's score) and across blocks (to compute the block average).

To examine if mood impacted learning, block two was split into positive mood (i.e. won the wheel draw) and negative mood (lost the wheel draw). Differences between blocks and mood states were assessed with non-parametric tests like the Wilcoxon rank sum test because data was not continuous and normally distributed.

2.5.2 H2. The mood manipulation will be successful in increasing momentary mood (after wins) and decreasing momentary mood (after losses).

The mood induction effect was computed by comparing the average momentary mood ratings which followed the WoF (ratings 4 to 6) with the average mood ratings before the wheel (ratings 1 to 3). Here, all outcomes of the wheel were included and only split by valence (won or loss). Paired t-tests were used to assess whether the mood induction was successful in increasing mood (after win) and decreasing it (after loss).

Mood change was defined as the average mood in block 1 subtracted from average mood in block 2. Positive mood change values meant participants were happier in block 2, while negative values meant they were happier in block 1. To examine the relationship between mood change and WoF reward magnitude, a linear regression analysis was used.

To investigate if there were any group differences in momentary mood ratings between high and low HPS participants (groups defined by median split), a repeated measures ANOVA was used. It looked at the effect of rating number, HPS group and WoF outcome on momentary mood ratings. Post-hoc analysis used t-tests. Additionally, a linear regression analysis assessed if there was a continuous relationship between mood change and psychiatric symptoms severity. This analysis included the following symptoms scales: HPS (mood instability), PHQ (depression), GAD (anxiety), and bAMI (apathy and motivation).

In an exploratory analysis, the impact of recent outcomes on momentary mood was also computed. A 2 [effect of outcome: getting a reward or not] x 2 [reward probability: choosing the more rewarding or less rewarding animal] ANOVA was used, followed up with post-hoc t-tests.

2.5.3 H3. When presented with options that were learned under different mood states (i.e. pre versus post mood induction), participants with high trait mood instability will prefer the block they were happier in during learning.

To test whether the WoF draw affected not only participants' mood, but also their valuation of stimuli in the second learning block, participants were presented at test with choices between stimuli which had objectively equal reward probabilities, learned about before and after the WoF draw. This analysis focused on the test comparison between the highly rewarding stimuli of each block, as a measure of mood bias. Specifically, the slider responses that participants gave, as they were a continuous measure of preference and an indirect measure of the confidence participants had in their responses. For example, on the scale of 0 to 1, a rating of 0.8 indicated stronger confidence in the choice of that animal than a rating of 0.53 (which is closer to the middle of the scale representing no preference for either one or the other). Comparison between low rewarding stimuli were omitted because participants rarely chose the low prob stimuli and therefore their exposure to these items was limited.

Participants' experience of the reward probabilities could have differed between blocks, impacting learning unevenly. While overall the probabilities for high prob animals in each block were set to reward participants 75% of the time, participants' freedom to choose either animal on each trial affected the total reward probabilities they actually experienced, one stimulus sometimes being rewarded more than the other (usually because it was chosen more frequently). For example, if a participant chose the high prob stimulus in block 1 six times and got rewarded four times, their experience of reward probability for that stimulus was 66%, while if in block 2 they chose the high prob stimulus eight times and got rewarded six times, their reward probability would be 75%. To account for these differences, I regressed out the difference in experienced probability from the high prob slider ratings. T-tests in residuals from the regression were used to compare test block preference in the positive versus negative mood conditions.

To test whether mood bias was different in participants with high versus low trait mood instability, a 2x [group: high or low HPS] x 2 [mood induction: won vs lost] ANOVA was used, followed by post-hoc t-tests.

The effect of demographics (age, gender) and other mental health symptoms (depression, anxiety, apathy) on mood bias were also explored. This was done with a mixed multiple regression model looking at the effects of these factors on mood bias as well as interaction effects.

The relationship between mood bias and mood change was investigated using linear regression, testing the prediction that larger changes in mood predicted larger mood bias in the same direction (i.e. preference for the block they were happier in).

2.5.3.1 Mood bias and memory over time

The free app-based nature of the game meant participants could play as many times as they wished, with varying amounts of time in between plays. From play 2 onwards, participants 'unlocked' test block comparisons of animals learned during previous games. This allowed me to look at how memory and mood bias decay over time. 'Memory' in this context, was measured as the ability to remember that the high probability animal was more rewarding than the low probability animal. This was

probed only on block 1 from previous games, because it was the neutral block and was free from potentially biasing mood effects.

Exploratory analyses looked at the correlation between memory for the more rewarding animal versus the number of days that passed between learning about that animal and the test probe. Similarly, I explored mood bias changes over time, under each mood induction condition (won vs lost WoF).

2.5.4 H4. The winning computational model will include a bidirectional effect of mood on rewards (i.e. rewards bias mood and mood biases rewards).

Model comparison was used to indicate which model best fit the behavioural choice data and mood ratings. This is explained in more detail below, in the section 'Model comparison'.

2.5.5 H5. The computationally derived mood bias parameter will be higher in people with high mood instability (indicating greater impact of mood bias on reward perception) and lower in those with lower mood instability.

T-tests and non-parametric alternatives were used to assess the differences in the model mood bias parameter between high and low HPS groups. Exploratory analyses also looked at the other model-derived parameters and their relationship with HPS groups.

2.6 Reinforcement learning model

In standard reinforcement learning, agents learn about the expected value of a stimulus based on a reward prediction error (RPE) – the difference between the reward obtained and the reward expected. Expected values and RPEs are linked to midbrain

dopamine activity, which tracks rewards in environment (Hollerman & Schultz, 1998; Pessiglione et al., 2006). A Q-learning model is a model-free reinforcement learning algorithm designed to learn the value of a particular action given a particular state. It will then find the optimal policy (i.e. course of action) to maximise the expected value of total rewards. See Figure 2 below for a representation of the Q algorithm.

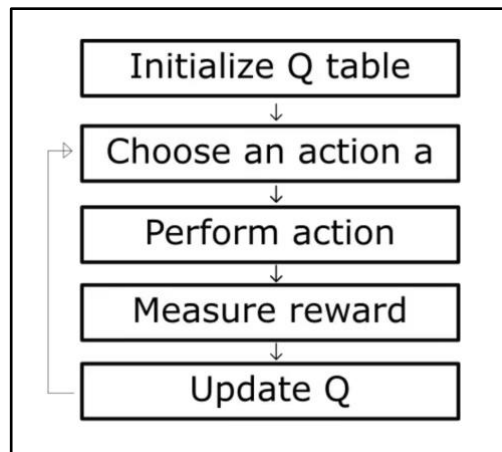


Figure 2. Q-learning algorithm steps.

However, the Q-value RL model (later referred to as the non-moody RL model) does not account for the effect of mood on valuation or reward. To address this, Eldar and Niv (2015) modified the model to compute RPEs based on reward perceived instead of actual reward received. This is described in the following equation:

Equation 1

$$RPE = r_{perceived} - EV$$

The reward prediction error is calculated as the difference between the perceived reward ($r_{perceived}$) and the expected value of reward (EV). The perceived reward accounts for the biasing effect of mood, as follows:

Equation 2

$$r_{perceived} = r * f^m$$

Equation 3

$$m = \tanh(m)$$

Where f is a free parameter which represents the direction and magnitude of the mood bias (larger f value means larger mood bias), while m indicates good ($0 < m < 1$) or bad mood ($-1 < m < 0$) and m is constrained to the range -1 to 1 by a sigmoid transformation. When $f = 1$, mood does not bias reward value and the reward perceived is the same as the actual reward. If $f > 1$, mood exerts positive feedback and rewards will be perceived as being larger than they are, when in a good mood ($0 < m < 1$) and smaller than they are, in a bad mood ($-1 < m < 0$). Conversely, if $f < 1$, mood exerts negative feedback and rewards will be perceived as larger when in a bad mood and as smaller when in a good mood.

Eldar and Niv (2015) note that the mood bias has been defined as a multiplicative effect to maintain scale invariance, but the same results were obtained when mood bias was modelled as an additive effect. In this paper, I also defined the effect of mood bias on reward as a multiplicative effect, for consistency with previous work.

The following equation was defined to model the effects of RPEs on mood. Here, mood reflects a recent reward prediction error history, weighted by a step-size parameter η_h (mrate).

Equation 4

$$mood_{(t)} = mood_{(t-1)} + \eta_h(RPE - mood_{(t-1)})$$

Expected values were updated after every trial based on the outcomes and the prediction error and weighted by a step-size learning rate parameter η_v , as below:

Equation 5

$$EV_{(t)} = EV_{(t-1)} + \eta_v * RPE_{(t-1)}$$

The main differences between the non-moody RL model and the Eldar and Niv (2015) moody model are summarised in Figure 3.

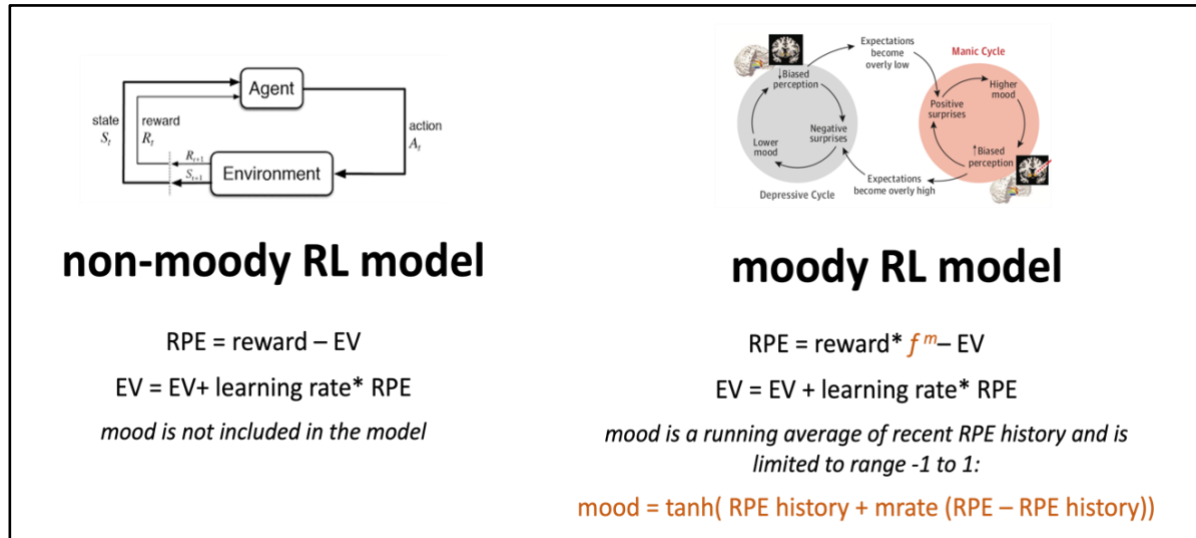


Figure 3. Brief description of the non-moody Q-value RL model (left) versus the moody model developed by Eldar and Niv (2015) (right).

In the process of model selection, a careful evaluation of existing computational models was conducted, placing emphasis on their capacity to capture the intricate interplay between mood and reward—a critical factor in understanding the mood dynamics observed in bipolar disorder. At the time of model selection, only two computational modelling approaches were published: the Eldar and Niv (2015) model and the Vinckier et al (2018) model. While the Vinckier model also included the recursive effect of mood conceptualised in a similar way as it was partially based on the Eldar and Niv (2015) model, their experimental set-up and modelling was based on utility theory, choices being considered based on potential gain and loss and probability of success vs. failure as opposed to investigating mood in the context of learning. As the current study was interested to examine the biasing effect of mood on learning and decision-making, the Eldar and Niv (2015) model was chosen.

2.6.1 Model-based behavioural analysis

Firstly, a Softmax function was used to derive each participant's trial-by-trial choice probability during the learning blocks. The softmax function is a mathematical operation used to convert a vector of numerical scores into a probability distribution. It exponentiates each score and normalizes the results, ensuring that the probabilities add up to one.

The probability $P(c_t = c, t)$ of choosing stimulus c at trial t was proportional to $e^{\beta v_{c,t}}$, where e is Euler's number, a mathematical constant approximately equal to 2.71828 and β is an inverse temperature parameter which controls choice stochasticity. If $\beta = 0$ choices are completely random while if $\beta = \infty$ the highest value option is chosen deterministically.

Secondly, I compared the mood inferred by the model, based on choices and outcomes during the learning blocks with the real mood ratings participants gave. To better account for any systematic mood rating differences between participants, I added the following parameters to model mood ratings: a multiplicative scaling parameter for mood ratings (β_{mood}) and an additive baseline mood parameter (b_{mood}) accounting for a lower/higher baseline mood, as follows:

Equation 6

$$\text{Mood ratings} = \text{mood ratings} \times \beta_{mood} + b_{mood}$$

I then computed the probability of observing a particular set of rescaled real mood ratings (rescaled from 0 to 1 to -1 to 1 to match model mood distribution) given the model mood values and added this quantity to the overall likelihood evidence for those models.

Thirdly, in the new slider model (see Figure 4.), I compared the probability of observing slider choices participants gave (z-scored) with the Q-value differences for each choice (z-scored) and added this quantity to the model evidence for the slider models.

Similarly to mood, slider ratings were adjusted with a scaling parameter (β_{slider}) and baseline slider parameter (b_{slider}), as follows:

Equation 7

$$\text{Slider ratings} = \text{slider ratings} \times \beta_{slider} + b_{slider}$$

The total likelihood value for each participant was a sum of the likelihoods of learning block choices, mood ratings and, only for the slider models, slider ratings.

2.6.2 Model parameters

To fit the parameters to subjects' decisions, I used importance patterns (Bishop & Nasrabadi, 2006). With this method, I sampled 40,000 random parameter value sets from previously defined distributions. I then computed the likelihood of observing participants' real choices and the likelihood of observing participants' real mood ratings given the model parameter values. For each set of parameter values, I computed an average value, weighted by likelihood that the model parameters explain the observed behaviours. The model resampled parameter values and repeated the process until the fit could no longer be improved. The best fitting parameters were selected from the best model fit.

The free parameters included in the models were: f , η_v , η_h , β , β_{mood} , β_{slider} , b_{mood} , b_{slider} .

The learning rate and mrate parameters (η_v , η_h) were modelled with Beta distributions (with shape parameters $a = 1$ and $b = 1$), which essentially corresponds to a uniform distribution across the $[0, 1]$ range. This allowed an initial lack of strong prior beliefs or preferences. The use of a Beta distribution with equal shape parameters reflected a neutral stance, where all values within the specified range are initially considered equally probable. As the game progressed and participants gathered more information, these parameters were updated.

The mbias parameter (f) was modelled with a normal distribution to allow for both positive and negative effects (initialised with $\mu = 0$ and $\sigma = 1$), with 0 being the most

likely value as the expectation was that most participants do not show a mood bias (except those with high mood instability).

The inverse temperature and scaling parameters (β , β_{mood} , β_{slider}) were modelled with Gamma distributions (initialised with $\kappa = 1$, $\theta = 1$), representing a distribution over positive real numbers as these parameters cannot take negative values. The inverse temperature parameter quantified the amount of stochasticity in participant responses, with higher inverse temperatures translating to more deterministic choices. Scaling parameters were used to adjust the mood and slider ratings based on the variability within each participant's ratings.

The baseline scaling parameters (b_{mood} , b_{slider}) were modelled with a normal distribution to allow positive or negative values (initialised with $\mu = 0$ and $\sigma = 1$), scaling the modelled value up or down depending on each individual's baseline rating. The model assumed 2 hyperparameters per parameter, to allow for more flexibility and control over the prior assumptions of the model.

2.6.3 Model comparison

To test the assumption that mood has a bidirectional effect on reward value, we compared between three types of models (see Figure 4). The first was a '*no moody*' model where mood had no impact on outcomes ($mbias$ was defined as 1) or on future RPEs ($mrate$ as 0). This was conceptually the same as a standard Q-learning model. The second was a '*partial moody*' (*PM*) model in which outcomes affected mood, but mood did not affect perception of outcomes ($mrate$ sampled, $mbias = 1$). The third was a '*full moody*' (*FM*) model that included both $mrate$ and $mbias$ parameters and thus modelled the effect of outcomes on mood and the effect of mood on perception on future outcomes.

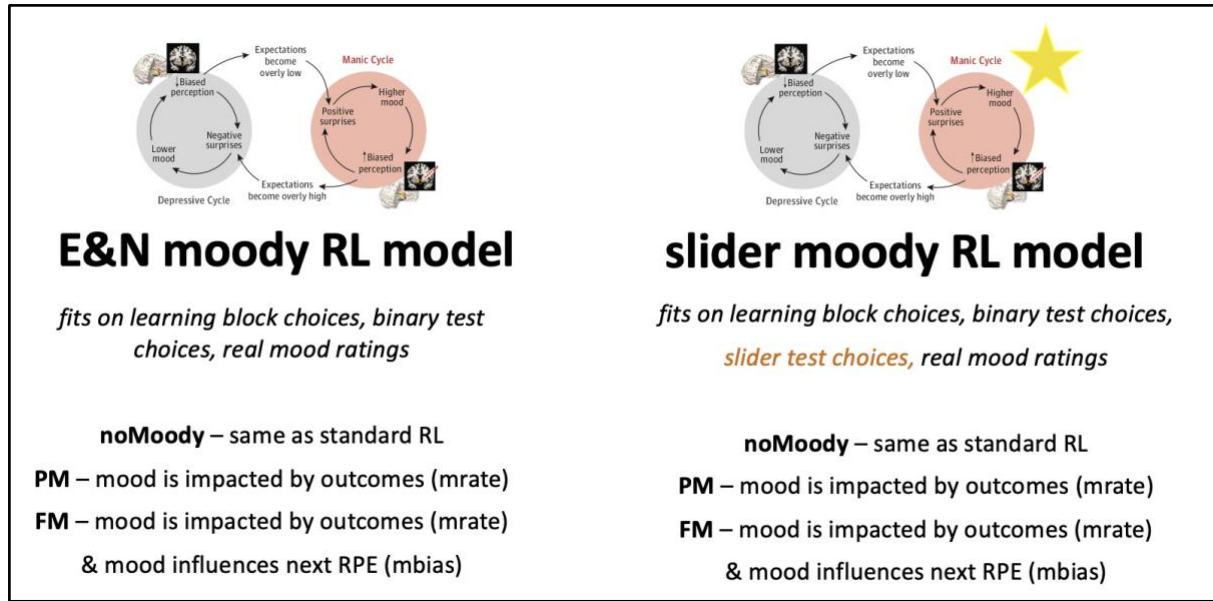


Figure 4. Eldar and Niv (2015) moody RL model family versus the slider version of the moody model family.

I defined two families of models. First, the model family developed by Eldar and Niv (2015) which fit learning trials, binary test trials and mood ratings and presented in Figure 4. as *E&N moody RL model*. Second, I extended these models to also include the continuous slider test choices participants made. Named suggestively the *Slider moody RL model* family, these models fit learning trials, binary test trials, mood ratings and continuous slider test ratings (see Figure 4). Models within families were compared using the Bayesian Information Criterion [BIC, (Gideon, 1978)] as defined below:

Equation 8

$$\text{BIC} = -2 \times \ln(\text{Lik}) + \ln(n_{\text{datapoints}}) \times k$$

Where \ln is the natural logarithm, Lik is the maximized value of the likelihood function of the model, $n_{\text{datapoints}}$ is the total number of data points being fit, and k is the number of free parameters being estimated. Model families were compared separately because they had different total number of data points being fit (only choices versus choices and slider ratings).

The BIC model comparison trades off between generalisability (i.e., how well this model can explain other data sets) and complexity (i.e. the number of parameters).

The BIC penalises models for any additional complexity, guarding against overfitting by adding more parameters that explain the variance in the dataset. BIC scores are used to compare between models, where a lower BIC generally means a better fit. Another way to easily compare BIC scores is to calculate the difference between the BIC for the model with the lowest score and the BIC score of other candidate models (Table 1.).

Table 1. Bayesian Information Criterion (BIC); ΔBIC is the difference between BIC values for two models (B minus A).

| | |
|---|---|
| $\Delta\text{BIC} = < 2$ | Little evidence to distinguish Models A and B. |
| $\Delta\text{BIC} = 4 - 7$ | Moderately less support for Model B over Model A. |
| $\Delta\text{BIC} = 8 - 9$ | Considerably less support for Model B over Model A. |
| $\Delta\text{BIC} > 10$ | Very little support for Model B. |

3 Results

3.1 Demographic information

Data from 4629 participants were included in the current study. Participants played a minimum of one up to a maximum of thirty *Wheel of Fortune* games, totalling 7412 plays overall. Demographic information is summarised in Table 2. for the 4629 unique players. The original questionnaire order of appearance in the app was: PHQ-8, GAD, bAMI and finally HPS, hence the different numbers of unique participants completing each measure.

Table 2. Demographic information for all participants who took part in the study.

| | N | Mean | SD | Range |
|--------------------------|----------|---|-----------|--------------|
| Age | 4629 | 41.99 | 15.14 | 16 – 80 |
| Gender | 4629 | 60.8% female 17.5% male 21.7% other | | |
| Education level | 4629 | 7.1% school (GCSE or similar) 12.5% school (A-levels, vocational or similar) 29.9% university degree 25.5% advanced degree (MA, PhD, etc) 25% prefer not to say | | |
| Life satisfaction | 4629 | 6.19 | 2.05 | 0 – 10 |
| PHQ-8 | 3153 | 7.58 | 5.76 | 0 – 24 |
| GAD | 3042 | 6.55 | 5.49 | 0 – 24 |
| bAMI | 1692 | 10.55 | 4.92 | 0 – 25 |
| HPS | 1052 | 32.34 | 8.62 | 0 – 60 |

3.2 H1. Participants will correctly learn which stimulus was more rewarding in each of the short learning blocks, evidenced by their choices during the learning blocks and at test.

Results showed that by the end of the learning blocks, 69.5% of participants were selecting the more rewarding animal. As expected, participants started at chance level, exploring the two options in each block equally. Performance improved, plateauing at

around the fourth trial. Performance between blocks did not differ by the last choice [$p = 0.89$], suggesting participants were able to correctly identify the more rewarding animal equally well within each block, and this was not affected by the mood induction (Figure 5).

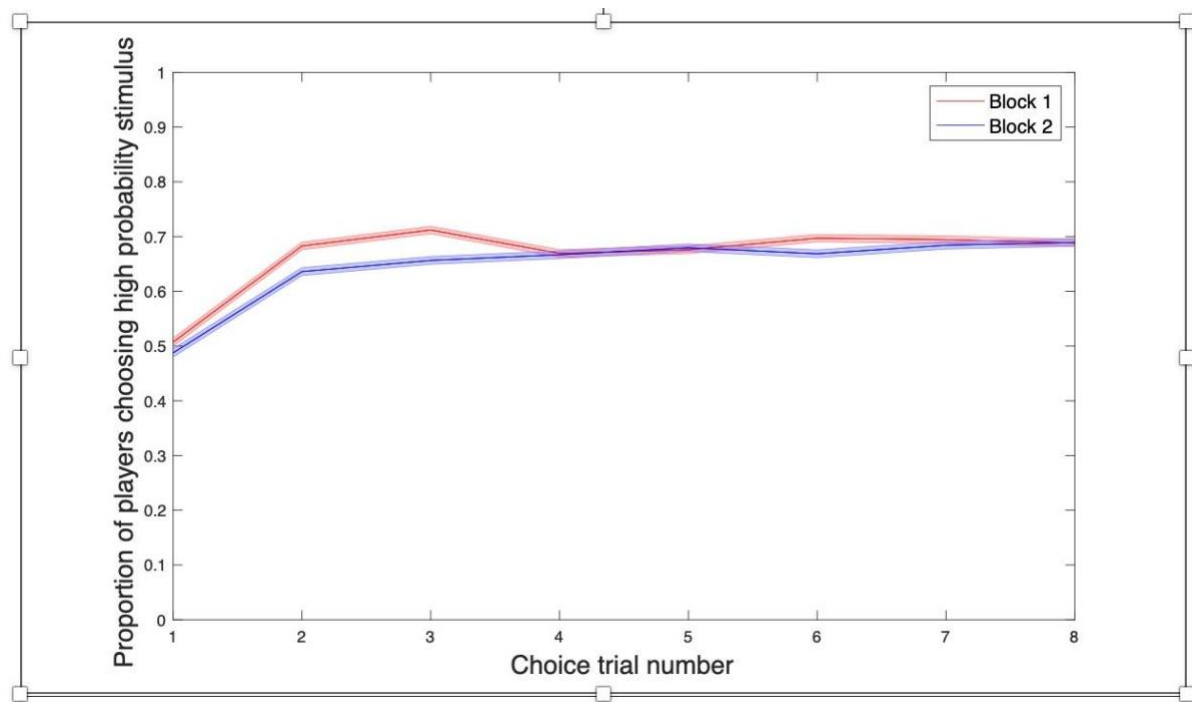


Figure 5. Proportion of participants correctly choosing the stimulus rewarded more often (i.e. the high probability of reward stimulus) at each choice trial, split by block 1 (red) and block 2 (blue). The lines are the average values while the shading is the SEM. By the end of the learning blocks performance was at 69.5% for each block. $N=4629$ players, play 1 only.

In the test block, when asked to choose which animal was better between the low probability and the high probability animals, more than 70% of the time participants correctly identified the high probability animal. As shown in Figure 6 below, participants were slightly more accurate when probed on animals they learned during block 1 [$M = 75.31$, $SD = 38.5$] than block 2 [$M = 72.35$, $SD = 40.51$], as indicated by a Wilcoxon rank sum test [$z = 3.21$, $p = 0.001$]. There was no significant difference in accuracy in

block 2 between the positive (won WoF) and negative (lost WoF) mood induction conditions [$z = -1.53$, $p = 0.23$].

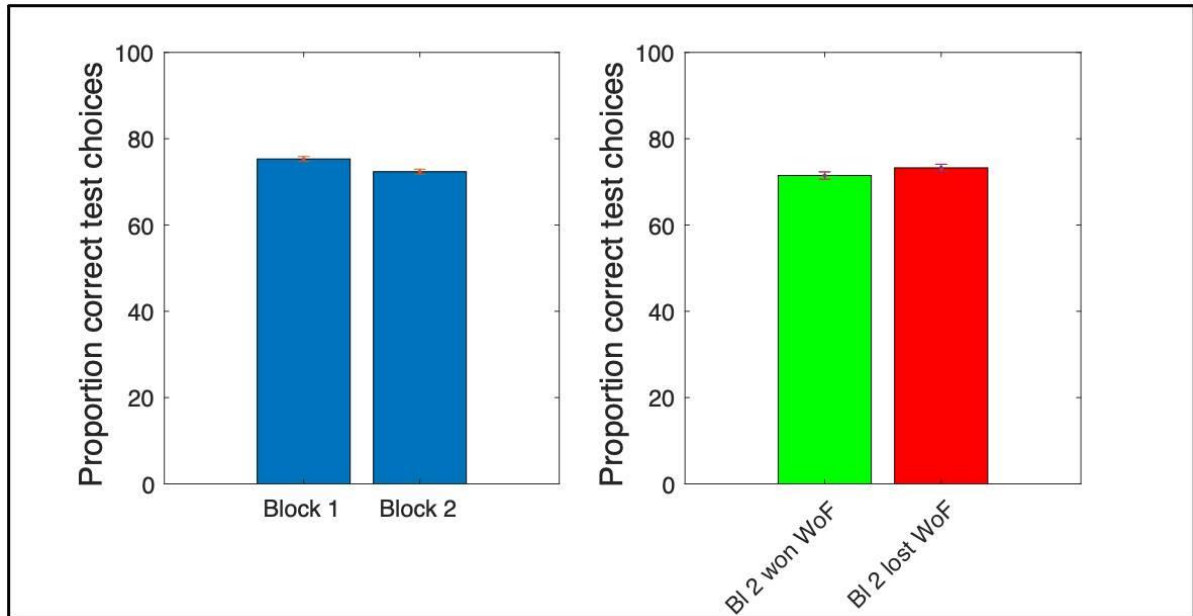


Figure 6. The average proportion of correct responses in test block comparisons of high versus low probability animals, for each block separately (left, blue) and for block 2 split by the mood induction (right, green/red). Bars are averages and error bars are SEM. $N=4629$ players (2314 won WoF, 2315 lost WoF), play 1 only.

3.3 H2. The mood manipulation will be successful in increasing momentary mood (after wins) and decreasing momentary mood (after losses).

The mood manipulation was successful in modulating participants' mood (see Figure 7). Participants reported significantly lower mood after losing on the WoF [$t(2315) = -9.97$, $p = 5.7 \times 10^{-23}$, $d = -0.42$] while winning on the wheel resulted in an increase in momentary mood [$t(2312) = 7.61$, $p < 0.0001$, $d = 0.32$].

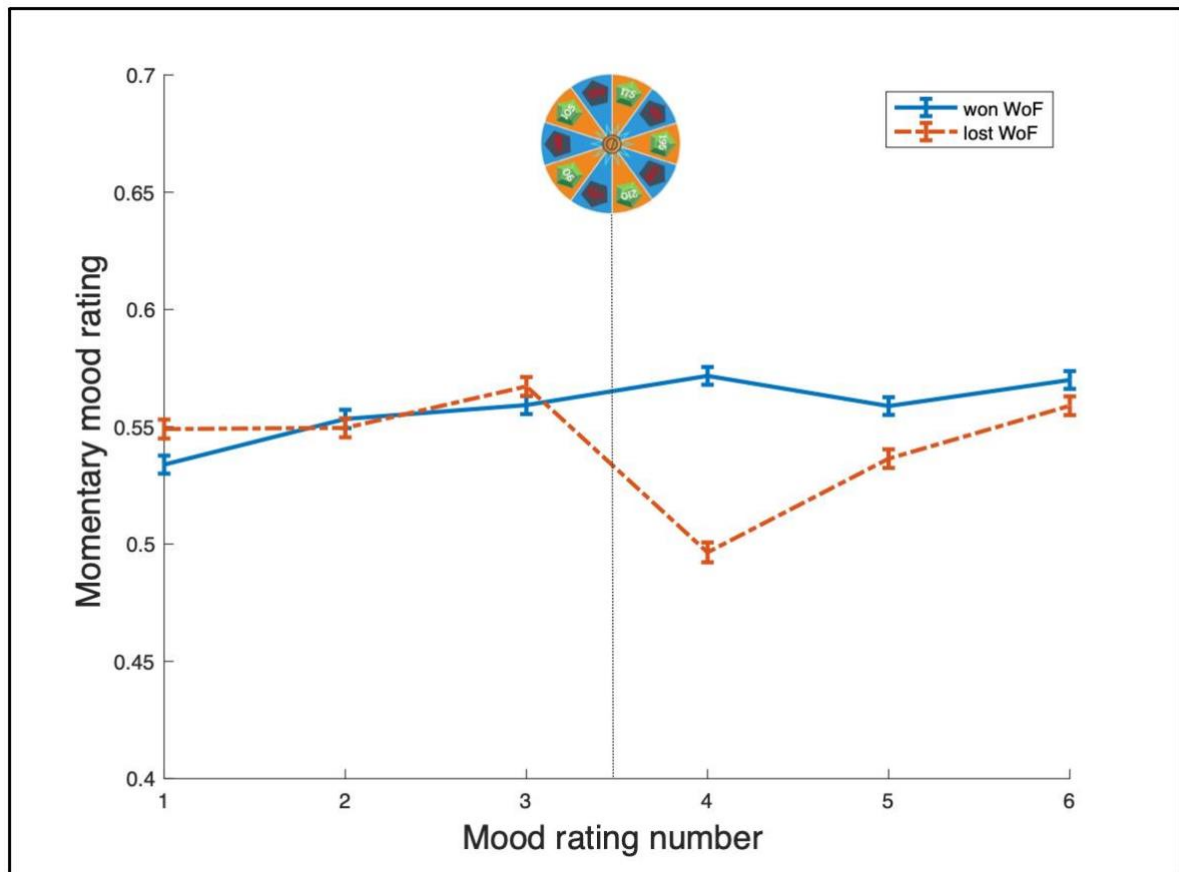


Figure 7. Self-reported momentary mood ratings averaged across all participants (mean and SEM), in block 1 pre-mood induction (ratings 1 to 3) and block 2 post-mood induction (ratings 4 to 6), split by the Wheel of Fortune outcome. On average, participants were happier after winning and less happy after losing the WOF spin. N=4629 participants, play 1.

Mood was modulated by reward magnitude [Figure 8; $\rho = 0.19$, $p = 7.34 \times 10^{-38}$], decreasing as a function of the loss magnitude (the more participants lost the unhappier they became) and increasing as a function of gain magnitude (the more they won the happier they became). The negative mood induction was more powerful in altering participants' moods than the positive mood induction, although these differences are small [Mean absolute mood change after wins = 0.02, SD = 0.11; Mean absolute mood change after losses = 0.03, SD = 0.12; $d = -0.09$; $p = 0.001$]. This is indicative of the notion of loss aversion, where losses are more impactful than wins of the same magnitude (Kahneman & Tversky, 1979).

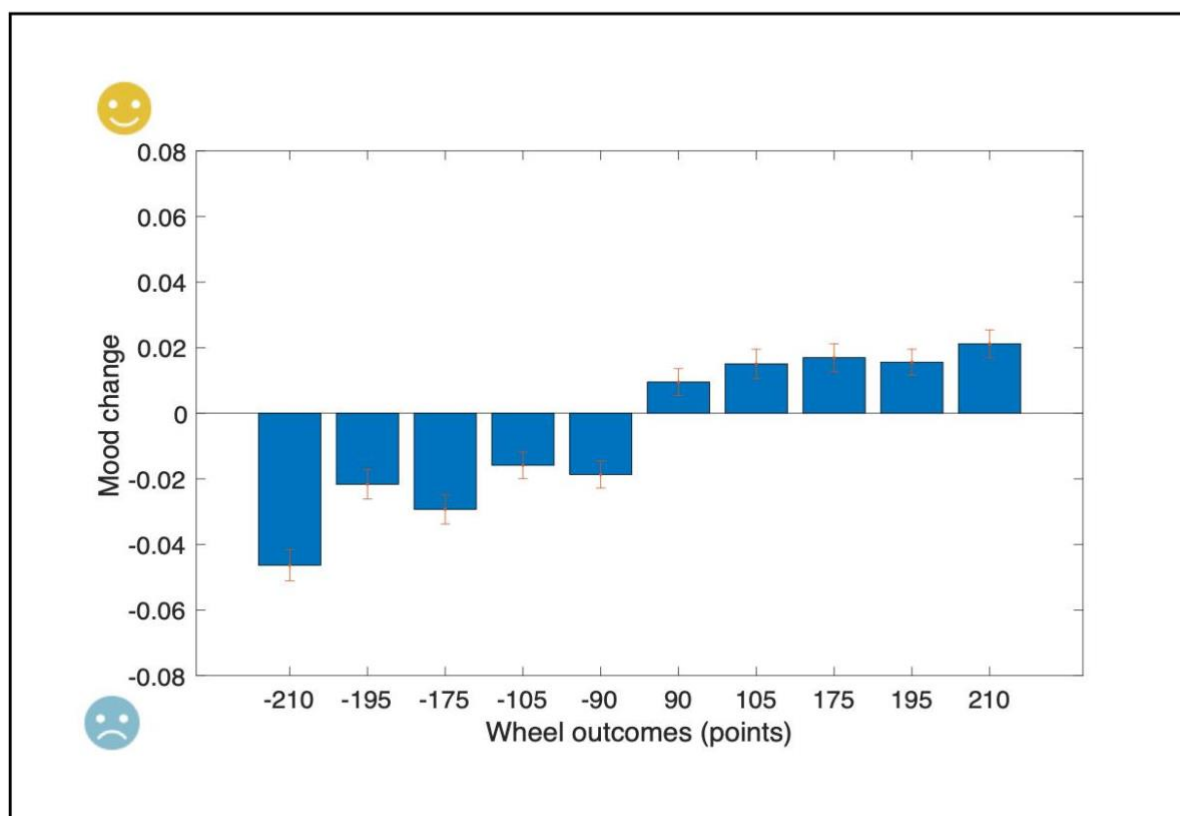


Figure 8. Average mood change (average mood in block 2 minus average mood in block 1; mean and SEM) for each of the 10 possible Wheel of Fortune outcomes. Reported mood change was proportional to the amount won or lost on the wheel spin. N=4629 players, play 1 only.

To investigate the effect of the mood induction on participants with high mood instability, they were median split into two groups based on their scores on the HPS. Participants with low hypomanic traits scored less than 33 on the HPS, while participants with high hypomanic traits scored 33 or above.

As seen from Figure 9, participants with high hypomanic traits reported lower momentary mood throughout the task, irrespective of the mood induction condition. A repeated measures ANOVA showed there was an effect of rating number on reported mood [$F(5,5285) = 11.55, p < 0.0001$] and an effect of HPS group [$F(1,1057) = 21.30, p < 0.0001$]. The effect of the wheel draw did not reach significance [$p = 0.41$], but a

pairwise comparison showed that ratings following the wheel draw differed significantly depending on the outcome [$p < 0.0001$] decreasing following loss and increasing following win, while the three ratings before the wheel of fortune did not differ [$p > 0.12$]. High and low HPS groups reported equal changes in mood following the mood induction [$p > 0.57$].

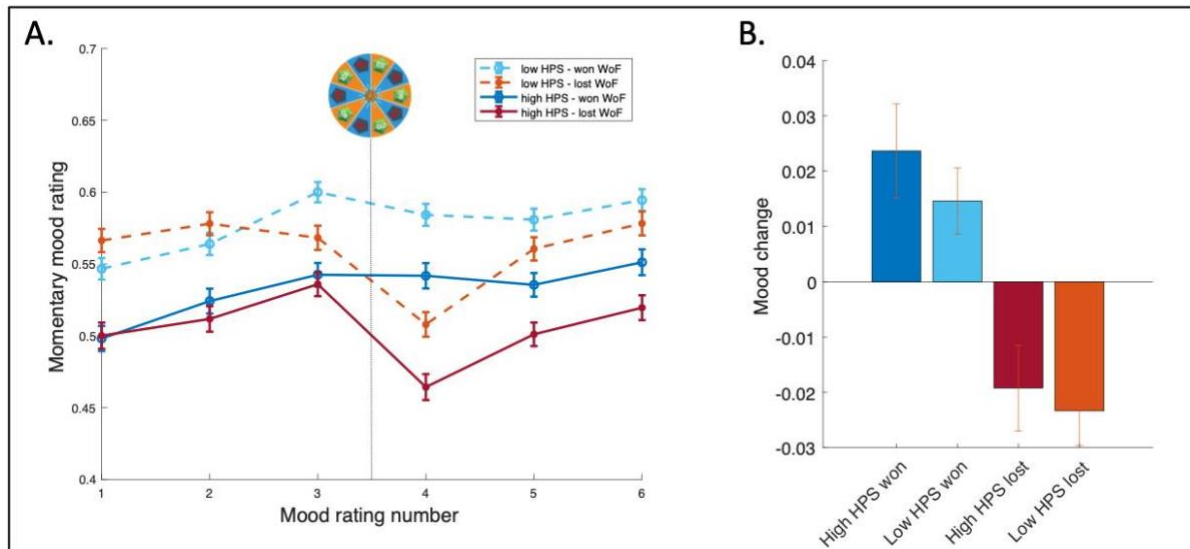


Figure 9. Momentary mood ratings before and after the mood induction, split by HPS group. A) Momentary mood ratings (mean and SEM) in block 1 pre-mood induction (ratings 1 to 3) and block 2 post-mood induction (ratings 4 to 6) split by high and low HPS groups and WoF outcome, on the left-hand figure. **B)** Mood change split by mood induction and HPS group. High and low HPS groups reported equal changes in mood following the mood induction [$p > 0.57$]. N=1052 players, play 1 only.

3.3.1 Mental health symptoms did not modulate response to the mood induction

Additionally, a linear regression analysis confirmed there was no relationship between mood change and psychiatric symptom severity [$F(3,974) = 1.13$, $p = 0.33$]. These included mood instability measured with HPS [$\beta = -0.0003$, $t(974) = -0.23$, $p = 0.82$, $d = -0.01$], depression measured with PHQ [$\beta = 0.006$, $t(974) = 1.31$, $p = 0.19$, $d = 0.07$], anxiety measured with GAD [$\beta = 0.001$, $t(974) = 0.41$, $p = 0.68$, $d = 0.26$] or behavioural

apathy measured with bAMI [$\beta = -0.002$, $t(974) = -1.07$, $p = 0.23$, $d = -0.06$]. This suggests the severity of mental health symptoms or hypomanic traits, did not impact mood change following the mood induction.

3.3.2 Outcomes and reward probabilities impacted momentary mood ratings

As expected, mood ratings during the learning blocks reflected the outcome as well as the choice preceding the rating (see Figure 10). There was a main effect of outcome [getting a reward or not; $F(1,18512) = 95.54$, $p < 0.001$], participants being happier after getting rewarded for their choice, irrespective of what they chose, compared to when they did not get rewarded [low prob $t(2805) = 11.01$, $p = 1.15 \times 10^{-27}$, $d = 0.42$; high prob $t(5165) = 18.33$, $p = 8.38 \times 10^{-73}$, $d = 0.52$].

There was a main effect of reward probability [choosing the more rewarding or less rewarding animal; $F(1, 18512) = 1540.86$, $p < 0.0001$], and an interaction between outcome and reward probability [$F(1,18512) = 3112.64$, $p < 0.0001$]. Participants reported higher mood when they did not get rewarded after choosing the more rewarding option (high prob) compared to the less rewarding option [low prob; $t(3691) = 3.91$, $p = 9.17 \times 10^{-5}$, $d = 0.13$]. When they were rewarded, participants were happier after choosing the more rewarding stimulus compared to less rewarding one [$t(4279) = -4.14$, $p = 3.48 \times 10^{-5}$, $d = -0.13$]. This is in line with previous work that showed momentary mood is modulated by learning-relevant variables, in this case selecting the more rewarding option (Blain & Rutledge, 2020).

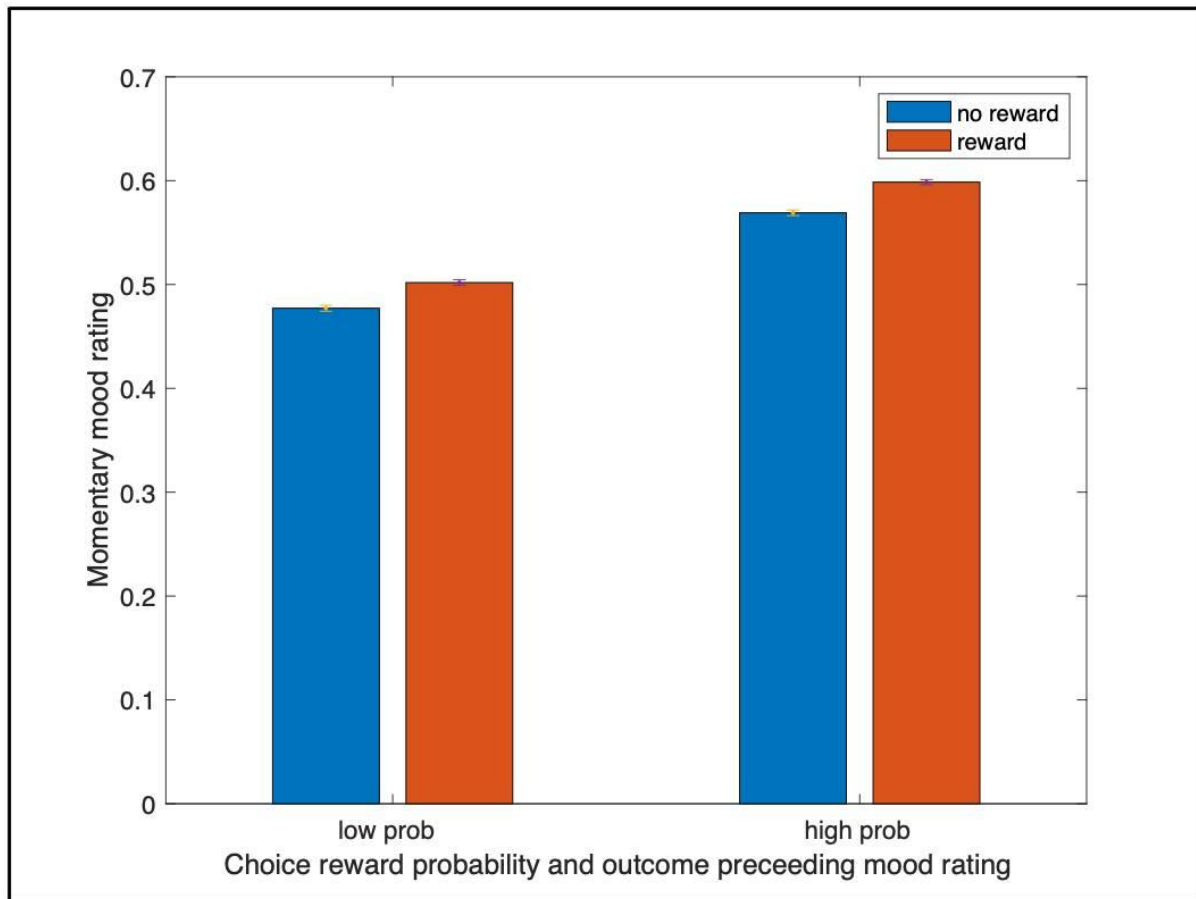


Figure 10. Average momentary mood reported immediately after outcome (reward, no reward) following choice of each option (low probability, high probability). Participants were happier when they were rewarded for their choices (irrespective if the choices were correct) and were happiest when they chose the more rewarding animal and got rewarded. N=4629 players, play 1 only.

3.4 H3. When presented with options that were learned under different mood states (i.e. pre versus post mood induction), participants with high trait mood instability will prefer the block they were happier in during learning.

As expected, the overall regression of experienced probabilities on slider test choices was statistically significant [$R^2 = 0.003$, $F(1, 4628) = 11.6$, $p = 0.0007$], experienced reward probability block difference predicting slider test preference [$\beta = 0.39$, $p = 0.0007$]. All following analyses use the residuals of this regression as the block preference measure to account for the effects of experienced reward probabilities, unless otherwise specified.

Counter to predictions, there was no overall difference in test block preference between participants who won the WoF draw and participants who lost the draw [$p = 0.31$; Figure 12A]. However, the extent of the impact of mood induction (i.e. the magnitude of mood change) strongly predicted preference [Figure 11; $\beta = 0.54$, $t(4627) = 7.43$, $p = 2.24 \times 10^{-9}$, $d = 0.22$]. In short, participants preferred the block that they were happier in, independently of the WoF outcome.

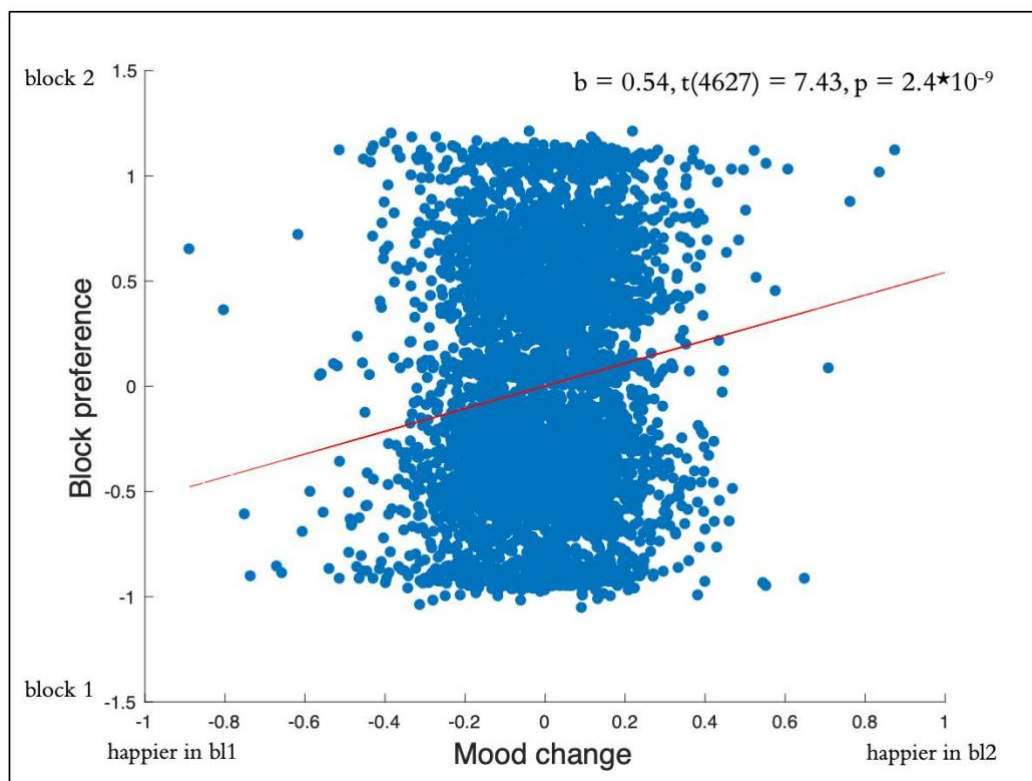


Figure 11. Scatterplot of test block preference by mood change. Negative block preference values indicate a preference for block 1, while positive values indicate a preference for block 2. Negative mood change values indicate more happiness in

block 1, positive values indicate more happiness in block 2. Mood change strongly predicted block preference, participants preferring the block in which they reported happier mood ratings [$\beta = 0.54$, $p < 0.0001$]. $N=4629$ players, play 1 only.

Based on this finding, I then split participants into two groups according to their momentary mood ratings: happier in block 1 versus happier in block 2 (see Figure 12B). There was a significant difference in block preference between these groups, participants preferring the block in which they reported being happier [$t(4352) = -4.23$, $p = 2.3 \times 10^{-5}$, $d = -0.13$; Figure 12B]. To better understand this effect, I split the data based on both the wheel draw and the block participants reported higher happiness (Figure 12C, 12D). Results showed that while some people reported being happier after losing the WoF and others unhappier after winning, all participants still significantly preferred the block they reported being happier in [$p < 0.01$].

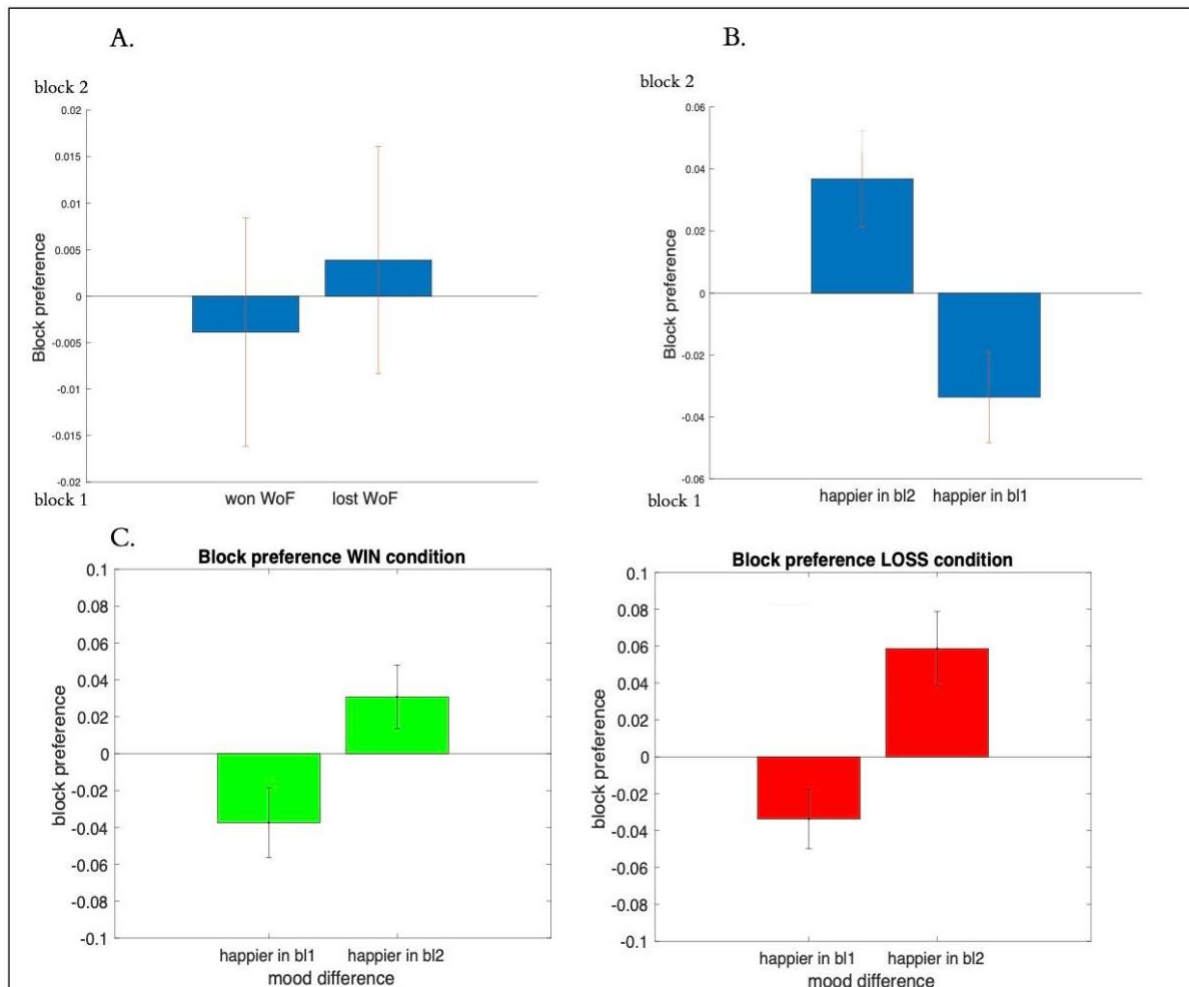


Figure 12. Average block preference as a function of mood change. A) Block preference split by wheel outcome. There was no difference in block preference between participants who won and those who lost the Wheel of Fortune draw. **B)** Block preference split by mood difference following WoF draw. Participants significantly preferred the block they were happier in. **C)** Block preference in the win (left, green; $N_{\text{happier in bl1}} = 924$, $N_{\text{happier in bl2}} = 1389$) and **D)** in the loss conditions (right, red; $N_{\text{happier in bl1}} = 1310$, $N_{\text{happier in bl2}} = 1006$) split by mood difference. Participants significantly preferred the block they were happier in, irrespective of the WoF outcome. $N = 4629$ players, play 1 only.

To understand the relationship between mood instability and mood bias on between-block preferences, I ran a 2 (group: high vs low HPS) \times 2 (happiness: happier in bl1 vs happier in bl2) ANOVA. It revealed an effect of block participants were happier in

[$F(3,1004)= 5.39$, $p = 0.02$], no effect of HPS group ([$F(3,1004)= 0.08$, $p = 0.77$], and no interaction between happier block and HPS group [$F(3,1004)= 0.87$, $p = 0.34$].

While the interaction effects were not significant, there were group differences in block preference likely masked by small effects and noise. Depicted in Figure 13, post hoc comparisons showed that participants with high trait mood instability (HPS) preferred the stimuli in the block they were happier in [$p = 0.02$]. In the low mood instability group, participants did not prefer one block over the other [$p = 0.31$]. As shown above in Figure 9B, there were no significant differences between the degree of mood change experienced by the low versus high HPS group [won WoF $p = 0.57$; lost WoF $p = 0.79$] that could lead to the differences observed in mood bias between HPS groups.

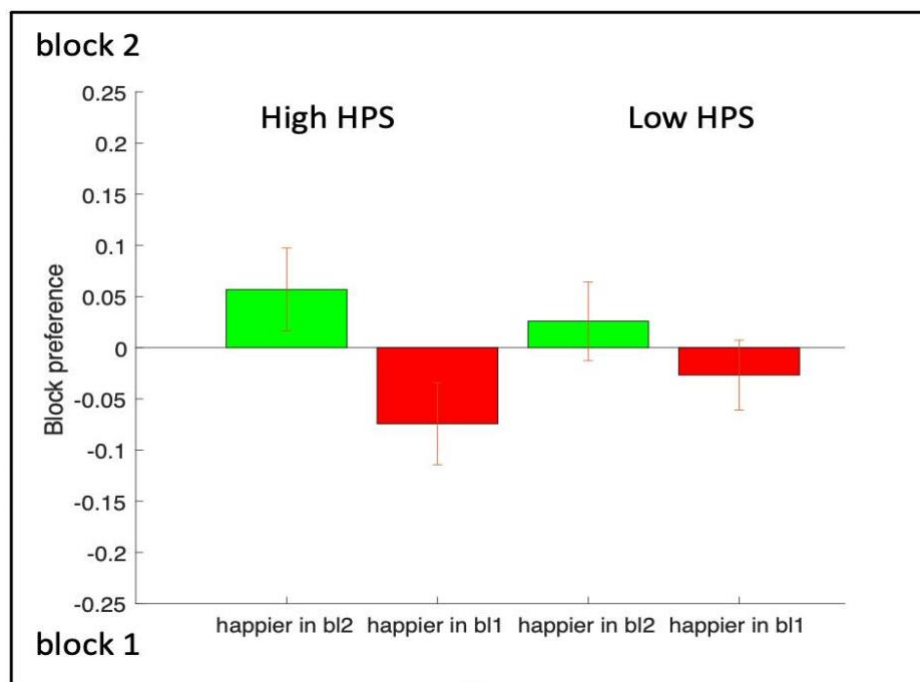


Figure 13. Block preference split by mood instability (high versus low HPS).

Participants with high trait mood instability showed a significant preference for the block they were happier in during test [$p = 0.02$], while those with low HPS score did not show this preference [$p = 0.32$]. $N=1052$ players, play 1 only.

3.4.1 No effect of depression, anxiety, apathy, age, or gender on mood bias block preferences

There was no effect of mental health symptoms on mood bias block preference. The overall regression was not statistically significant [$R^2 = 0.002$, $F(3,1654) = 2.3$, $p = 0.08$]. The effect of the following predictors was not significant: depression measured with PHQ [$p = 0.73$], anxiety measured with GAD [$p = 0.32$], or apathy and motivation measured with bAMI [$p = 0.44$].

A multiple regression analysis revealed that there was no effect of age [$p = 0.11$] or gender [$p = 0.81$] on mood bias. The overall regression was not statistically significant [$R^2 = 0.0001$, $F(2,3643) = 1.34$, $p = 0.26$].

3.4.2 Memory for neutral stimuli decayed over time, memory for mood biased stimuli did not

Participants correctly remembered the more rewarding animal in the previous play when asked about it during a second game happening on the same day (see Figure 14). This memory decayed over time [$r = -0.14$, $p = 1.8 \times 10^{-5}$] with no preference remaining after 7 days.

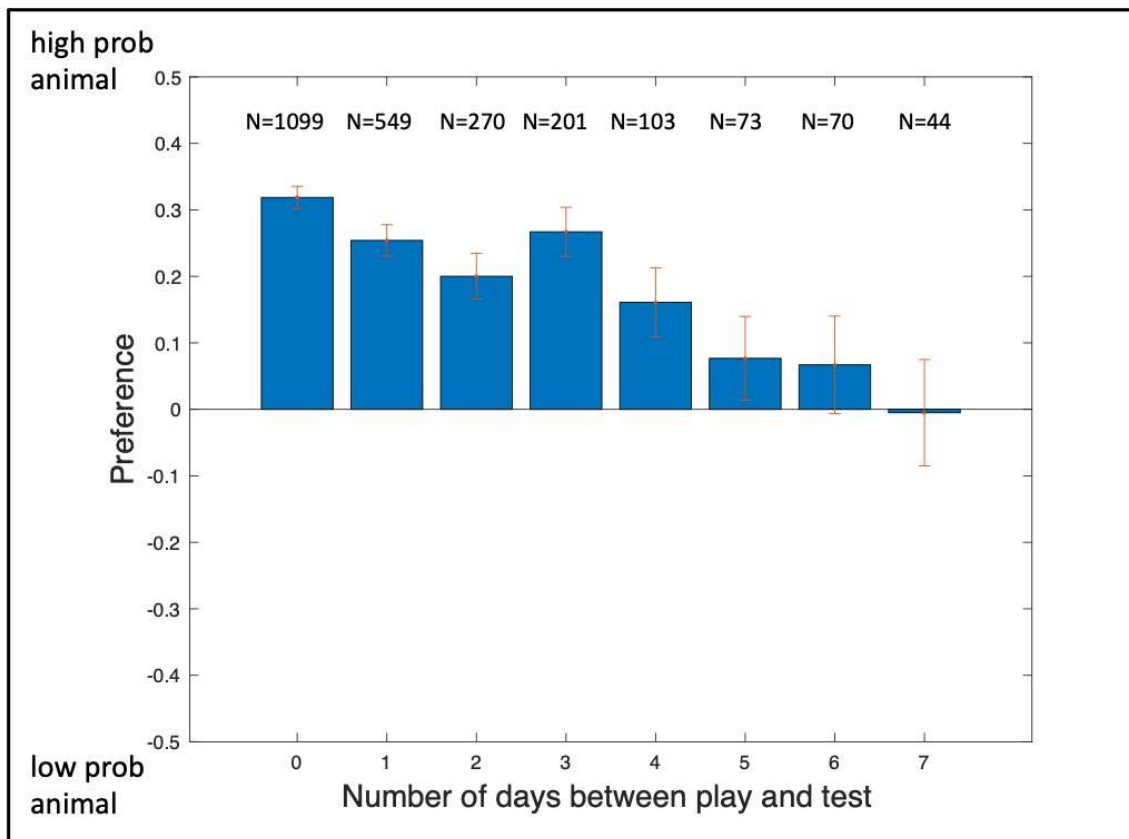


Figure 14. Bar chart of test slider preference for less rewarding (low prob) vs more rewarding (high prob) animals learned during block 1 (neutral block), plotted against the number of days passed between first and current play (0 to 7 days). Memory for the correct (high prob) animal decayed as a function of time passed between plays [$r = -0.14$, $p < 0.0001$]. $N=2409$ players, plays 2+ only.

Results indicated that while memory for which was the more rewarding neutral stimulus fades over time, memory for mood bias preferences does not. As shown in Figure 15, when asked which block they preferred in the previous game played, participants did not change their responses as a function of time. There was no correlation (Kendall's Tau chosen because data were not normally distributed) between block preference and time, split by mood change. When participants reported being happier in block 1, they preferred block 1 and their preference did not correlate with days passed between play and test [green; $\tau = -0.03$ $p = 0.49$]; similar for participants who reported being happier in block 2 and preferred block 2 over time [red; $\tau = 0.05$ $p = 0.26$]. Participants

continued to prefer the block they were happier in, irrespective of how many days had passed since they played that game.

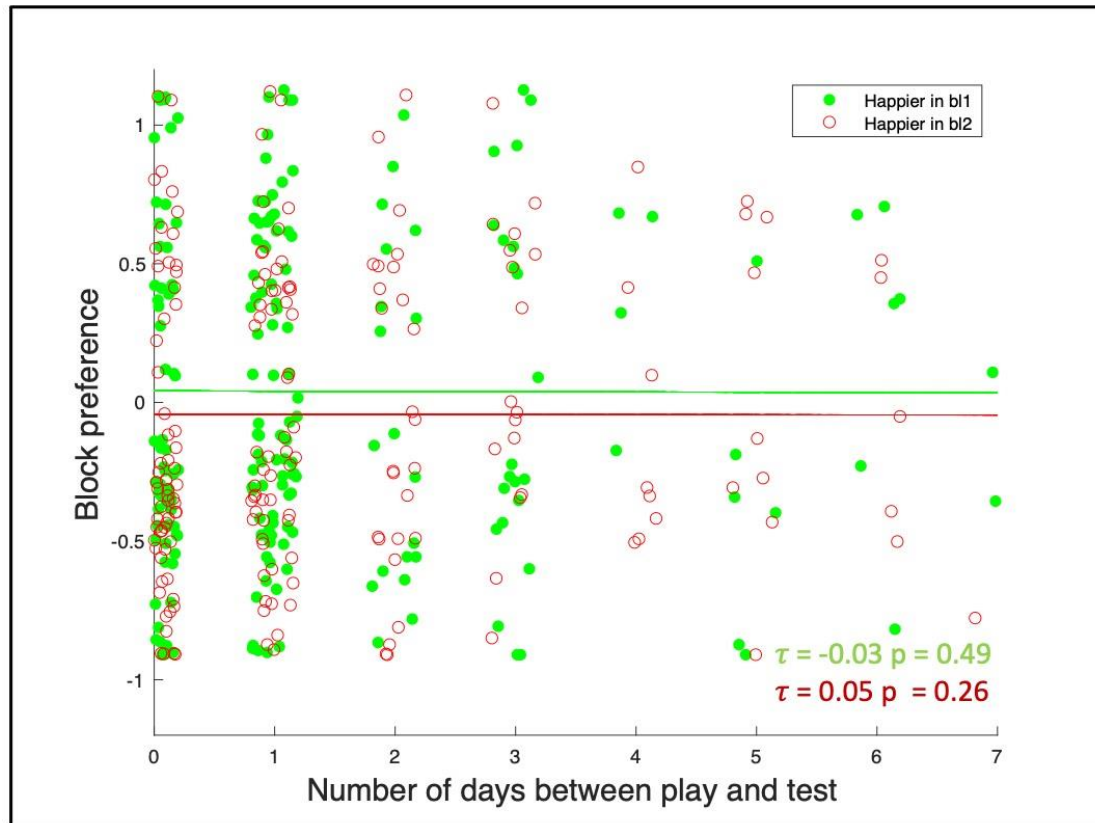


Figure 15. Mood bias block preference split by the block in which participants reported being happier (happier bl1 vs happier bl 2) plotted against the number of days passed between previous and current play. Mood bias remained constant over time in both conditions [$p = 0.49$ happier in bl1; $p = 0.26$ happier in bl2]. $N=2409$ players, plays 2+ only.

3.5 H4. The winning computational model will include a bidirectional effect of mood on rewards (i.e. rewards bias mood and mood biases rewards).

In terms of explaining participants' behaviour in this task, model comparison showed that full moody (FM) models significantly outperformed the partial moody (PM) or no moody models, both when including and when excluding slider choices, as shown in Figure 15 and Table 3.

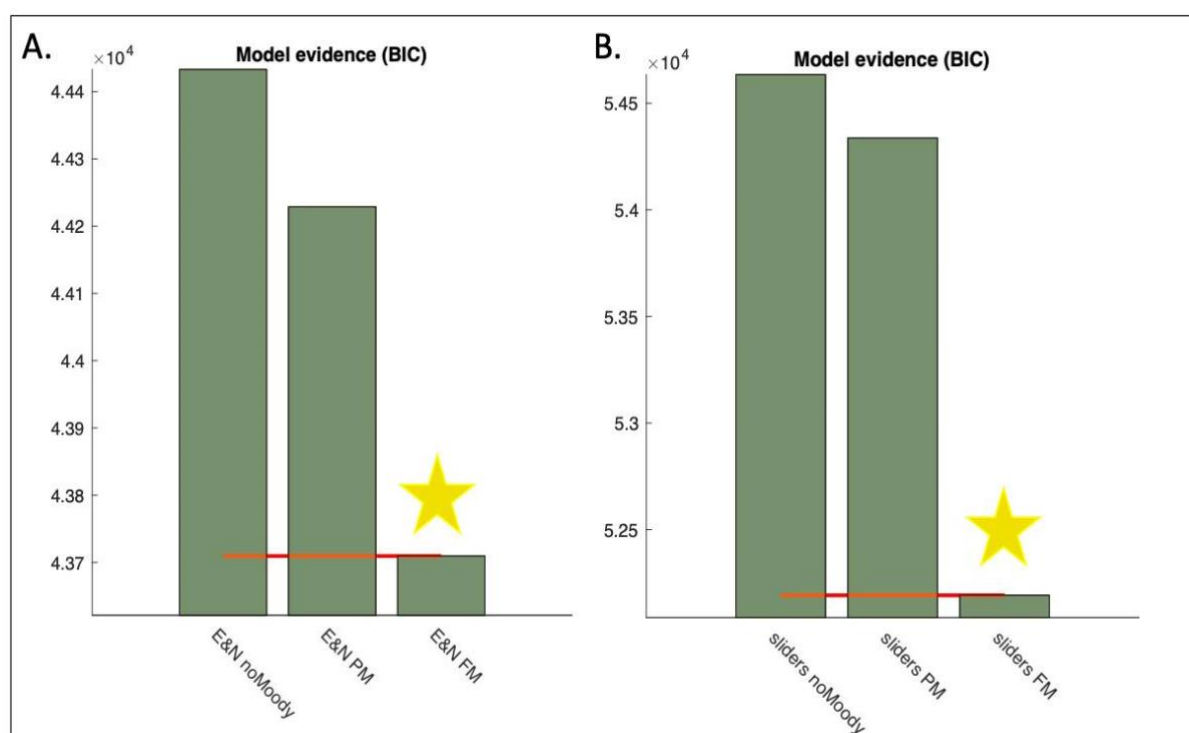


Figure 15. Bayesian Information Criterion (BIC) total scores for each model family. The gold star shows the winning model in each comparison was the FM model. The red line shows the value of the winning model. **A)** Eldar & Niv family of models (E&N) modelling test trials using binary choices only. **B)** Slider family of models modelling test trials using binary and continuous slider ratings.

Table 3. BIC measures are summed across the within-subject dataset (N = 1052).

Both model families included the same parameters. E&N models were fit to choices only, while the slider models were fit to choices as well as slider ratings (See Figure 4). The final column is the difference between the model BIC and BIC for the full moody model.

| <i>Model</i> | <i>BIC</i> | <i>BIC – BIC_{FM}</i> |
|------------------------|-------------------|--------------------------------------|
| E&N noMoody | 44433 | 723 |
| E&N PM | 44229 | 519 |
| E&N FM | 43710 | 0 |
| | | |
| slider noMoody | 54634 | 2442 |
| slider PM | 54337 | 2145 |
| slider FM | 52192 | 0 |

Using the winning full moody (FM) models from each family, I examined whether the model parameters were able to predict the test choice data analysed above. As shown in Figure 16, there was a highly significant positive correlation between mbias and test block preference for participants who won the WoF draw [*E&N FM model*: $r = 0.34$, $p = 1.5 \times 10^{-15}$; *slider FM model*: $r = 0.36$, $p = 4.1 \times 10^{-17}$], indicating that the higher the mbias value the more participants preferred block 2 after wins. There was also a significant negative correlation mbias and block preference for those who lost the WoF draw [*E&N FM model*: $r = -0.30$, $p = 2.9 \times 10^{-12}$; *slider FM model*: $r = -0.25$, $p = 4.1 \times 10^{-9}$], suggesting higher mood bias was associated with a stronger preference for block 1 after losses. A Fisher's z test showed that the two models were equally good at capture test preferences [$z = -1.24$, $p = 0.12$].

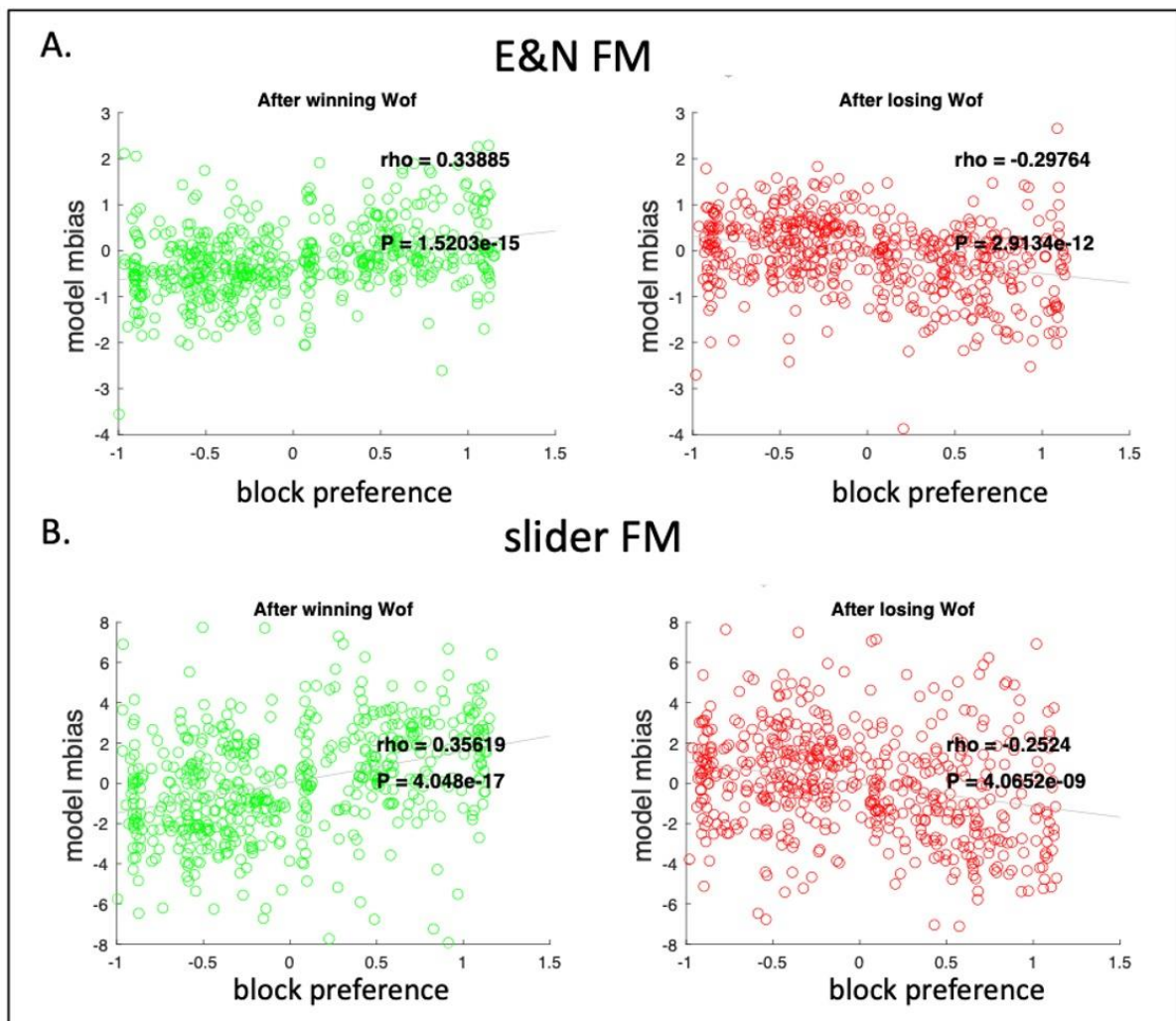


Figure 16. Scatterplots of model mbias and block preference for each model family, split by WoF outcome (green = won WoF; red = lost WoF), including on each plot the correlation coefficient 'rho' and p value 'P' in A) Eldar & Niv FM model and B) slider FM model. Model mbias was positively correlated with block preference in the win condition and negative correlated in the loss condition.

To assess whether the models were able to capture the real mood people experienced, I compared the model mood values on the trials when participants gave mood ratings, with their reported mood ratings ($N = 6$ ratings). A correlation coefficient (see Figure 17) was computed for each participant individually. To compute the average correlation across participants, I transformed each correlation coefficient using Fisher's Z, calculated the mean of the z values, and transformed back to the correlation coefficient.

Overall, both models captured real mood ratings very well [*E&N FM model*: $r = 0.51$; *slider FM model*: $r = 0.39$]. A Fisher's z test showed that the E&N FM model was better at capturing momentary mood ratings [$z = 3.29$, $p = 0.001$] than the slider model.

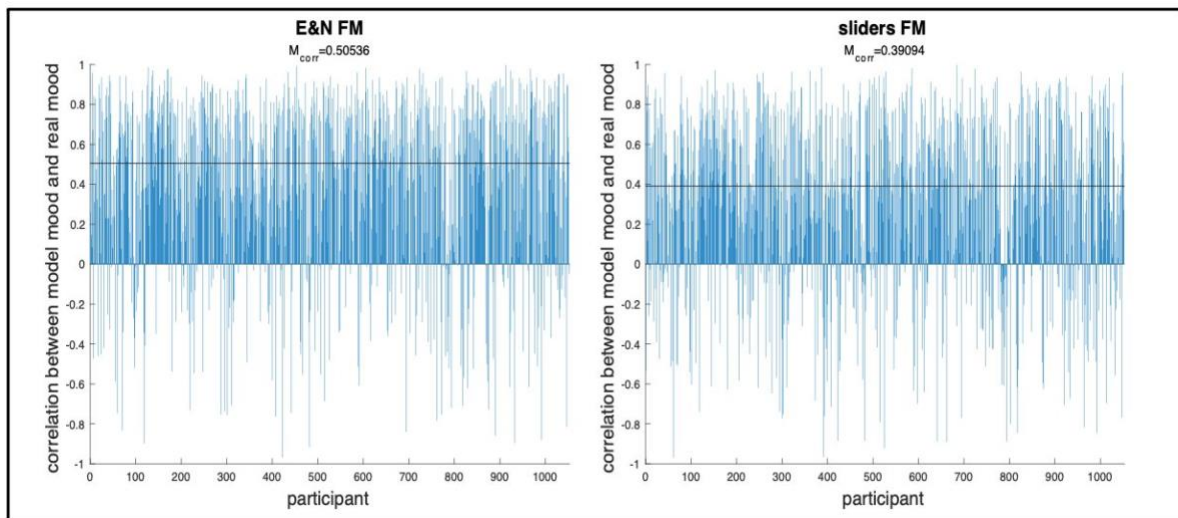


Figure 17. Bar plot of correlation coefficients between real mood reported during the task and model mood, for each participant. The black horizontal lines denote the average correlation across the sample, in each model (*E&N FM model*: $r = 0.51$; *slider FM model*: $r = 0.39$). $N=1052$ players, play 1 only.

3.6 H5. The computationally derived mood bias parameter will be higher in people with high mood instability (indicating greater impact of mood bias on reward perception) and lower in those with lower mood instability.

As seen in Figure 18, in the E&N FM model, the high mood instability group and the low mood instability group did not differ in their learning during the task [*rate*: $M_{\text{high HPS}}$

= 0.19, $SD_{\text{high HPS}} = 0.06$; $M_{\text{low HPS}} = 0.20$, $SD_{\text{low HPS}} = 0.06$; $p = 0.41$], neither in the impact of recent outcomes on their mood [$mrate$: $M_{\text{high HPS}} = 0.40$, $SD_{\text{high HPS}} = 0.06$; $M_{\text{low HPS}} = 0.40$, $SD_{\text{low HPS}} = 0.05$; $p = 0.99$], nor in the amount that mood biased reward perception [$\log(mbias)$: $M_{\text{high HPS}} = 1.55$, $SD_{\text{high HPS}} = 0.18$; $M_{\text{low HPS}} = 1.56$, $SD_{\text{low HPS}} = 0.19$; $p = 0.62$].

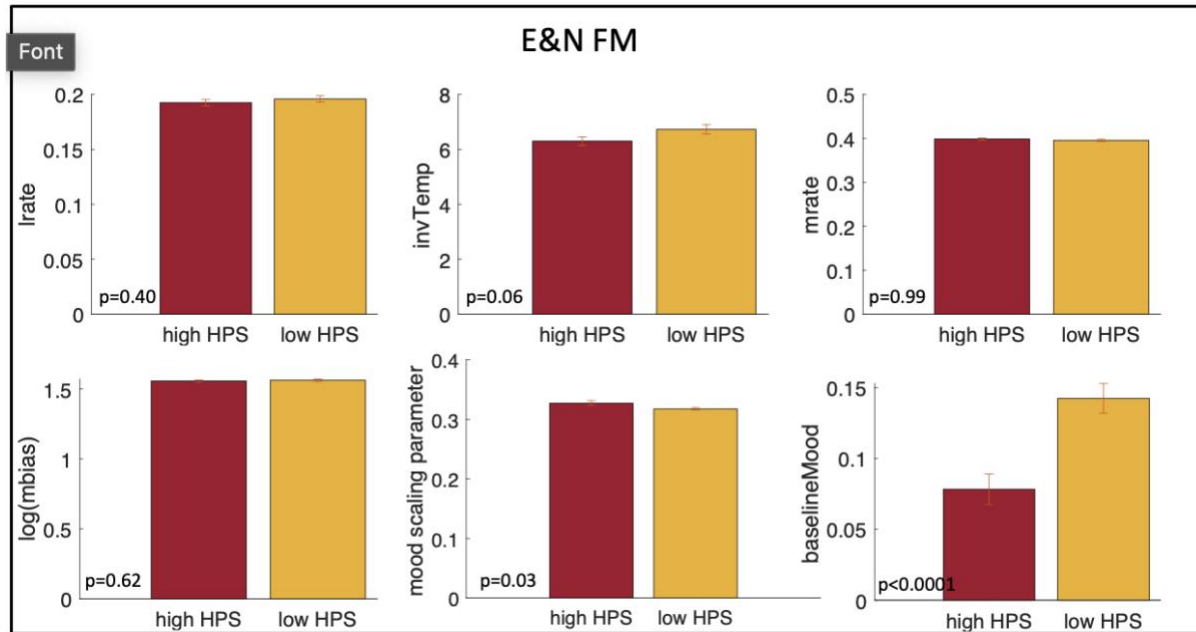


Figure 18. The E&N FM model parameters split by HPS group.

There were trend level differences in choice stochasticity during the learning blocks, with high HPS participants making more stochastic choices and low HPS making more deterministic choices [$invTemp$: $M_{\text{high HPS}} = 6.30$, $SD_{\text{high HPS}} = 3.69$; $M_{\text{low HPS}} = 6.73$, $SD_{\text{low HPS}} = 3.81$; $p = 0.06$, $d = -0.11$]. There was a significant difference in the mood scaling parameter [$mood\ scaling\ param$: $M_{\text{high HPS}} = 0.33$, $SD_{\text{high HPS}} = 0.09$; $M_{\text{low HPS}} = 0.32$, $SD_{\text{low HPS}} = 0.05$; $p = 0.03$, $d = 0.13$].

The highly significant difference in the baselineMood parameter is consistent with the lower mood reported by high HPS participants throughout the task [$baselineMood$: $M_{\text{high HPS}} = 0.08$, $SD_{\text{high HPS}} = 0.25$; $M_{\text{low HPS}} = 0.14$, $SD_{\text{low HPS}} = 0.23$; $p = 0.00002$, $d = -0.25$].

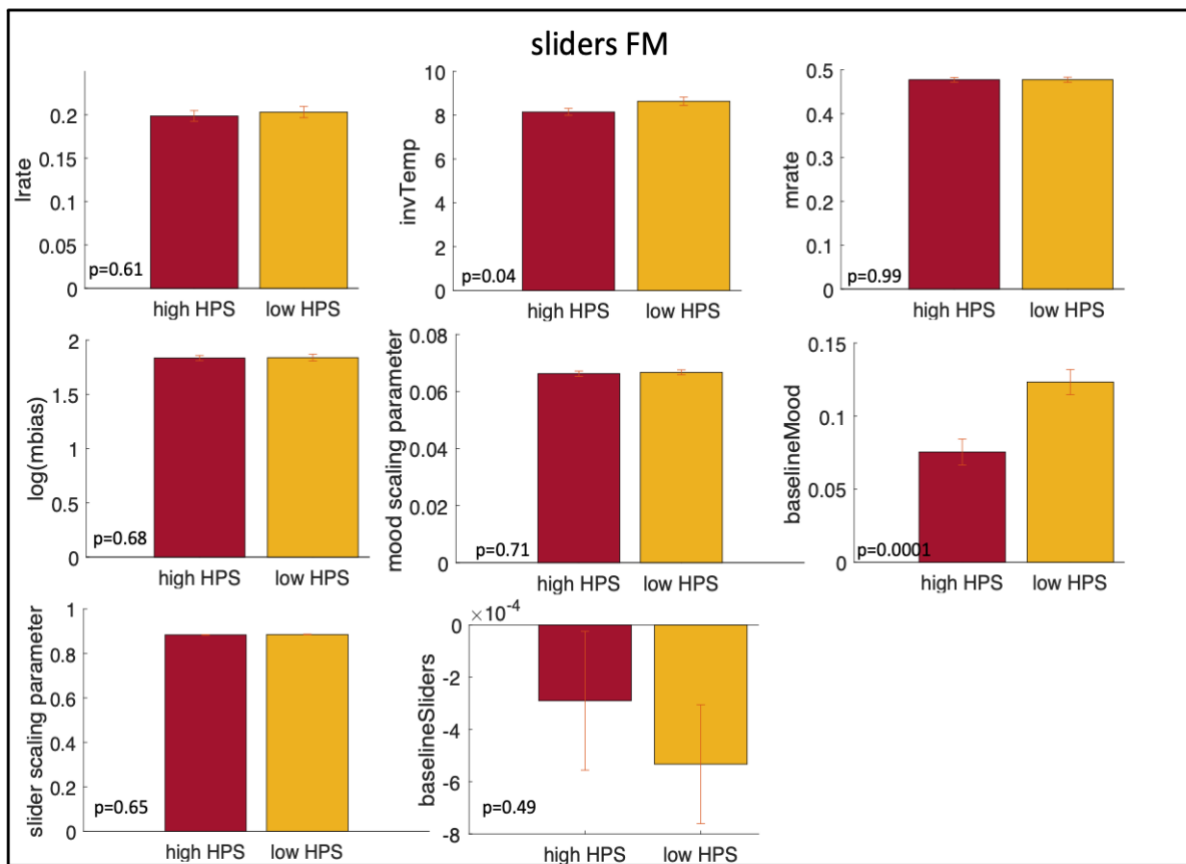


Figure 19. The slider FM model parameters split by HPS group.

The results for the sliders FM model were similar (see Figure 19) to the E&N model. There were no group differences in learning [*lrate*: $M_{\text{high HPS}} = 0.19$, $SD_{\text{high HPS}} = 0.15$; $M_{\text{low HPS}} = 0.20$, $SD_{\text{low HPS}} = 0.14$; $p = 0.61$], or in the impact of recent outcomes on mood ratings [*mrate*: $M_{\text{high HPS}} = 0.47$, $SD_{\text{high HPS}} = 0.13$; $M_{\text{low HPS}} = 0.47$, $SD_{\text{low HPS}} = 0.13$; $p = 0.99$], or in mood bias [*log(mbias)*: $M_{\text{high HPS}} = 1.81$, $SD_{\text{high HPS}} = 0.35$; $M_{\text{low HPS}} = 1.90$, $SD_{\text{low HPS}} = 0.36$; $p = 0.68$].

Low and high HPS participants did not differ on the additional slider scaling parameter [*invtempSliders*: $M_{\text{high HPS}} = 0.88$, $SD_{\text{high HPS}} = 0.03$; $M_{\text{low HPS}} = 0.88$, $SD_{\text{low HPS}} = 0.03$; $p = 0.65$], or mood scaling parameter [*Mood scaling param*: $M_{\text{high HPS}} = 0.07$, $SD_{\text{high HPS}} = 0.02$; $M_{\text{low HPS}} = 0.07$, $SD_{\text{low HPS}} = 0.02$; $p = 0.71$], or in the baseline slider parameter which accounted for possible systematic group differences in slider ratings [*baselineSliders*: $M_{\text{high HPS}} = -0.0003$, $SD_{\text{high HPS}} = 0.01$; $M_{\text{low HPS}} = -0.0005$, $SD_{\text{low HPS}} = 0.01$; $p = 0.49$].

= 0.01; $p = 0.49$]. Notably, the mood scaling parameter was much smaller in the slider model than the E&N model, suggesting that model mood went to very large values and had to be ‘dampened down’ with the scaling parameter to fit the real mood reports.

Participants with higher mood instability scores again showed more choice stochasticity during the learning blocks [*invtemp*: $M_{\text{high HPS}} = 8.15$, $SD_{\text{high HPS}} = 3.77$; $M_{\text{low HPS}} = 8.63$, $SD_{\text{low HPS}} = 4.16$; $p = 0.04$, $d = -0.12$] and reported lower mood throughout the task [*baselineMood*: $M_{\text{high HPS}} = 0.07$, $SD_{\text{high HPS}} = 0.21$; $M_{\text{low HPS}} = 0.12$, $SD_{\text{low HPS}} = 0.18$; $p = 0.0001$, $d = -0.26$].

Additionally, I explored if the lack of HPS effects in the mbias parameter was due to a significant proportion of people having a paradoxical mood change (i.e. reporting more happiness after losing the WoF or less happiness after winning). This would make it difficult for the model to correctly predict mood ratings or choices and could cause mbias to go to extreme values to fit choices. A t-test comparing mbias values only in people with expected mood change showed no differences in either FM models [$N=652$; E&N FM: $p = 0.73$; slider FM: $p = 0.42$], suggesting paradoxical mood change was not the reason for these findings.

4 Discussion

The first aim of this study was to demonstrate that a novel, app-based, gamified *Wheel of Fortune* task is an adequate redesign of the original task by Eldar and Niv (2015) (Hypotheses 1 & 2). Confirming the predictions (Hypothesis 1), players successfully learned which of the two stimuli was more rewarding very early in each block (by the fourth choice; Figure 2), demonstrating that the shorter design was appropriate for the task. Furthermore, at test, players correctly identified the more rewarding animal more than 70% of the time. Despite rewards being in the form of gems which had no real monetary value for players, the mood induction procedure (Wheel of Fortune spin) was successful (Hypothesis 2) and mood changed linearly with the amount of reward received.

The second, and perhaps more important aim of the study was to ascertain how robust was the effect of mood bias on reward perception and whether it held up in a context where rewards were essentially inconsequential (Hypothesis 3). Replicating previous findings (Eldar & Niv, 2015) in a significantly larger group (N=1052), I showed that participants with higher trait mood instability had a mood bias on reward perception, preferring the block they were happier in, while those with low trait mood instability did not have a preference.

Extending previous findings, I found that on average, in a very large sample of the general population (N=4629), individuals exhibited a mood bias on reward perception that increased with the magnitude of mood change between blocks. However, the generalisability of findings should be approached with caution, considering the absence of main effects in the analysis of variance (ANOVA), the small effects within specific groups, and the substantial amounts of noise present in the dataset. Although individuals with high trait mood instability exhibited a discernible mood bias effect in response to non-monetary rewards, it is important to note that the strength or robustness of this effect was relatively modest.

Finally, I used a computational modelling approach to demonstrate that mood had a bidirectional effect on reward valuation: rewards influenced mood and mood biased the valuation of rewards (Hypothesis 4), replicating previous work (Eldar & Niv, 2015).

Contrary to predictions and other findings (Eldar & Niv, 2015), I found that the mood bias parameter did not differ between players with high versus low trait mood instability (Hypothesis 5).

The novel app-based *Wheel of Fortune* task introduced several modifications to the original design by Eldar and Niv (2015). To enhance playability and user engagement, the game length was reduced by 66% to only 12 trials per block instead of the original 42. Additionally, the task was simplified by including two stimuli instead of three, to ensure participants learned which was more rewarding during the shorter blocks. To ensure participants explored both options adequately, forced-choice trials were included. These adaptations significantly reduced the game duration from over 30 minutes in the laboratory to approximately 3.5 minutes on the app, enabling the collection of multiple gameplays from the same individuals across several days. In terms of rewards, the monetary component was replaced with gems of no real-life value, allowing the examination of mood changes without relying on large monetary incentives typically used in lab-based experiments. The goal was to develop a brief probe for mood bias that could be conveniently utilized on any smartphone, anytime. However, it should be noted that as the game was freely downloadable by the public, thus ensuring participants' adherence to instructions and minimizing distractions during gameplay was beyond the researchers' control.

Confirming predictions (hypothesis 2), the mood induction via a wheel of fortune draw was successful in modulating participants' moods, even though the outcome of the draw did not have any real monetary value, supporting previous findings using non-monetary rewards (Joseph et al., 2020; Vinckier et al., 2018). Negative mood induction affected participants' mood to a larger degree than positive mood induction despite being worth an equivalent number of gems (Figure 4). This was consistent with a recent meta-analysis of mood induction procedures, which found a systematic negativity bias in the literature, effect sizes of negative mood inductions being significantly larger than those for positive mood inductions (Drueke et al., 2020; Joseph et al., 2020; Vinckier et al., 2018). The negativity bias is a psychological mechanism by which humans attend to and give greater weight to negative stimuli, compared to positive stimuli (Ito et al., 1998). This bias serves an evolutionarily adaptive function, allowing humans to evade dangerous situations (Vaish et al., 2008). Another possible explanation for the

reduced potency of the positive mood induction manipulation is due to “Mood Drift Over Time” effect. This effect describes how mood gradually declines with time as participants complete simple tasks (Jangraw et al., 2023). In the present study, this could translate as a lower mood in block 2 which was only partially offset by the positive effect of the mood induction. On the other hand the negative mood induction could have amplified the reduction in mood seen over time, leading to unequal mood changes for positive and negative conditions. However, given that the overall duration of the *Wheel of Fortune* game was under 4 minutes, the Mood Drift Over Time effect would be small.

The relationship between participants' susceptibility to mood instability, as measured by the HPS questionnaire, and the extent to which their moods were influenced by the mood induction was then explored. The HPS measure has been developed as an indicator of the risk for developing bipolar affective disorders (Eckblad & Chapman, 1986; Meyer & Hautzinger, 2003). There were no differences in mood change between the high and low HPS groups, suggesting that reactivity to the mood induction manipulation did not relate to mood instability traits (Figure 5B). Mood change following the Wheel of Fortune spin was not modulated by depression, anxiety or behavioural apathy either. Although reported mood in the task was consistently lower for participants with higher mood instability, there was no association between mood symptoms and degree of mood change (Figure 5A). This contradicted previous findings by Eldar and Niv (2015) who reported that higher HPS scores were associated with greater change in mood following the mood induction. However, in a more recent study, Drueke et al. (2020) found no significant differences in mood change following a mood induction between patients diagnosed with bipolar disorder (either manic or depressed), patients with depression and healthy controls. Other work has shown that relative to low mood instability, participants with high mood instability differed in the variability of positive and negative mood reports, while having comparable mean positive mood over the course of 10 weeks (Panchal et al., 2018). Therefore, it may be that mood instability was related to greater variability in mood change following our mood induction, rather than larger mean mood change scores. Future work could investigate the variability of mood change following the wheel draw between groups with high HPS and low HPS.

The second aim of this chapter was to replicate and extend the findings of Eldar and Niv (2015) and show in a larger and more diverse sample of the general population and in a non-monetary reward context, that mood bias on reward valuation was related to symptoms of mood instability (Hypotheses 3).

Previous results of Eldar and Niv (2015) were replicated: only those with high trait mood instability scores showed a mood bias during test, while those with lower scores did not. Furthermore, mood change did not differ between HPS participants, while the mood bias on reward perception did. This refutes the possibility that mood bias on reward perception is identical between participants with high and low mood instability symptoms and any differences observed stem from some participants experiencing more extreme mood changes than others, addressing one of the main limitations of the of Eldar and Niv (2015) study.

On average, participants preferred the animal learned in block 1 if they were happier during block 1 and vice-versa for block 2 (Figure 7B). However, when comparing those who won the wheel (positive mood induction) with those who lost (negative mood induction), there were no differences in block preferences (Figure 7A). The large variability in these results was likely due to participants for whom the mood induction did not go in the expected direction, adding significant amounts of noise that masked differences in block preference (Figure 7C). While the mood induction was successful overall, inducing, on average, positive moods following wins and negative moods following losses, the mood changes reported following some of the smaller wheel outcomes were not as clear cut. Some of the participants who won small amounts of gems on the wheel may have felt unhappy because they could have won larger amounts, while some of those who got small losses could have been happy because they avoided larger losses. This inconsistency was due to the design of the wheel being fair and landing on all ten possible outcomes, as opposed to the task designed by Eldar and Niv (2015) who rigged the wheel to only give participants the second largest possible outcomes. This design choice enabled participants to play more than once while maintaining the illusion of a real wheel of fortune draw each time. Future work could address this limitation by analysing the choices made by participants who got the largest wheel outcomes (i.e., won or lost 210 gems). It is also possible that the smaller prizes on the wheel may not seem as valuable to participants compared to the

rewards received during learning. For example, in the learning blocks on each trial, the reward was 0 or 40 gems while on the wheel the smaller prizes were two to three times that reward magnitude (i.e., 90, 105 gems). Future work may benefit from making the wheel outcomes proportionally larger to the in-trial rewards, leading to a larger emotional experience of wins or losses.

The final aim was to use computational modelling to further investigate the bidirectional relationship between mood and reward perception (hypothesis 4) and if this predicts mood instability (hypothesis 5). I fitted the original family of models developed by Eldar and Niv (2015) as well as novel extended versions of these models that included continuous confidence ratings (slider test choices).

The present study results showed a bidirectional effect of mood on reward valuation which was confirmed by the winning model that included both a parameter for mood bias on reward (mbias) as well as a reward bias on mood parameter (mrate). The full moody model best fit the test choice data and momentary mood ratings in both model families, suggesting that behaviour in this task was best explained by a model that included a bidirectional relationship between mood and reward. However, there were no differences in mbias or mrate between high and low mood instability participants, suggesting that the dynamics of mood and reward were comparable across the two mood instability groups.

One reason for these null findings stems from the model set-up including the WoF wins versus losses instead of the subjective happier splits, as discussed above. However, when looking only at participants whose happier split was identical to the WoF win/loss split, there still was no differences between HPS groups. Secondly, the significant yet small mood bias effects reported in the non-modelling analysis are based on the slider preference for the more rewarding stimuli after regressing out the effects of experienced reward probabilities. There were no mood bias effects when looking at all binary and slider test choices together. It was not possible to include the same assumptions in the model. Here, the models fit all test choices (only binary choices in the E&N model family, no sliders; all binary and all sliders in the slider model family). This was necessary because these reinforcement learning models need multiple learning and test trials to fit the parameters for each participant. It is likely that under the new design of the task, the sensitive measure of mood bias is shifted to the test

slider ratings of the more rewarding stimuli, as opposed to all test choices. Future work would need to reconceptualise the modelling analysis approach to reflect this change, as it currently does not lend itself to this set-up.

4.1 Implications

Previous work has proposed that the interaction between emotional state and learning may play a significant role in the emergence of mood instability (Eldar & Niv, 2015) and of bipolar disorder (Mason et al., 2017). This model of mood instability posits that large, unexpected surprises (large RPE like our Wheel of Fortune draw) lead to changes in mood (increasing or decreasing momentary mood) which then lead to a biased perception of future outcomes (i.e., mood bias). In a good mood, outcomes are perceived as better than they objectively are, leading to further mood escalations that bias future outcomes, triggering a (hypo)manic cycle. In a bad mood, outcomes are perceived as worse, leading to a lower mood, leading to the perception of rewards as less valuable, and maintaining a depressive cycle. The cycle is broken when expectations and reality become so divergent that this causes another large surprise (large RPE) in the opposite direction than the current mood state.

While this theory has not yet been empirically tested in patients, evidence to support it comes from computer simulations of mood bias parameters (Mason et al., 2017). A larger positive mbias parameter value translates to more intense and frequent mood oscillations, while a smaller positive mbias value is characteristic of a stable mood. Future work using the *Wheel of Fortune* game can further explore this theory of mood instability in patients with bipolar disorder compared to healthy controls. By using longitudinal repeated measures designs combined with real-life mood tracking using techniques like experience sampling methods, studies could assess if mood bias parameters predict the onset of real mood oscillations experienced by patients with mood instability and bipolar spectrum disorders. The Happiness Project app has the necessary infrastructure to implement these designs.

In the future, the task could be used as a cognitive probe of mood bias, using computational models that can predict the trajectory of mood instability from performance in the game. This could be a valuable tool for clinicians and

psychotherapists to track mood bias over time and tailor care according to the client's needs. It could also serve as a potential tool for the evaluation of treatment interventions through their impact on mood bias overtime. A recent study has successfully used a variant of this task to measure antidepressant effects on learning and reward valuation (Michely et al., 2020).

4.2 Limitations

The current work has several limitations. Because the game was freely downloaded and played, there was no experimenter control and all task measures including performance on the game had a larger amount of noise than an equivalent lab-based study. It is also likely that some participants did not follow the instructions or simply responded randomly to game choices. The nature of the game design did not allow for attention checks that usually serve as measures of attention to the task. One way to distinguish good performance from poor or chance performance was to look at test choices comparing stimuli of different reward probabilities (four choices). Choosing the high probability of reward stimuli was the correct response. Participants were classified as 'good performers' if their cumulative performance on those trials was 75% correct or higher, otherwise they were 'poor performers'. I first analysed the whole sample and then looked the 'good performers' only. There were no differences in main outcomes between the reported results (i.e., all participants) and the results from the "good performers" group.

Another possible explanation for the model-based findings may stem from small variability in responses. The mood induction effects were significant, but small, with most people rating their mood close to 0.5 on a scale from 0 to 1. There was a similar trend in test slider responses, most participants rating close to 0.5, which then translated into very small preferences for one block over the other. Given the association between mood change and block preference, it is hard to know whether the non-significant mood bias effects measured were due to the mood induction not being potent enough or if participants truly wanted to indicate a lack of preference for one block over another.

In the model, the reward prediction error following the WoF was computed as a ratio of the trial rewards (e.g., trial rewards were 40, WoF outcome was +210, WoF was modeled as $210/40 = 5.25$ and trial rewards as 1). However, this proportion was much smaller than in the original task design (trial rewards 25 cents, WoF $\pm 7\$$, WoF modeled as $7/0.25 = 28$). This may also explain the small mood changes observed, and larger response to negative mood induction. Participants did not receive a much larger prize on the wheel compared to what they could collect during learning trials (the WoF prize was worth between 2.25 and 5.25 learning block rewards), so their mood was not much increased. For the loss trials, however, it is more complicated to calculate because during learning blocks they could not lose any points (instead they got 0), so losing had an increased impact compared to other rewards.

In the computational models, the WoF outcome was modelled symmetrically for win and losses as the ratio described above (i.e. winning 210 points was 5.25; losing 210 points was -5.25), as done by (Eldar & Niv, 2015), however a more recent study modelled wins and losses separately (Michely et al., 2020). I explored models including a WoF scaling free parameter (normally distributed) that could amplify or reduce the perceived value of reward in on the WoF trial. Early results showed that these models did not outperform the models without the scaling parameter and were therefore not explored further. Modelling wins and losses separately would not work in the current study as it would require a balanced within-participants design. However, future studies enrolling multiple plays could address these limitations.

Across all participants, there was a strong primacy bias in test choices, most participant preferring block 1 irrespective of the mood induction condition or reported happiness. The dataset focused on the first play for each participant, so it is possible that the first block was more salient as participants did not know what to expect from the game. By the time they got to the second learning block, they had formed some expectations of the task. This is also reflected in the slightly reduced proportion of participants choosing the high reward animal during the first few choices of the second block. One possible explanation is that in the first block, when the game was more unclear, participants focused on maximizing their earnings, while in the second block, they spent more time exploring the two stimuli before sticking with one option. Here, 'exploration' is defined as selecting options with non-maximal expected values (Daw et al., 2006). Previous

work has described this as directed exploration, a strategy in which decisions are biased toward more uncertain or more informative options as they hold greater potential for gain (Bellman, 1956). Directed exploration has been related to risk-seeking behaviours (Hertwig et al., 2004; Weber et al., 2004) (ref) and has extensive empirical support (Frank et al., 2009; Speekenbrink & Konstantinidis, 2015).

A general limitation of all online studies as opposed to lab-based work is that the data collected are noisier and effect sizes are smaller, so more power is needed (Chetverikov & Upravitelev, 2016; Reips, 2000). Therefore, our sample was 82 times larger than the original lab-based study (Eldar & Niv, 2015), compensating for the noise and variability of the data. Moreover, the very large and diverse sample size increased the generalizability of the findings and allowed us to investigate more symptom associations with task measures.

4.3 Conclusion

Overall, the study demonstrated the usefulness of the new app-based *Wheel of Fortune* game as a measure of mood bias and replicated previous findings on the relationship between mood bias and mood instability in a larger sample of the general population. The accessibility of the task will allow future researchers to sample mood bias multiple times per day with little burden on participants, while investigating how it relates to real-life mood changes and clinical symptoms of mood instability, making it a valuable tool for researchers and clinicians. The study also provided new insights into the bidirectional relationship between mood, reward perception and mood instability through computational modelling. This deepened our understanding of processes underlying mood biased learning and decision-making, providing a valuable avenue for exploration to better understand mood instability and bipolar spectrum disorders.

CHAPTER 4. The Social Learning Study:

Measuring mood bias on social reward valuation

Abstract

Mood can bias the perception of rewards, making them appear more valuable when in a good mood and less valuable when in a bad mood (Eldar & Niv, 2015). Previous studies have quantified mood bias only for monetary reward perception [Chapter 2; (Eldar & Niv, 2015)], but none have investigated it in the context of social reward. Other work has shown that in social interactions, self-esteem – a closely related construct to mood, tracks outcomes, surprises, and even social standing, similar mechanistically to learning from non-social rewards. The effect of mood on social reward perception remains unexplored. The present study had two main aims: (1) to assess whether mood biases reward perception in social contexts and (2) to assess whether mood influences self-esteem tracking social feedback. The study recruited 85 participants who completed the ‘Social Learning Task’, a novel probabilistic learning task, and several questionnaires. Results showed that while negative mood appeared to bias people’s social predictions, there was no effect of mood in biasing social reward perception. Although the study did not find conclusive evidence of social mood biases, it identified alternative possible heuristics that motivated participants’ choices. Results replicated previous findings that self-esteem tracked social reward outcomes, but mood did not impact this relationship. Future work is needed to further explore these complex relationships and clarify the impact of mood on self-esteem and social reward valuation.

1 Introduction

Mood bias is the influence of one's emotional state on the processing and interpretation of information, which can result in biased perceptions, judgments, and behaviours. For example, individuals in a positive mood state are more likely to approach rewards and make more optimistic decisions, whereas those in a negative mood state are more likely to avoid rewards and make more pessimistic decisions (Forgas, 1995; Isen & Daubman, 1984; Verkuil et al., 2010). Mood enhancement is also associated with increased risk-taking (Shahrabi Farahani et al., 2022). This can promote a self-perpetuating cycle in which an individual's current mood state influences their decisions and actions, causing that mood state to be reinforced (Elhai et al., 2017; Kuppens et al., 2008) and possibly leading to the development of psychiatric symptoms such as mania or depression.

The *Mood as Momentum* model (Eldar et al., 2016) posits that mood tracks the momentum of recent outcomes and how surprising they were. Mood is improved by unexpected rewards and by positive outcomes and worsened by missed rewards and negative outcomes (Eldar & Niv, 2015; Mellers et al., 1997; Rutledge et al., 2014; Shepperd & McNulty, 2002). Mood can also bias the perception of outcomes, such that rewards are perceived as better when in a good mood and worse when in a bad mood [Chapter 2; (Eldar & Niv, 2015; Mason et al., 2017; Pessiglione et al., 2023)]. Recent work in computational modelling research has demonstrated that mood flexibility serves an adaptive function of guiding behaviour towards achieving goals and adjusting to changing circumstances, by maximising rewards and minimising costs (Pessiglione et al., 2023). However, extreme mood flexibility or having an increased sensitivity to how much mood was biased by rewards has been shown to lead to the appearance of short manic episodes and long depressive episodes (Pessiglione et al., 2023). Similarly, Eldar and Niv (2015) and Mason et al. (2017) showed how large mood biases on reward valuation could lead to the pathology of mood disorders such as bipolar disorder. Consistent with these theories and simulations, Chapter 3 has empirically shown that a higher mood bias on non-social reward valuation was associated with a proneness to changeable and unstable mood.

Mood has also been shown to impact social processes, such as impression formation, interpersonal attraction, and communication (Isen & Daubman, 1984; Kitayama et al., 2006; Matsumoto & Hwang, 2011; Pham, 2004; Smith & DeCoster, 2000). For example, research has shown that positive moods can enhance social engagement and increase the likelihood that people will experience social rewards, while negative moods can lead to disengagement from social situations and a decrease in social rewards (Giner-Sorolla, 2001; Gross, 1998). Individuals in positive moods tend to perceive others more positively and engage in more prosocial behaviours as well as take more risks (Noval & Stahl, 2017), while those in negative moods tend to perceive others more negatively (Noval & Stahl, 2017) and are more prone to engage in aggressive behaviours (Schoel et al., 2014; Verona et al., 2002). This suggests mood could bias social rewards as has been shown with non-social rewards, leading to the development or maintenance of mood symptoms. Yet, no studies have attempted to directly investigate how mood can bias the value of social feedback.

1.1 Social vs non-social rewards

According to the social exchange theory (Homans, 1958; Lawler & Thye, 1999; Thibaut & Kelley, 1959), actions are primarily motivated by the desire to optimize the ratio of social rewards to social costs, similar to rational decision-making in an economic context. According to this theory, individuals engage in certain social behaviours (e.g. helping somebody), only when the benefits of the action outweigh the costs. Here, benefits (or rewards) can range from monetary compensation to social approval from others (Izuma et al., 2008).

The idea of a common neural network (Flores et al., 2015; Oumeziane et al., 2017; Ruff & Fehr, 2014) and a 'common neural currency' for rewards (Montague & Berns, 2002) is based on findings that monetary and social rewards activated the same neural structures (striatum and medial prefrontal cortex) during the processes of cue detection, reward anticipation, and feedback evaluation, as well as activating similar scalp topographies and neural response speeds (Guyer et al., 2012; Izuma et al., 2008; Lin et al., 2012; Olino et al., 2015; Saxe & Haushofer, 2008; Zink et al., 2008). Findings

show the striatum was activated when participants received feedback that others liked them (Davey et al., 2009; Meshi et al., 2013; Moor et al., 2010; Powers et al., 2013), understood them (Morelli et al., 2014), or wanted to meet them (Cooper et al., 2013). Striatal activation was also seen during outcomes that indicate changes in the social status of social interaction participants (Zink et al., 2008), suggesting it tracks longer timescale value of social rewards as well as shorter timescales. Moreover, choices between receiving smaller social rewards now versus larger rewards later follow the same economic principles (such as delay discounting) as choices between non-social rewards (Hayden et al., 2007; Kampe et al., 2001). The 'common currency' theory put forward Montague and Berns (2002) proposes that the striatum plays a critical role in turning rewarding stimuli, such as money or good reputation, into a "common currency", in order for the individual to make decision that maximises rewards (Montague & Berns, 2002). This could explain why some people participate in prosocial action while foregoing monetary gains (Bateson et al., 2006; Haley & Fessler, 2005; Kurzban et al., 2007).

There are also differences between how social and monetary rewards are perceived. Adolescents were found to be more sensitive to social rewards compared to monetary rewards (Wang et al., 2017). Both children and adolescents showed higher motivation to seek rewards than adults (Wang et al., 2020) and adults and children were more motivated by monetary rewards than social rewards (Barman et al., 2015; Demurie et al., 2011, 2012; Flores et al., 2015; Spreckelmeyer et al., 2009; Wang et al., 2017). These findings suggest that social and non-social rewards share common pathways but may also differ depending on context and other factors such as age.

1.2 The role of self-esteem in social contexts

Self-esteem is defined as how we feel about ourselves (Mecca et al., 1989), and is rooted in affective processes (Brown, 1993). Self-esteem is not an objective self-evaluation of one's capabilities. Instead, it is better characterised as a subjective emotional evaluation of one's own worth (Jordan et al., 2020). For example, individuals are not only aware that they might have some desirable (e.g. being intelligent) or undesirable characteristics (i.e. being lazy), but they feel positive or negative emotions

when they reflect on them. When they succeed, individuals are not only evaluating their objective performance but also feel good about themselves. Whereas when they fail (even if not due to their own performance), they tend to feel bad about themselves, experiencing a mood-biased decrease in self-esteem (Jordan et al., 2020).

Two types of self-esteem have been defined, each with different temporal properties. Trait self-esteem refers to what James (James, 1890) described as the “average tone of self-feeling”. It is a stable (but not immutable) sense of personal worth that reflects an individual's overall evaluation of themselves.

State self-esteem, on the other hand, refers to the level of self-esteem experienced by an individual in a particular moment or situation. It fluctuates over time and in response to situational factors. Low state self-esteem and instability in feelings of self-worth are related to vulnerability to psychiatric disorders (Will et al., 2020; Will et al., 2017). State self-esteem is usually assessed with the question “How good do you feel about yourself right now?” (Leary et al., 1998; Low et al., 2022; Will et al., 2020; Will et al., 2017).

Despite their distinct natures, trait and state self-esteem are dynamically interconnected. Trait self-esteem can influence state self-esteem by providing a baseline for how we evaluate ourselves in different situations. For example, individuals with high trait self-esteem may be more likely to view temporary setbacks as isolated events rather than reflections of their overall worth, leading to higher state self-esteem in the face of challenges. One study found that individuals with high trait self-esteem were more resilient to the negative effects of negative feedback, suggesting that their stable self-worth buffered them from temporary setbacks (Robins et al., 2001).

Conversely, state self-esteem can also influence trait self-esteem over time. Repeated exposure to positive or negative experiences can gradually shift an individual's overall self-evaluation. For instance, consistent experiences of success or praise may reinforce a high trait self-esteem, while repeated failures or social rejection may gradually erode it.

The classic ‘sociometer’ theory of self-esteem (Leary & Baumeister, 2000; Leary et al., 1998) proposes that individuals have a psychological monitoring system that tracks and evaluates their social connections with others, and this system generates feelings of high state self-esteem when social acceptance is perceived and feelings of low self-esteem when social rejection is perceived (Leary et al., 2003). According to the theory, self-esteem does not only reflect the individual's evaluation of the self but also reflects the individual's perception of how others view them. Computational modelling has refined the classic ‘sociometer’ theory of self-esteem, confirming that self-esteem indeed varies with social approval. However, it is surprises about social approval (i.e. social prediction errors), rather than its amount per se, which are most important (Will et al., 2017). Furthermore, state self-esteem tracks the direction and rate of change of one's beliefs of being accepted within a group, rather than one's social position. This can be useful to quickly adapt to changes in the environment, yet over-reliance on such signals may give rise to mood instability (Eldar & Niv, 2015; Low et al., 2022). Until now, no studies have explored how mood may interact with the ‘sociometer’ theory of self-esteem.

1.3 Aims and Hypotheses

The first aim of the present study was to design a task that could quantify mood bias on social reward value. Thus, I first hypothesised the following:

H1.1. During the ‘Social Learning Task’ participants will learn which rater group was more rewarding.

H1.2. Mood induction will lead to increased mood ratings after wins and decreased mood ratings after losses.

The second aim was to test whether the prior finding that mood biases reward perception extends to the social reward domain. Based on previous findings from the literature and Chapter 3, I hypothesised the following:

H2.1. Mood will bias predictions: expectations that others will like them will be increased under positive mood, and decreased under negative mood, compared to baseline mood (prior to mood induction).

H2.2. Mood will bias perception of social feedback value: participants will prefer raters encountered in the block they were happier in during learning. This effect will be stronger in participants with higher levels of trait mood instability (HPS), consistent with Eldar and Niv (2015).

The final aim of the study was to replicate previous findings showing that state self-esteem tracks social outcomes and prediction errors, and to extend these findings to evaluate whether mood biases this relationship (Will et al., 2017).

H3.1. State self-esteem will track social outcomes and prediction errors in the environment, replicating the findings of Will et al. (2017)

H3.2. Mood will impact state self-esteem tracking outcomes and social prediction errors.

The latter was an exploratory hypothesis and hence it is two-tailed. It is possible that positive mood will increase the value of rewards leading to increased state self-esteem, while negative mood will decrease self-esteem, consistent with Eldar and Niv (2015). On the other hand, positive mood could lead to increased expectations that result in more negative social prediction errors, decreasing self-esteem, while negative mood may lower expectations leading to more positive prediction errors, increasing self-esteem.

2 Methods

2.1 Design

Data for this study was collected as part of a larger project, the COVID-19 Psychological Research Consortium (*COVID-19 Psychological Research Consortium Study*). The Consortium brought together a multi-disciplinary team of international clinical and research psychologists to study the psychological, social, political and economic impact of the COVID-19 pandemic on the general population. The first wave of data collection was launched on 23 March 2020, the day that the lockdown was enforced in the UK. This was followed by the second wave in April 2020 and the third in July/August 2020. The Consortium research framework had five main objectives: (1) to recruit a large, nationally representative sample of adults from each country involved; (2) to collect baseline measures of a broad range of outcomes; (3) to assess several protective and risk factors known to influence health outcome and behaviours; (4) to re-contact respondents regularly during the pandemic and collect longitudinal data; and (5) to produce high-quality research outputs.

The focus of this chapter will be on the Social Learning Task (SLT) task which was introduced in the third wave of data collection (July/August 2020). Other findings from this project are beyond the scope of the current paper and will be reported elsewhere see <https://www.sheffield.ac.uk/psychology-consortium-covid19/about-project>).

Ethical approval was obtained from the University of Sheffield Ethics Committee. If the participants indicated they were 16 or older, they were asked to read the participant information sheet and state if they agree to a set of consent-based statements. The statements reminded participants of their rights; stated that the responder understood the aims and procedure of the online task; and asked if the responder agrees to take part in the survey. If participants indicated that they are under 16 years old, then an extra step was included in the consent process. The parent/guardian of the young person was asked to read the information participation sheet and was required to state if they agree to a set of consent-based statements.

2.2 Participants

All participants from wave two were invited to take part in the third wave of data collection. A specific sampling method was adopted to reduce potential population

biases in the sample. The invitation to take part in the online task was first sent to eligible participants who are both from a BAME (Black, Asian and minority ethnic) and low SES (socio-economic status) group, followed by those who are separately from BAME or low SES groups. Finally, the invitation was sent to the eligible participants within the general population, who are from non-BAME and non-low SES groups. Quota sampling methods were employed to achieve a representative sample in terms of age and sex (using 2016 population estimates from Eurostat [\[2020\]](#)) and household income (using 2017 income bands from the Office for National Statistics [\[2017\]](#)). This recruitment strategy was used to ensure the inclusion of participants representative of the broader population.

Participants were required to be able to provide informed consent themselves or via their parents or guardians (if they were younger than 16), be able to read and write in English, and be a resident of the UK. No other exclusion criteria were applied.

2.3 The Social Learning Task (SLT)

The Social Learning Task was designed as an adaptation of the task used by Will et al. (2017) and the Wheel of Fortune game. The task was ran using Gorilla, a cloud-based research platform that allows researchers to create to create and deploy behavioural experiments online (*Gorilla*).

The Social Learning Task was designed to measure: 1) to what extent participants update their expectations of social feedback when learning about whether groups were generally kind or critical of them, and 2) examine the extent to which mood impacts perception of social feedback and social rewards. The overall SLT design is depicted in Figure 1.

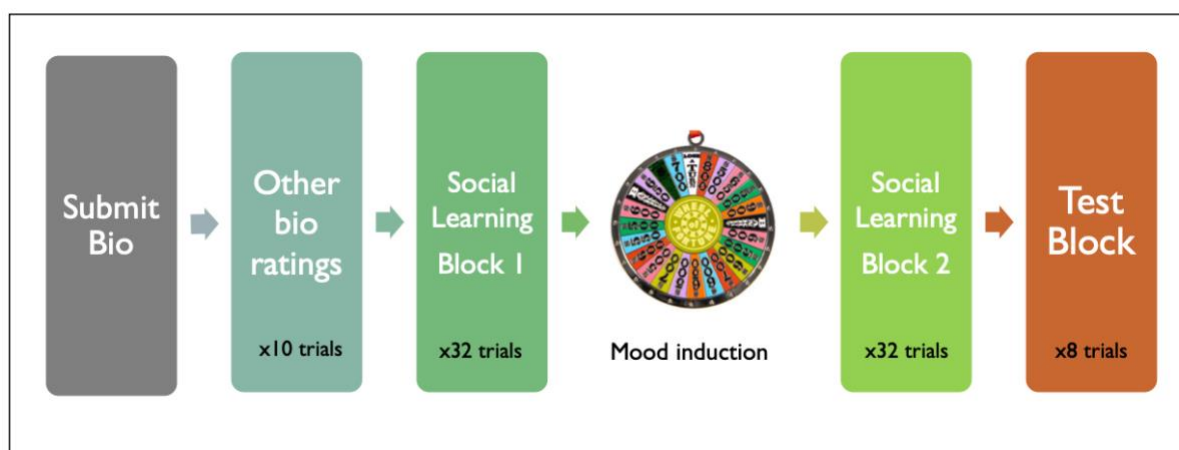



Figure 1. Diagram showing a schematic version of the Social Learning Task design.

First, participants created an online profile of themselves by choosing an avatar (a male or female; black and white pictures; See Figure 2), along with giving their first name and the first letter of their surname. Participants were asked to write a short personal biography (Bio), by answering five questions, as shown below in Figure 2.

BIO questions

1. If we asked your friends and family about your best qualities, what might they say?
2. And what would they say were your worst qualities?
3. What are you most afraid of?
4. What are your favorite things in life?
5. You really dislike people who... (e.g., people who are mean, or make annoying noises when they eat).

Please chose an avatar for your profile.






Figure 2. Example of the Bio questions asked and the avatar choice options.

The cover story for participants was: “Your Bio will be rated by a group of people also taking part in the study. They would be asked what they thought about you. They could choose to like or dislike you based on your profile”. Participants were also encouraged

to give detailed responses (a few sentences), instead of one-word answers. They were instructed that there were other people completing the task at the same time as them. Other participants would rate the participant's profile to indicate whether they liked or disliked them. Participants were told that the young people who rated their profile were split into two groups, reflected by different colours: those who were generally *nice* (liked more profiles than they disliked) and those who were generally *harsh* (disliked more profiles than liked) raters. The participants were told that it was their task to figure out which group would like them more often and which group disliked them. The objective reward probabilities for each colour group are shown in Figure 3. The learning blocks had equivalent rewards, with the *nice* group liking participants 75% of the time and the *harsh* group liking them 25% of the time. The group colours were permuted randomly, to avoid any order effects.













| | | | |
|---------|--|---|---|
| BLOCK 1 | Harsh  | 25%  | 75%  |
| | Nice  | 75%  | 25%  |
| BLOCK 2 | Harsh  | 25%  | 75%  |
| | Nice  | 75%  | 25%  |

Figure 3. Reward probabilities for the nice and harsh rater groups in each block.

After completing their profile, participants were asked to rate 10 profiles from other players. These bios were in fact written by the researchers. The aim of this deception was to convince participants that the ratings in the task (likes/dislikes) are really coming from actual participants, as this belief was crucial to measuring social reward perception. Afterwards, participants completed a series of questionnaires for

approximately 30 minutes. They then returned to the SLT where they completed two Learning Blocks with a mood induction (spinning a Wheel of Fortune where they could win or lose money) in between the blocks, as depicted in Figure 1 and Figure 4. The last part of the task was a surprise test where participants were asked which rater groups preferred them during the learning blocks. Comparisons between nice and harsh groups learned within each learning block served as a “memory test” to probe if participants correctly learned and remembered which rater group preferred them. Mood bias was assessed by comparing nice-versus-nice and harsh-versus-harsh groups that participants had learned about before and after the mood induction. Given that the reward probabilities for the rater groups were equivalent between blocks, a preference for one group over the other would indicate an effect of mood-biasing reward valuation.

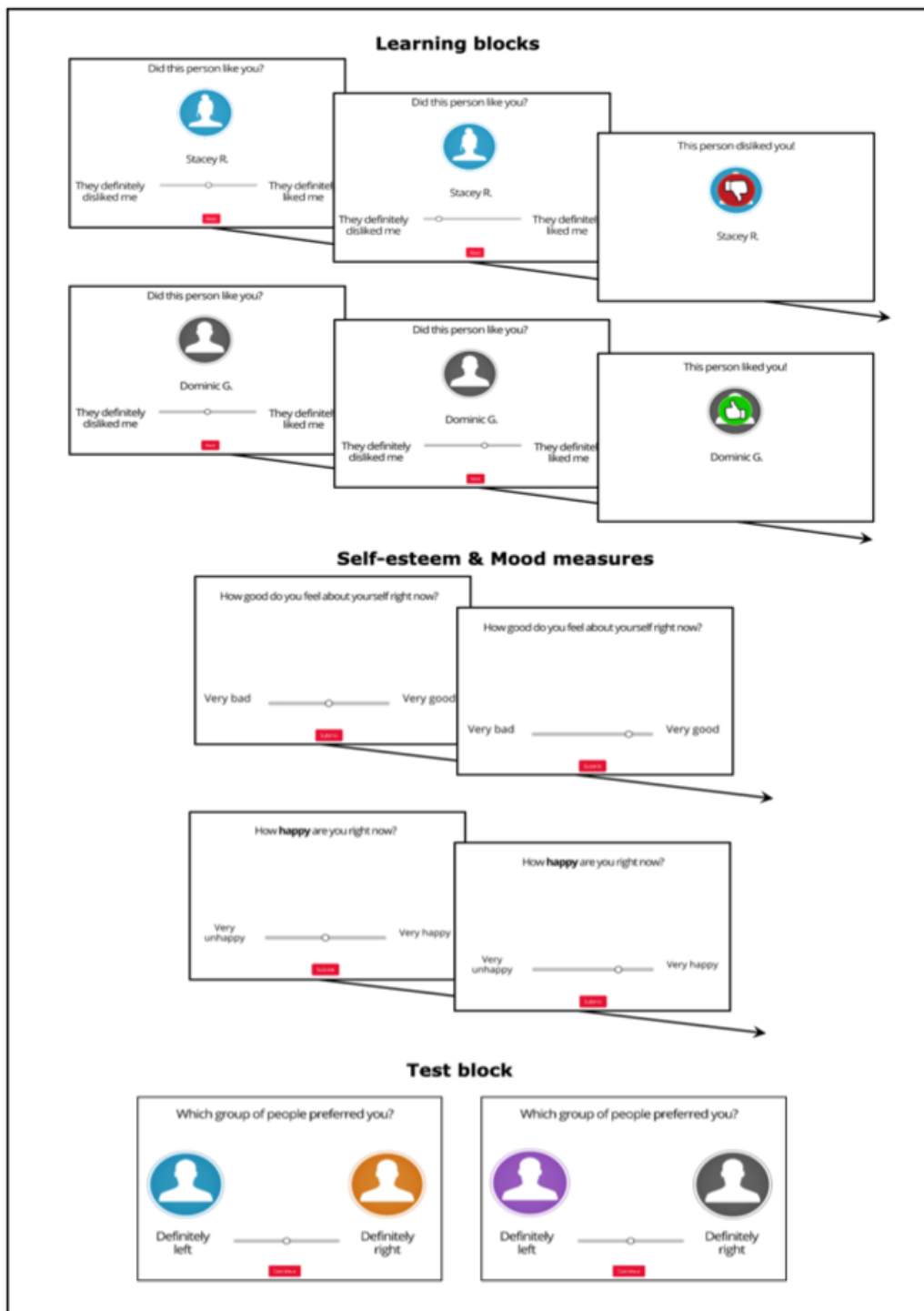


Figure 4. SLT design including Learning Blocks and Test Block examples.

Participants rated how much they thought each rater liked them (slider scale), then got a thumbs up if they were liked and a thumbs down if they were disliked (binary outcomes). Learning trials were interspersed with trait self-esteem ratings ("How good do you feel about yourself right now?") and mood ratings ("How happy are you right

now?”) as illustrated in Figure 4. During the test block participants indicated which group preferred them via slider rating. Comparisons included nice versus harsh raters from each block (memory test) and nice versus nice/ harsh versus harsh between blocks (mood bias test).

2.4 Questionnaires

The following questionnaires were collected together with the SLT: a trait measure of proneness to strong and changeable moods - the Hypomanic Personality Scale [HPS, (Eckblad & Chapman, 1986)]; a measure of severity of depression symptoms - Patient Health Questionnaire [PHQ-8, (Kroenke et al., 2001)]; a measure of severity of anxiety symptoms - Generalised Anxiety Disorder Scale [GAD-7, (Spitzer et al., 2006)]; and a trait measure of self-esteem - Rosenberg Self-esteem Scale [RSE, (Rosenberg, 1965)].

2.5 Planned statistical analyses

All statistical analyses were conducted using MATLAB (*MATLAB*). Mean and standard deviation (SD) were used to report all averages in tables and text, while mean and standard error of the mean (SEM) were used in figures. Statistical significance was set at $p = 0.05$. Data distribution was assessed visually and with a Kolmogorov-Smirnov test where applicable. Parametric tests were used for normally distributed data and non-parametric tests were used otherwise.

2.5.1 H1.1. During the Social Learning Task participants will learn which rater group was more rewarding.

Learning curves were computed as the average percentage of participants who predicted they would be liked on each trial. Participants were expected to start the game above 50% (expecting to be liked by others more than being disliked) and increase expectations of being liked by the nice group while decreasing their

expectations of being liked by the harsh group, as they gathered more information in the probabilistic learning task. A repeated measures ANOVA was used to measure learning, for each rater group (nice vs harsh), in each block (block 1 vs block 2) and over time (trial number).

Learning was also tested by the “memory test”, asking participants to indicate which group of people preferred them in each learning block (the harsh or the nice group). Participants responded by slider rating on a scale of 1 to 100. Responses were rescaled to -1 to 1 where 0 is no preference, for ease of interpretation. Negative values indicate a choice of the harsh group while positive values indicated a choice of the nice group. The presentation of rater groups was counterbalanced (left/right) and this was considered when transforming the ratings. The expectation was that participants would indicate that the nice group preferred them in each block. One sample t-tests were used to assess if on average participants significantly chose one rater group over the other.

2.5.2 H1.2. Mood induction will lead to increased mood ratings after wins and decreased mood ratings after losses.

The success of the mood induction manipulation was assessed with a 2 (time: rating before vs after mood induction) x 2 (WoF: win vs loss) ANOVA. Post hoc t-tests were used to further explore group differences. Mood change was defined as the average mood in block 1 subtracted from average mood in block 2. Positive mood change values meant participants were happier in block 2, while negative values meant they were happier in block 1.

2.5.3 H2.1. Mood will bias predictions: expectations that others will like them will be increased under positive mood, and decreased under negative mood, compared to baseline mood (prior to mood induction).

Similar to test preferences, participants made predictions by slider rating from definitely disliked me (value 0) to definitely liked me (value 100). For ease of interpretation,

predictions were rescaled on a scale from -1 to 1, where 0 represented uncertainty if liked or disliked.

A 2 (mood induction: won vs lost WoF) x 2 (rater groups: harsh vs nice) ANOVA was used to assess significant mean differences in the predictions made by participants under a positive compared to a negative mood. Post hoc t-tests were used to further examine the group differences.

Associations between trait mood instability (measured with the HPS questionnaire, as used by Eldar & Niv (Eldar & Niv, 2015)) and mood bias on predictions were also explored. Participants were median split into high and low HPS groups and a 2 (HPS: high vs low) x 2 (mood: won vs lost WoF) x 2 (rater groups: harsh vs nice) ANOVA was used to assess the main effects and interactions.

2.5.4 H2.2. Mood will bias perception of social feedback value: participants will prefer raters encountered in the block they were happier in during learning. This effect will be stronger in participants with higher levels of trait mood instability (HPS), consistent with (Eldar & Niv, 2015).

In the mood bias test choices, participants were asked to indicate which rater group preferred them: the one before or the one after the mood induction. Test choices asked about nice and harsh groups separately. Responses were rescaled to -1 to 1, where 0 is no block preference, for ease of interpretation. Negative values indicate a choice of block 1 raters (pre mood induction) while positive values indicated a choice of block 2 raters (post mood induction). Given that the nice/harsh groups were equally rewarding across the two learning blocks, there should not have been a block preference. The expectation was to see a mood bias in the form of participants preferring the block they were happier in during learning.

The Kolmogorov-Smirnov test was used to test whether data were normally distributed. Wilcoxon signed-rank tests (non-parametric alternative to t-tests) were used to assess if block preference differed from 0 in the harsh group and the nice groups, respectively.

Spearman rank correlations were then used to assess whether there was an association between block preference and mood change. This was done separately for the harsh group and the nice group. Linear regression was used to assess the effect of mood, HPS, and their interaction on test preference.

2.5.5 H3.1. State self-esteem will track social outcomes and prediction errors in the environment, replicating the findings of Will et al. (2017).

A mixed-effects regression model was used to investigate if self-esteem tracked outcomes and social prediction errors (SPEs), with a random intercept at the participant level, defined as follows:

Equation 9

$$\text{Self-esteem} \sim 1 + \text{outcome} + \text{SPE} + (1 \mid \text{participant})$$

This model was compared to two simpler models in which self-esteem tracked only SPEs or only outcomes. Model comparison was done by comparing the Bayesian Information Criterion (BIC) value for each model, with lower BIC values indicating a more parsimonious model fit.

2.5.6 H3.2. Mood will impact state self-esteem tracking outcomes and social prediction errors.

A mixed-effects regression model was used to investigate if mood impacted self-esteem tracking outcomes and SPEs, with a random intercept at the participant level, defined below. Interaction terms were included to measure if mood had an impact on SPEs or outcomes.

$$\text{Self-esteem} \sim 1 + \text{outcome} + \text{SPE} + \text{WoF block} + (\text{outcome} \times \text{WoF block}) + (\text{SPE} \times \text{WoF block}) + (1 \mid \text{participant})$$

3 Results

3.1 Demographic information

A total of 85 young people took part in the SLT study. As shown in Table 1, participants were aged between 14 and 26, with a mean age of 18.26. A majority were female at 60% (n = 51), the rest were either male at 35.3% (n = 30), non-binary at 3.5% (n = 3), or their gender was not disclosed 1.1% (n = 1). The sample was predominately White at 82.3% (n = 70), followed by those who reported that they were Asian/Asian British at 15.2% (n = 13), Black/African/Caribbean/Black British or have a mixed ethnic background at 2.3% (n = 2).

Table 1. Summary of demographic information for all participants (N = 85).

| | Mean (Standard Deviation) | Range |
|--|---|---------|
| Age | 18.26 (2.95) | 14 – 26 |
| Gender | 60% female 35.3% male 3.5% non-binary 1.1% not disclosed | |
| Anxiety measure (HADS – anxiety) | 8.34 (4.59) | 2 – 19 |
| Depression measure (HADS – depression) | 7.02 (2.92) | 4 – 19 |
| Generalised anxiety measure (GAD) | 13.6 (6.26) | 7 – 28 |
| Depression measure (PHQ) | 6.94 (6.86) | 0 – 24 |
| Trait self-esteem measure (RSES) | 23.03 (2.96) | 10 – 29 |

| | | |
|--------------------------------------|--------------|---------|
| Trait mood instability measure (HPS) | 35.78 (7.02) | 19 – 55 |
|--------------------------------------|--------------|---------|

Abbreviations: Hospital Anxiety and Depression Scale (HADS), Generalised Anxiety Disorder Scale (GAD), Rosenberg Self-esteem Scale (RSES), Hypomanic Personality Scale (HPS).

3.2 H1.1. During the Social Learning Task participants will learn which rater group was more rewarding.

A repeated measures ANOVA revealed an effect of time [$F(15,68) = 3.58, p < 0.0001$; see Figure 5.], an effect of rater group [$F(1,82) = 47.51, p < 0.0001$], and no effect of block [$F(1,82) = 0.43, p = 0.6$]. There was a time \times rater group interaction showing participants learned about the rater groups over time [$F(15,68) = 0.55, p < 0.0001$]. There were no time \times block [$p = 0.5$] nor rater \times block interactions [$p = 0.7$] suggesting that learning was comparable across the two blocks.

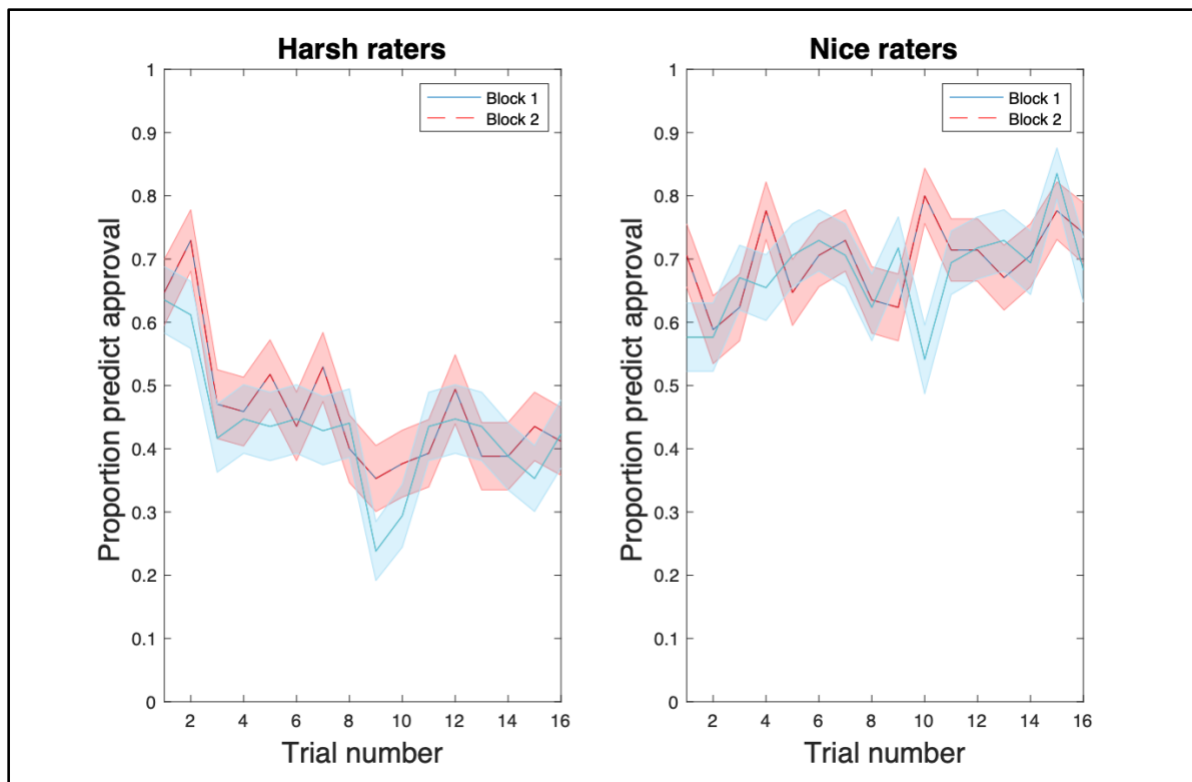


Figure 5. Participants adapted their predictions of being liked by the raters according to their group membership (harsh or nice raters); mean and shaded SEM for each trial.

Opposite to our predictions, at test, participants did not accurately recall which rater group preferred them; rather they indicated that the harsh group preferred them more in block 1 [$t(84) = -2.01$, $CI = [-0.14 -0.001]$, $p = 0.04$, $d = -0.43$] and had no preference for one rater group or the other in block 2 [$t(84) = -1.28$, $CI = [-0.11 0.02]$, $p = 0.2$, $d = -0.27$].

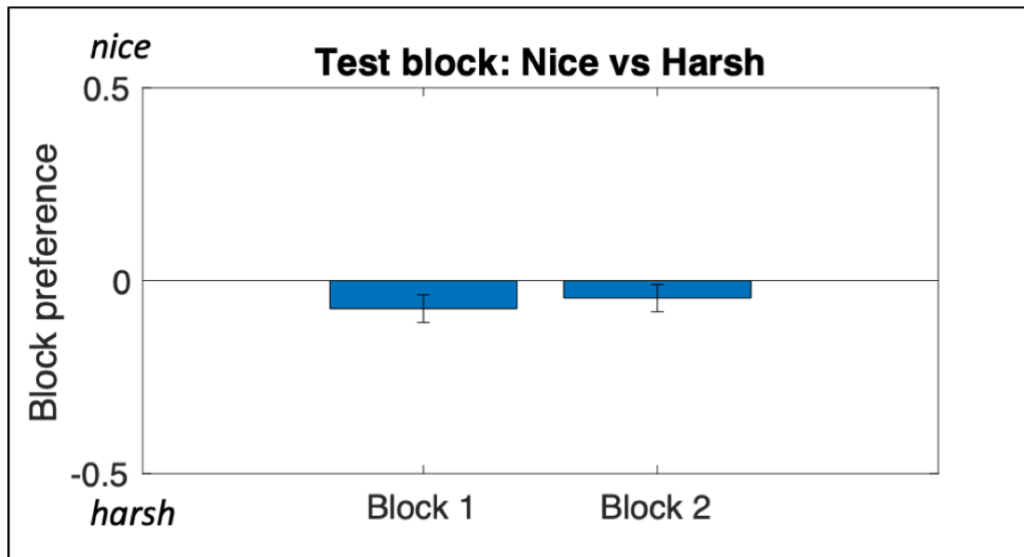


Figure 6. Test block average preference for each block. Participants indicated that the harsh group preferred them in block 1 [$p = 0.04$] and had no rater group preference in block 2 [$p = 0.2$]; mean and SEM.

3.3 H1.2. Mood induction will lead to increased mood ratings after wins on the Wheel of Fortune and decreased mood ratings after losses.

As shown in Figure 7 below, there was a significant main effect of WoF outcome [$F(1,83) = 6.62, p = 0.01$], and a significant interaction between time and WoF outcome [$F(1,83) = 7.15, p = 0.008$], but no significant effect of time [$F(1,83) = 1.88, p = 0.17$]. Post-hoc t-tests revealed that the mood manipulation reduced happiness after a loss on the WoF [$t(82) = 3.06, CI = [5.15, 24.22], p = 0.002$], but failed to significantly increase happiness after a win [$t(84) = -0.869, CI = [-15.55, 6.09], p = 0.38$].

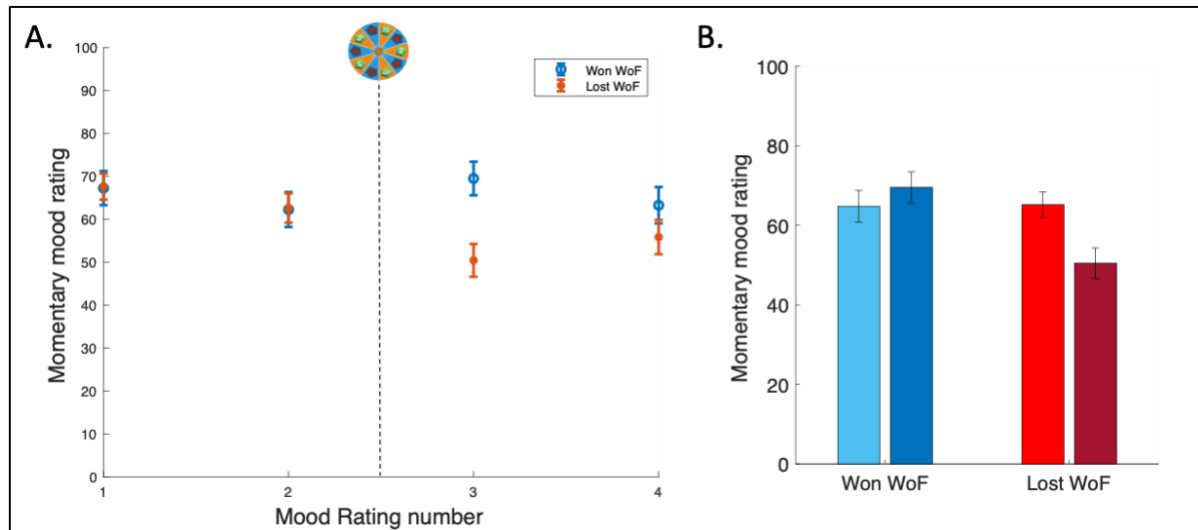


Figure 7. Mean momentary mood ratings before and after the Wheel of Fortune (WoF) mood induction. Mood did not change significantly after wins [$p = 0.38$] but decreased significantly after losses on the WoF [$p = 0.002$]. A) Mean and SEM mood for each of the four mood ratings. B) Bar chart showing the average mood before (ratings 1 & 2) and after the mood induction (rating 3); mean and SEM

3.4 H2.1. Mood will bias predictions: expectations that others will like them will be increased under positive mood, and decreased under negative mood, compared to baseline mood (prior to mood induction).

A mixed ANOVA showed a significant effect of rater group, participants predicting nice raters will like them more than harsh raters [harsh vs nice: $F(1,83) = 41.88$, $p < 0.001$], but no effect of mood [win vs lost WoF: $F(1,83) = 2.41$, $p = 0.12$], nor an interaction mood \times rater group [$F(1,83) = 0.14$, $p = 0.70$]. While mood did not bias participant predictions of being liked by the nice group [$t(83) = 1.14$, $CI = [-2.44, 9.1]$, $p = 0.25$, $d = 0.21$], there was a trend level difference in prediction for the harsh group [$t(83) = 1.83$, $CI = [-0.5, 12.72]$, $p = 0.07$, $d = 0.39$], participants predicting they would be liked less by harsh raters when in a negative mood compared to a positive mood.

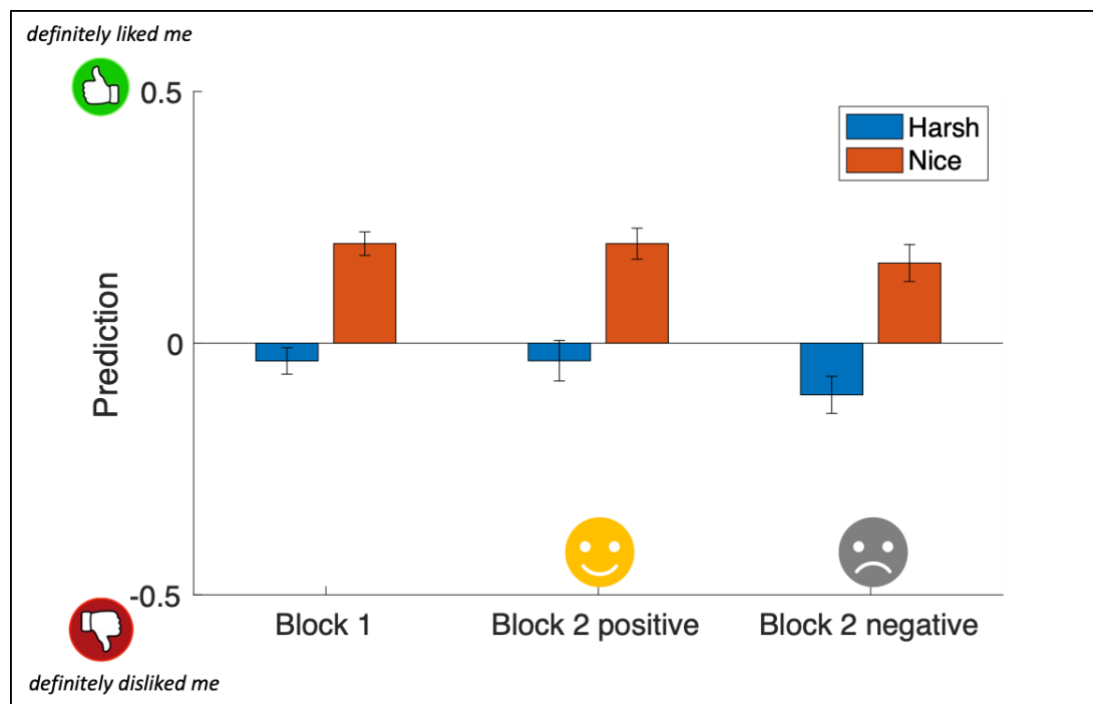


Figure 8. Mood bias on predictions made by participants. Mood did not significantly bias participant predictions of being liked by the nice group [$p = 0.2$]. There was a trend level difference between positive and negative mood in predictions for the harsh group [$p = 0.07$]; mean and SEM.

I then investigated whether there was a difference in predictions between participants with high HPS scores and participants with low HPS scores, as illustrated in Figure 9. The results showed again a significant effect of rater group [harsh vs nice: $F(1,81) = 43.12$, $p < 0.001$], with all participants predicting the nice group will like them more than the harsh group. However, there was no main effect of HPS group [high vs low: $F(1,81) = 1.65$, $p = 0.20$], no main effect of mood condition [win vs lost WoF: $F(1,81) = 1.88$, $p = 0.17$], and no significant interactions [$p > 0.22$].

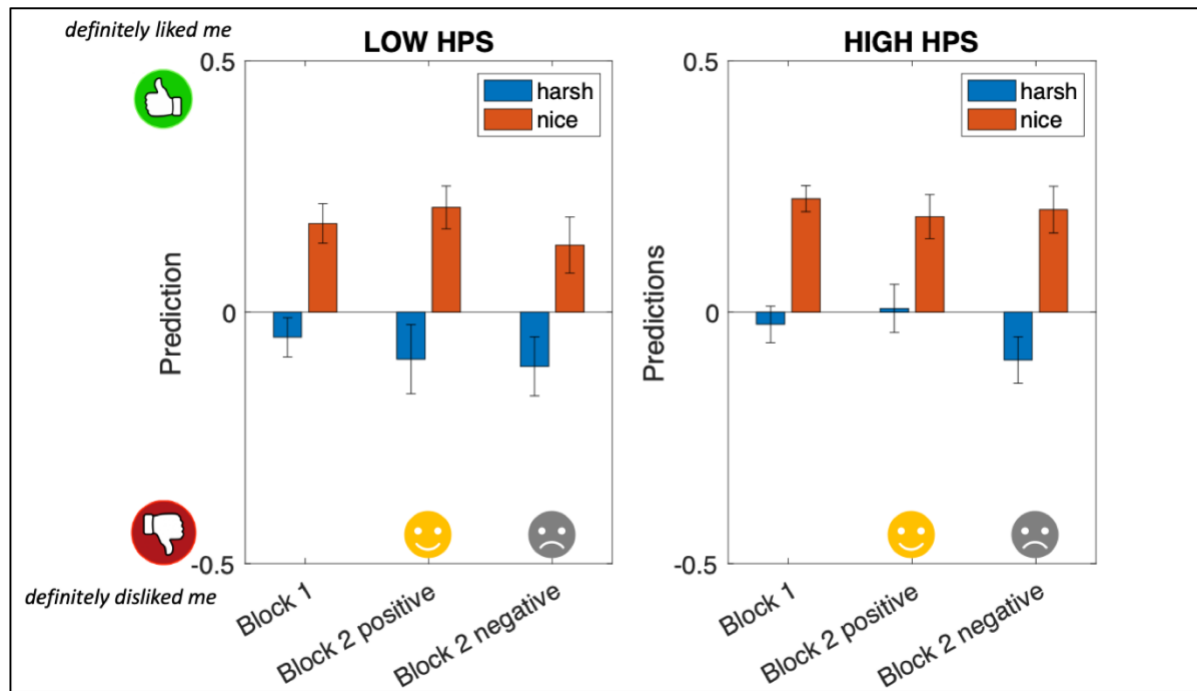


Figure 9. Mood bias on predictions made by participants with high versus low trait mood instability (HPS). There were no differences in predictions between high versus low HPS participants during the learning blocks.

3.5 H2.2. Mood will bias perception of social feedback value: participants will prefer raters encountered in the block they were happier in during learning. This effect will be stronger in participants with higher levels of trait mood instability (HPS), consistent with (Eldar & Niv, 2015).

Test preference data were not normally distributed [Kolmogorov-Smirnov test; $p < 0.0001$], so the non-parametric Wilcoxon signed-rank tests were used. They revealed that there was no significant test block preference following positive mood induction [$p = 0.25$], or following negative mood induction [$p = 0.60$, see Figure 10.].

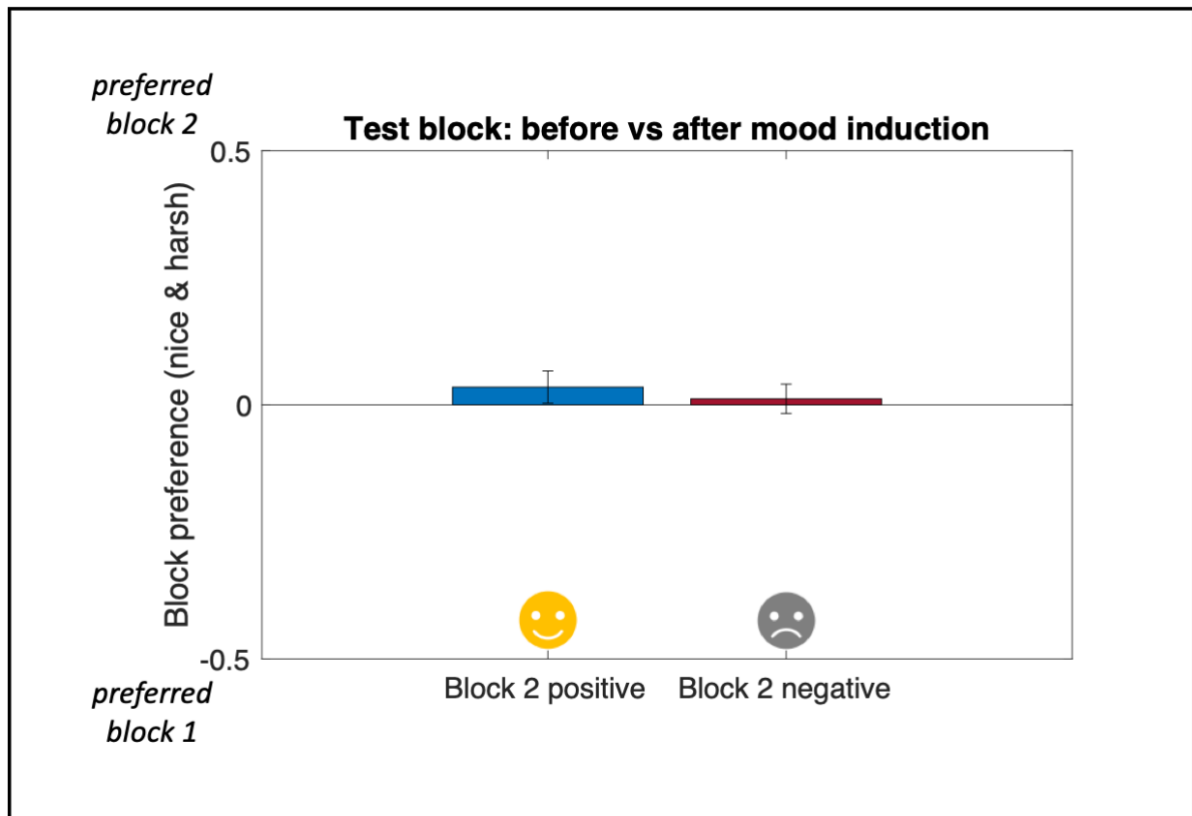


Figure 10. Average test preferences for mood bias test comparisons. Overall, participants did not show a mood bias on social reward value following positive mood [$p = 0.25$] or negative mood inductions [$p = 0.60$].

As seen in Figure 11 below, after positive mood induction participants believed the harsh raters they learned about in block 2 liked them more [$W = 701.5$, $z = 2.03$, $p = 0.004$], showing a mood bias towards the block they were happier in. Opposite to our predictions, when participants were happier in block 2 they believed nice raters from block 1 will like them more [$W = 188$, $z = -3.52$, $p < 0.001$].

In the negative mood induction condition, participants also preferred harsh raters from block 2 [$W = 251.5$, $z = -2.54$, $p = 0.01$], showing a bias toward the block they were unhappier in, and had no preference for the nice raters [$W = 441$, $z = -0.13$, $p = 0.89$].

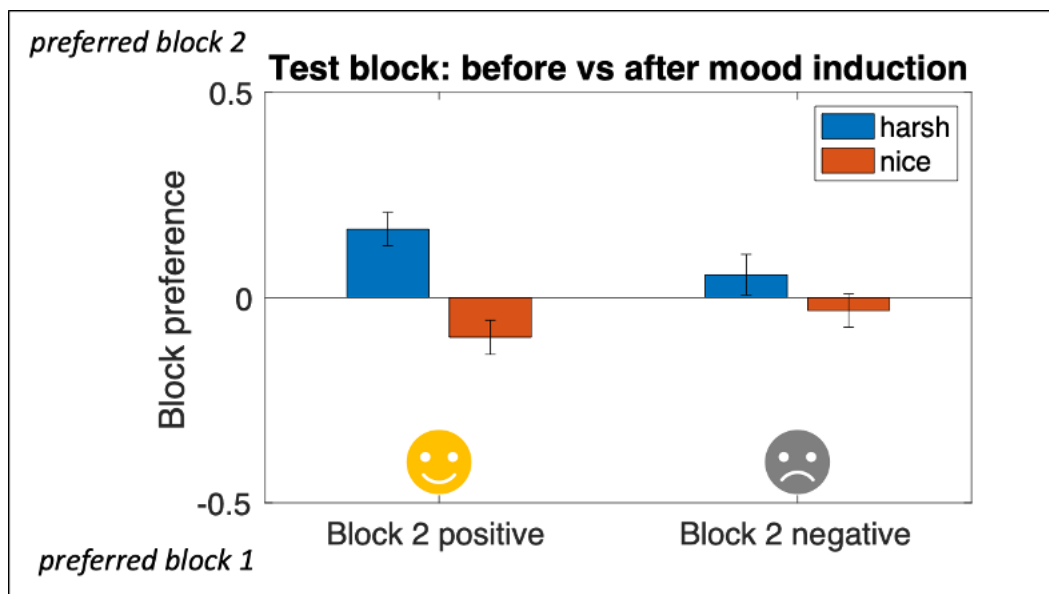


Figure 11. Average test preferences for mood bias test comparisons split by rater groups. Participants preferred nice raters from block 1 and harsh raters from block 2, following the positive mood condition, while after the negative mood condition, they preferred raters from block 2 and had no preference for nice raters.

When examining the relationship between test block preference and mood change (see Figure 12), a Spearman rank correlation showed no significant association in either the harsh [$r = 0.03$, $p = 0.73$] or the nice groups [$r = 0.05$, $p = 0.62$].

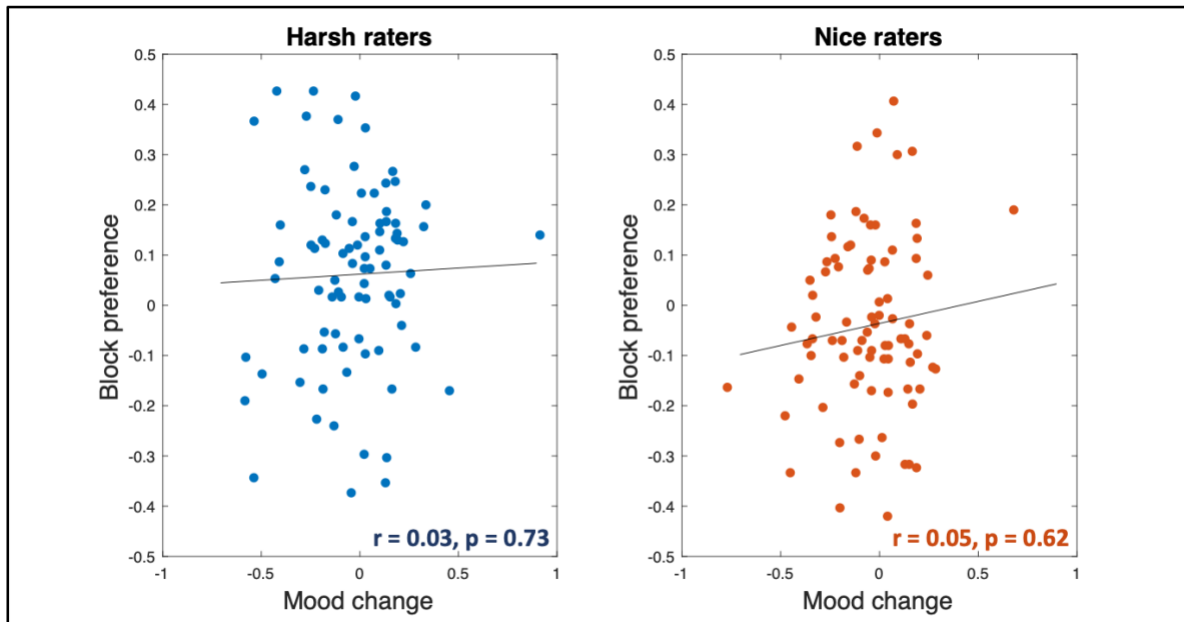


Figure 12. Scatterplot of mood change experienced versus block preference, for each of the rater groups (harsh or nice). There was no relationship between test block preference and mood change for either the harsh [blue; $r = 0.03$, $p = 0.73$] or the nice groups [orange; $r = 0.05$, $p = 0.62$].

The regression analysis of block preference in harsh raters showed a significant intercept [$\beta = 0.60$, $SE = 0.04$, $p < 0.001$], no effect of HPS [low vs high: $\beta = 0.02$, $SE = 0.06$, $p = 0.74$], a significant effect of mood [won vs lost WoF: $\beta = 0.09$, $SE = 0.04$, $p = 0.04$], and no interaction mood and HPS [$\beta = -0.08$, $SE = 0.06$, $p = 0.19$].

As can be seen in Figure 13 below, a Wilcoxon signed rank showed the mood effect was driven by low HPS and high HPS participants preferring block 2 harsh raters in a positive mood [both $p_s = 0.01$] and having no block preference in a negative mood [low HPS $p = 0.80$; high HPS $p = 0.16$].

For the nice rater test choices, there was a significant effect of intercept [$\beta = 0.44$, $SE = 0.04$, $p < 0.001$], and no effect of HPS [low vs high: $\beta = -0.01$, $SE = 0.06$, $p = 0.80$], mood [won vs lost WoF: $\beta = -0.03$, $SE = 0.04$, $p = 0.41$], or interaction WoF and HPS [$\beta = 0.007$, $SE = 0.06$, $p = 0.90$].

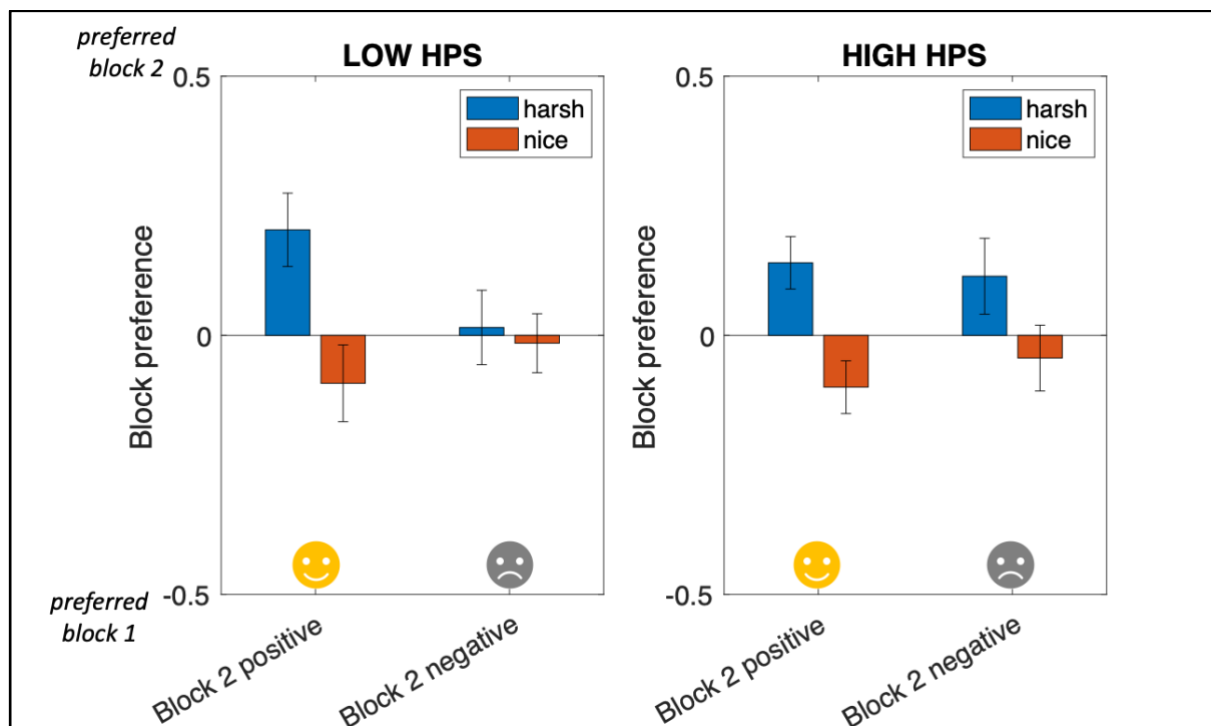


Figure 13. Block preference for the mood bias test choices, split by mood induction condition and HPS group. There was no main effect of HPS group [$p = 0.80$]. Participants preferred harsh raters from block 2 in a positive mood [$p = 0.01$] and had no block preference in a negative mood [$p \geq 0.16$]. Participants had no block preference for the nice raters [$p > 0.19$].

3.6 H3.1. State self-esteem will track social outcomes and prediction errors in the environment, replicating the findings of Will et al. (2017)

Three mixed-effects regression models were compared to assess whether self-esteem tracked only SPEs, only outcomes or both SPEs and outcomes, as shown in Table 2. The winning model showed self-esteem tracking both SPEs and outcomes.

Table 2. Regression model comparison.

| Models | BIC | Δ BIC |
|--------------------------------------|--------|--------------|
| Self-esteem tracks SPEs only | 1395.3 | 3.5 |
| Self-esteem tracks outcomes only | 1400.5 | 8.7 |
| Self-esteem tracks SPEs and outcomes | 1391.8 | 0 |

The model that best fit the data showed a significant effect of SPE [$\beta = 0.12$, $SE = 0.03$, $p < 0.0001$], a significant effect of outcome [$\beta = 0.21$, $SE = 0.06$, $p = 0.001$], and a significant intercept [$\beta = 0.09$, $SE = 0.03$, $p = 0.01$], indicating both SPE and outcomes impacted state self-esteem.

As seen in Figure 14 below, t-tests confirmed that trait self-esteem increased significantly following positive SPEs and decreased following negative SPEs [$M_{+SPE} = 0.11$, $M_{-SPE} = -0.11$, $t(84) = 3.49$, $CI = [0.09 \ 0.35]$, $p < 0.0001$, $d = 0.76$]. Similarly, self-esteem increased after receiving positive outcomes (being liked) and decreased following negative outcomes (being disliked) [$M_{liked} = 0.11$, $M_{disliked} = -0.9$, $t(84) = 3.23$, $CI = [0.08 \ 0.33]$, $p = 0.001$, $d = 0.70$].

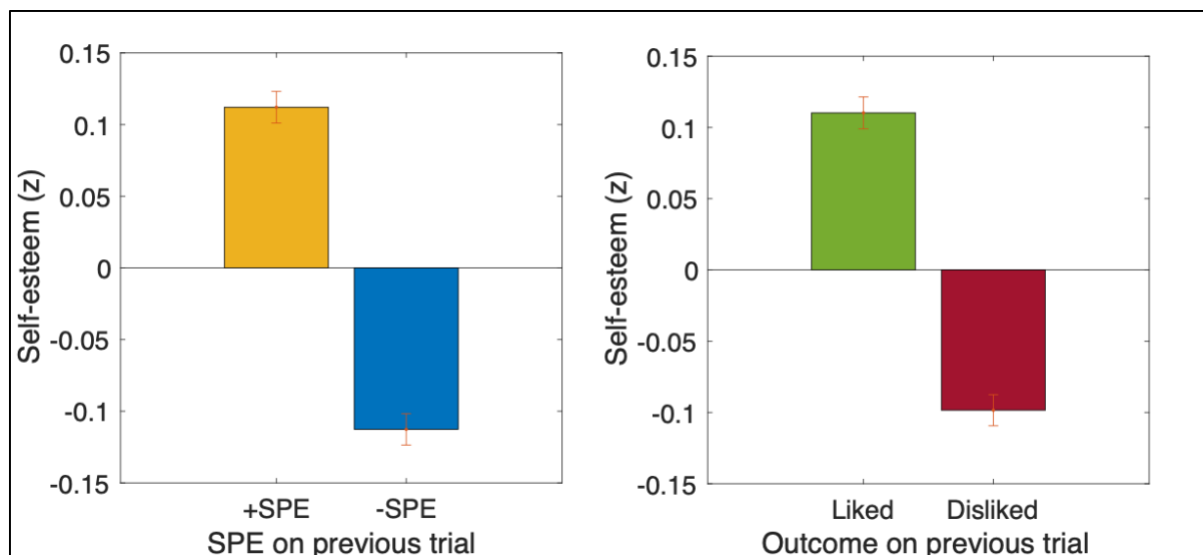


Figure 14. State self-esteem tracked social prediction errors [left, $p < 0.0001$] increasing following +SPEs and decreasing following -SPEs; State self-esteem

also tracked outcomes received, increasing when liked and decreasing when disliked by the raters [right, $p = 0.001$].

Notably, since SPEs were defined as the predictions subtracted from the outcomes, the two quantities were inevitably correlated [$r = 0.72$, $p < 0.0001$]. To measure how much the regression coefficients were inflated due to multicollinearity, I calculated the variance inflation factor (VIF) for each predictor variable in the model. A VIF value of 1 means no multicollinearity, while a VIF value between 5 and 10 suggests severe multicollinearity. There is no upper limit for the VIF. The results were as follows: VIF_{Participant number} = 1.00, VIF_{SPE} = 3.31, VIF_{Outcomes} = 3.29, suggesting small to moderate multicollinearity effects.

3.7 H3.2. Mood will impact state self-esteem tracking outcomes and social prediction errors.

The multilevel regression model indicated a significant main effect of SPE on state self-esteem [$\beta = 0.12$, $SE = 0.03$, $p = 0.0001$], a significant effect of outcome [$\beta = 0.10$, $SE = 0.03$, $p = 0.001$] and a significant intercept [$\beta = 0.21$, $SE = 0.02$, $p < 0.0001$]. However, as shown in Figure 15, there was no effect of mood [WoF block: $p = 0.82$], nor were there significant interactions between mood and SPE [$p = 0.29$] nor mood and outcome [$p = 0.43$], suggesting that mood did not impact self-esteem tracking outcomes or SPEs.

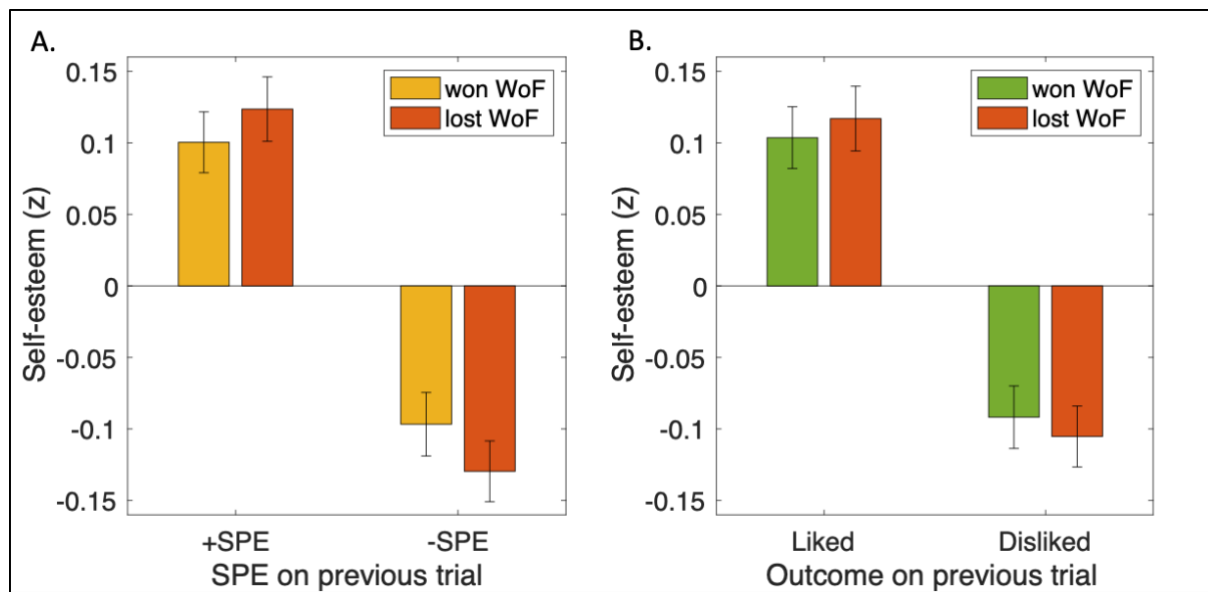


Figure 15. Mood did not impact average state self-esteem ratings following different types of prediction errors or outcomes. A) Self-esteem in block 2 split by positive and negative social prediction errors on the previous trial and WoF outcome; mean and SEM. **B)** Self-esteem in block 2 split by outcomes (liked versus disliked) on previous trial and WoF outcome; mean and SEM.

4 Discussion

The Social Learning Task (SLT) was designed with two main aims: (1) to assess if mood biases reward perception in social contexts and (2) to assess if mood influences self-esteem tracking social feedback and prediction errors. The results showed mood did not bias reward perception, with other heuristics motivating participants' choices. However, negative mood appeared to bias participants' predictions of how much others will like them (trend level). I replicated previous results by Will et al. (2017) to show momentary self-esteem tracked outcomes and social prediction errors, but there was no evidence to suggest that mood influenced self-esteem tracking feedback and prediction errors.

The SLT design combined the Wheel of Fortune task [from Chapter 3,(Eldar & Niv, 2015)] with a task on learning from social feedback (Eldar et al., 2016; Low et al., 2022). Rewards were received in the form of positive (being liked) or negative feedback (being disliked) from other people, as opposed to monetary or points rewards. At the start of the task, without having any prior information, participants expected to be liked by the rater groups more than disliked, as shown previously (Will et al., 2020). Throughout the learning blocks, participants expected nice raters to like them more than they expected harsh raters to dislike them, when in fact the probabilities were yoked (i.e., *harsh* liked them 25% of the time and *nice* liked them 75% of the time). This is in line with the observation that people tend to see themselves positively (Leary, 2007) and expect to receive more positive than negative feedback (Hepper et al., 2011). It has been proposed that humans achieve and maintain a positive self-concept based on cognitive processing mechanisms that distort incoming information in a positive direction (Taylor & Brown, 1988). For example, people update their beliefs about themselves and others more following desirable rather than undesirable feedback (Korn et al., 2012; Sharot, 2011). These biases serve an adaptive purpose, being associated with higher levels of well-being and better mental health outcomes, by allowing individuals to maintain a positive outlook on life and cope with adversity (Sharot, 2011).

By the end of the learning blocks, participants adapted their predictions of being liked by the two groups, showing they learned which group preferred them. There was a trend for mood to bias predictions, such that participants in a negative mood predicted harsh raters would like them less compared to participants in a positive mood. This suggests that mood may have influenced learning from previous outcomes, possibly by biasing the perceived value of social rewards received, leading to biased predictions in the same direction. The effect of the mood induction was strongest immediately after the WoF and decayed until the end of the block, so it is also possible that the largest biases occurred after the WoF and were reduced as time passed resulting a small overall effect. The findings of this study align with the concept of the "mood congruency effect" (Mayer et al., 1992; Rusting, 1998), where emotional information that is consistent with the current mood state is processed preferentially. This effect has implications for shaping future expectations in the same direction (Loewenstein &

Lerner, 2003). Recent research further suggests that positive moods default to expecting rewards, leading them to perceive such outcomes as unsurprising, even when unlikely, while negative feedback is seen as unexpected (Paul & Pourtois, 2017).

Contrary to expectations, when probed at the end of the game, participants either failed to recall which rater group gave rewards more often (in block 2) or chose the harsh one (in block 1). It is possible that participants learned about the raters but did not recall which group was better by the time of the surprise test. Another possibility is that the harsh group was more salient during learning and thus better remembered. Negativity bias is a phenomenon in psychology that refers to the tendency for negative information to have a greater impact on impression formation than positive information (Baumeister et al., 2001; Rozin & Royzman, 2001). In other words, people tend to give more weight to negative information than to positive information they encounter. One possible reason for the negativity bias is the rarity of negative social events which leads to them being perceived as more surprising. In real life, it is indeed rare for a group of people to express their dislike of you repeatedly (like the harsh raters). Reinforcement-learning models have shown that surprising outcomes are better remembered, irrespective of their valence (Rouhani & Niv, 2021; Rouhani et al., 2018; Rouhani et al., 2020). It is thus likely that participants did not remember the values of the options learned about in learning blocks, but the salience of the harsh groups drove them to choose this group. Future work could explore if participants remembered the actual rewards probabilities for the rater groups by asking them to explicitly rate this during test trials, as done previously by Eldar and Niv (2015).

4.1 Mood bias on social reward perception

The first aim of this study was to assess mood bias on reward perception in social contexts. However, it was not possible to do this reliably, because participants did not 'pass' the memory test requiring them to identify the more rewarding rater group. In addition, the mood induction was sufficiently potent for negative mood but not positive mood, similar to previous work [Chapter 3; (Eldar & Niv, 2015)], and in spite of design changes made to overcome it. The choice pattern for mood bias comparisons was similar across mood induction conditions, with participants preferring harsh raters they

encountered in block 2 over those in block 1 and nice raters from block 1 over those from block 2.

One possible explanation is that participants had different implicit expectations and strategies in each block. Starting the task participants expected with some certainty to be liked by both rater groups and were negatively surprised to discover the harsh group did not like them very often (creating large negative SPEs), lowering this group's overall reward value. This experience contrasted with the nice group which liked them more often than expected (large positive SPEs), possibly enhancing its reward value overall. Going into the second block, participants were now familiar with the task design and while starting off with the same expectations of being liked, they were less surprised by the harsh group not liking them (smaller negative SPEs). This led participants to perceive harsh block 2 as better than harsh block 1. Similarly, the nice raters in block 2 generated smaller surprises (smaller positive SPEs) leading to nice block 1 being perceived as better. At test, when asked to select who preferred them out of the two equally rewarding blocks, participants indicated nice block 1 (largest positive experience) and harsh block 2 (least negative experience). On the other hand, if this were true, one would have expected to also see a clear preference for the nice over the harsh group in block 1 during the memory test, not the opposite.

4.2 Mood bias on self-esteem

The second aim was to replicate previous findings that showed self-esteem tracked social prediction errors in the environment (Will et al., 2017) and to extend them by investigating if mood biased this process. I replicated previous work and showed that state self-esteem tracked SPEs (Will et al., 2017) and additionally found that self-esteem tracked outcomes. This is not inconsistent with the work of Will et al. (2017) who showed separately that self-esteem was predicted by an outcome valence-only model, as well as an SPE-only model, with the SPE model better fitting the data. The authors did not directly combine both outcomes and SPE effects into one model predicting self-esteem, so it is not possible to know if this model would have outperformed the SPEs-only model. However, the winning model included SPE and

expectations [similar to the Happiness Model (Rutledge et al., 2014)], which following mathematical transformations could be seen as resembling the SPE and outcomes model. This would be consistent with the present results.

Contrary to initial predictions, there was no evidence of a mood bias on self-esteem tracking outcomes and SPEs. This could be due to the mood induction not having a sufficient effect to then further bias self-esteem evaluations, or the study being underpowered overall. Speculatively, negative mood appears to make trait self-esteem more reactive to positive and negative reward prediction errors and outcomes. High self-esteem reactivity has been shown to be associated with the presence of affective disorders such as depression or anxiety (Tuijl et al., 2018). Low trait self-esteem has been associated with more volatile state self-esteem and an increased tendency to use SPEs to determine one's self-worth (Will et al., 2020). In that study, participants with low self-esteem were selected from the lowest 10% of trait self-esteem scores. However, these participants also scored highly on measures of depression, anxiety and inter-personal sensitivity. The study then compared them to the top 10% scoring participants, who did not report any mental health symptoms. It could thus be that overall low mood and vulnerability drove the observed reactivity in state self-esteem and overreliance on SPEs, as well as leading to lower reported trait self-esteem, instead of the other way around.

The sociometer theory, developed by Leary et al. (1998), is based on the notion that human beings have an innate need to belong and be connected to others. The theory posits that social interactions and relationships serve as a gauge of our social acceptance and belonging. More recent work has shown self-esteem is not a mere tally of social acceptance, but rather, reflects expectations about social milieu as well as the extent of change in one's social standing (Low et al., 2022). This is consistent with the present study findings that self-esteem did not just track the outcome values of the rater groups but also the direction and rate of change of social acceptance, increasing following positive outcomes and positive SPEs and decreasing following negative outcomes and negative SPEs. Additional work could further confirm this theory by using a computational modelling analysis approach on our data. This would entail adapting the belief-based model developed by Low et al. (2022) to fit the current task design and comparing it to other reinforcement learning models such as Q-value

models which simply track the cumulative reward in the environment for taking a specific action in a given state.

4.3 Limitations

The present study has some limitations that warrant discussion. First, the experimental design may have had insufficient learning trials, impacting the participants' ability to accurately recall the more rewarding groups. Previous studies have used a larger number of trials (46 per rater group compared to 16 in the current design) to ensure proper learning (Will et al., 2017). This was part of a more complicated design that involved learning about four rater groups (instead of 2) in a single block, which is significantly more difficult.

Second, although the wheel was rigged to give participants the second largest possible prize (\pm £5), similar to previous work (Eldar & Niv, 2015) and based on insights from Chapter 2., the mood induction was not strong enough in inducing positive moods. It may be that the younger participant sample in this study did not respond to the monetary incentive the same as adults have in similar contexts (Eldar & Niv, 2015; Wang et al., 2017). Future studies could benefit from using different approaches to experimental mood manipulation (Brosschot et al., 2002) such as videos with instructions. It may also be worth exploring internal mood manipulation procedures such as recalling an emotional episode, as opposed to external ones, as there is evidence that they may be more effective (Joseph et al., 2020).

Third, the task may not have been sensitive enough to detect mood biases. The choice pattern observed across the two different mood induction conditions suggests that other heuristics may have been at play. This may be specific to social contexts, as it was not observed in non-social contexts. Other work in non-social domains has demonstrated that participants show a positive mood bias, preferring the block they were happier in [Chapter 2, (Eldar & Niv, 2015; Michely et al., 2022)]. Another explanation may be poor task performance. One way to distinguish good performance from poor or chance performance was to look at test choices comparing stimuli of

different reward probabilities (i.e., the 'memory test'). As seen above, participants failed this check and chose the harsh group.

Additionally, the design of the task relied on previous work that quantified momentary mood and state self-esteem (Eldar & Niv, 2015; Rutledge et al., 2014; Will et al., 2017) and kept the same wording for these measures. Different colours and fonts were used for each of the questions to further underline the distinction between them. Exploratory analyses revealed that the measures of trait self-esteem and momentary mood were strongly correlated and thus probing a similar concept that likely incorporated both self-esteem and mood. This is in line with previous work showing the association between self-esteem and mood in both adolescents and adults (Choi et al., 2019; Salmela-Aro & Tuominen-Soini, 2010; Sato & Yuki, 2014; Simsek, 2013). In adolescents, it has been shown that self-esteem acts as a protective factor and mediates the relationship between mood and psychopathological symptoms. More work is needed to clarify how these processes interact and overlap.

Fourth, participant testing was conducted online with limited experimenter control. Participants were sent the link to the task, and they completed it in their own time. This online setup can be very convenient for participants but can lead to more noisy data and smaller effect sizes compared to lab-based studies. Online data collection methods lower-quality data, as a result of respondents' "mechanical" responses (Matzat & Snijders, 2010), and more power is needed to compensate for this noise (Chetverikov & Upravitelev, 2016; Reips, 2000). As the current study was part of the third wave of data collection from a sample of participants who consented to take part in the original project, I was unable to recruit additional people to increase power.

Finally, the study could have benefited from a measure of the believability of the task and cover story. Due to the long study design, I was unable to add follow-up questions about how the task was perceived. Ultimately believing that feedback during the task was *actually* received from other humans was at the core of this design. If participants did not believe this, then feedback could no longer be classified as being in the social domain. Excluding participants who did not believe the cover story would allow a more stringent analysis as well as investigations into possible differences between perceiving feedback as social versus non-social. Overall, future studies could address

current study limitations by using a larger number of trials, stronger mood induction methods, measures of task sensitivity, participant attention checks, and task believability questions.

4.4 Conclusion

The Social Learning Task showed that negative mood appeared to bias people's predictions, making them believe that harsh raters will like them less. However, the SLT design may not have been sensitive enough to measure mood bias on social reward perception, as the positive mood induction was not potent enough to change mood and participants did not pass the memory test at the end of the task. Although the study did not find conclusive evidence that mood biases reward perception, it identified alternative possible heuristics that motivated participants' choices. The study also confirmed the cognitive bias of individuals to see themselves positively and expect more positive than negative feedback, which has been associated with higher levels of well-being and better mental health outcomes. Moreover, it provided insights into how mood congruency effects may impact expectations for the future and how negativity bias can influence impression formation. Future research could benefit from exploring alternative mood induction procedures and different types of social feedback to gain a more comprehensive understanding of these complex relationships. The implications of this study extend to the wider literature by shedding light on the interplay between mood, learning, social reward perception, and self-esteem.

CHAPTER 5. BIMODAL: Measuring the effect of mood on reward valuation in bipolar disorder

Abstract

Bipolar disorder, a prevalent public health concern affecting approximately 1-3% of people (Ferrari et al., 2016), is believed to stem from dysregulation of the Behavioural Activation System [BAS, (Johnson, Edge, et al., 2012)] which governs goal-directed behaviour. However, the mechanisms through which real-life events influence fluctuations in BAS activation remain unclear. Previous theoretical frameworks proposed by Eldar and Niv (2015) and Mason et al. (2017) suggest that mood biases in reward perception contribute to shifts in BAS activation by biasing rewards to seem better or worse than they actually are. The bias leads to increases or decreases in activation and mood which then further bias reward perception and thus maintain the cycle of mania or depression. The present study aimed to empirically test this theory and measure mood bias on reward valuation, for the first time, in participants diagnosed with bipolar disorder versus healthy controls. Participants ($N_{BPD}=17$; $N_{CTRL}=13$) played the app-based *Wheel of Fortune* game and completed questionnaires measuring mania and depression symptoms and trait mood instability. Results showed groups performed the task accurately and experienced comparable mood changes following the mood manipulation. Among the participants, only those with bipolar disorder displayed a mood bias on reward value, where outcomes were perceived as more favourable during positive moods and less favourable during

negative moods. Additionally, this mood bias was found to be positively associated with residual symptoms of mania. This study was the first to demonstrate that individuals with bipolar disorder exhibit a mood bias on reward valuation, advancing our understanding of cognitive mechanisms that may maintain manic cycles characteristic of bipolar disorder.

1 Introduction

Bipolar Disorder (BPD) is a public health issue, ranked the fifth most significant cause of disability globally (Angst, 2004; WHO, 2001), affecting between 1 and 3% of individuals (Ferrari 2016). It is associated with completed suicide rates that are 58 times higher compared to the general population (Plans et al., 2019), high rates of substance abuse (Mosheva et al., 2020) and high comorbidity with other disorders (Fajutrao et al., 2009). Bipolar disorder is associated with reduced quality of life (Judd et al., 2005), high unemployment rates (Shippee et al., 2011), increased stigma and social marginalisation (Michalak et al., 2011), and impairments in social relationships (Greenberg et al., 2014). Even euthymic and remitted individuals with bipolar report lower functioning and well-being compared to patients diagnosed with chronic medical illness, major depressive disorder (Cooke et al., 1996), or the general population (Arnold et al., 2000). The disease burden is further amplified by significant delays in diagnosis and treatment initiation (Patel et al., 2015). Individuals are also often misdiagnosed with unipolar depression and are given inadequate treatment that can exacerbate manic symptoms (Patella et al., 2019).

Bipolar disorder is characterised by episodes of mania or hypomania, involving periods of elevated mood, increased energy and confidence, racing thoughts, and risky decision-making. Manic episodes are often followed by periods of depression, characterized by feelings of sadness, hopelessness, low energy, and loss of interest in activities (APA, 2013). Very commonly, individuals experience mixed episodes, a combination of elevated, irritable, restless, or agitated mood, along with depressive symptoms such as sadness, guilt, or hopelessness (Phillips & Kupfer, 2013). Previous research showed high mood, low mood and functional impairment can vary on a weekly cycle (Proudfoot et al., 2014). Mood instability frequently persists outside of mood episodes, with residual symptoms accounting for around a third of patients' lifetime (Judd et al., 2002).

According to a prominent theory, bipolar disorder arises from the dysregulation of a system known as the Behavioural Activation System [BAS, (Depue & Iacono, 1989;

Gray, 1982; Gray, 1987; Gray, 1990; Johnson, Edge, et al., 2012)]. The BAS directs behaviour towards goals and desired rewards. Temporary increases and decreases in the functioning of the BAS are believed to result in manic and depressive episodes, respectively. During manic episodes, the BAS becomes excessively activated, leading to heightened positive affect, increased energy, impulsivity, goal pursuit and a strong drive to pursue pleasurable rewards. On the other hand, during depressive episodes, the BAS experiences a decrease in activity, resulting in feelings of sadness, lethargy, loss of interest, and reduced motivation. Central to the BAS theory is the view that sensitivity to rewards is increased in bipolar disorder, however there is mixed evidence of both increased (Nusslock & Alloy, 2017) and decreased (Johnson, Edge, et al., 2012; Schreiter et al., 2016) reward sensitivity in this group.

Eldar and Niv (2015) proposed a model of mood instability which stems from a bidirectional relationship between mood and reward perception. They theorised that unexpected outcomes, whether positive or negative, impact not only mood, as demonstrated in previous studies linking prediction errors with dopamine release (Schultz, 2002; Schultz et al., 1997), but can also affect future valuations of rewards in a recursive cycle. The authors show experimentally that participants scoring high on trait mood instability measured with the Hypomanic Personality Scale [HPS, (Eckblad & Chapman, 1986)] experience biased reward perception following unexpected large surprises (i.e., following large positive reward prediction errors future rewards are perceived as better than they are, and the opposite happens following negative reward prediction errors). Participants with more stable moods, on the other hand, experience momentary mood changes following unexpected outcomes, but do not show biased reward valuation. This finding was formalised in a computational model where the effect of mood on the subjective perception of reward was controlled by a 'mood bias' parameter, computed for each individual. The mood bias parameter functions as an intensity dial, allowing for a range of mood biases on reward value, varying from no bias to significant biases. This parameter was positively correlated with trait mood instability. It has been argued that a moderate mood bias parameter serves an adaptive function guiding individuals towards rewards in the environment (Eldar & Niv, 2015; Mason et al., 2017). An excessive propensity for mood to bias reward perception, however, can give rise to mood instability.

Indeed, Mason et al. (2017) theorised that this two-way interaction between reward sensitivity and mood might explain the symptoms of bipolar disorder including positive, negative, and mixed affective states. As illustrated in Figure 1 in blue, the theory suggests that momentary upward shifts in mood can lead to a biased perception of subsequent rewards as being better than their actual value (via mood bias). This biased reward value generates positive prediction errors (i.e., the difference between the expected and received outcome), further enhancing mood and thus reinforcing a cycle of positive mood. Conversely, negative mood changes produce a downward shift in mood state, causing rewards to be perceived as less valuable, resulting in negative surprises that further diminish mood, maintaining a cycle of negative mood (Figure 1, right side of the diagram, in red). The authors use simulated data to theoretically demonstrate how an increase in the mood bias parameter can lead to mood oscillations consistent with mania and depression. The model adds that a switch from one mood cycle to the other occurs when expectations become increasingly high (or low) and do not match reality causing a negative (or positive) large prediction error and triggering the opposite cycle.

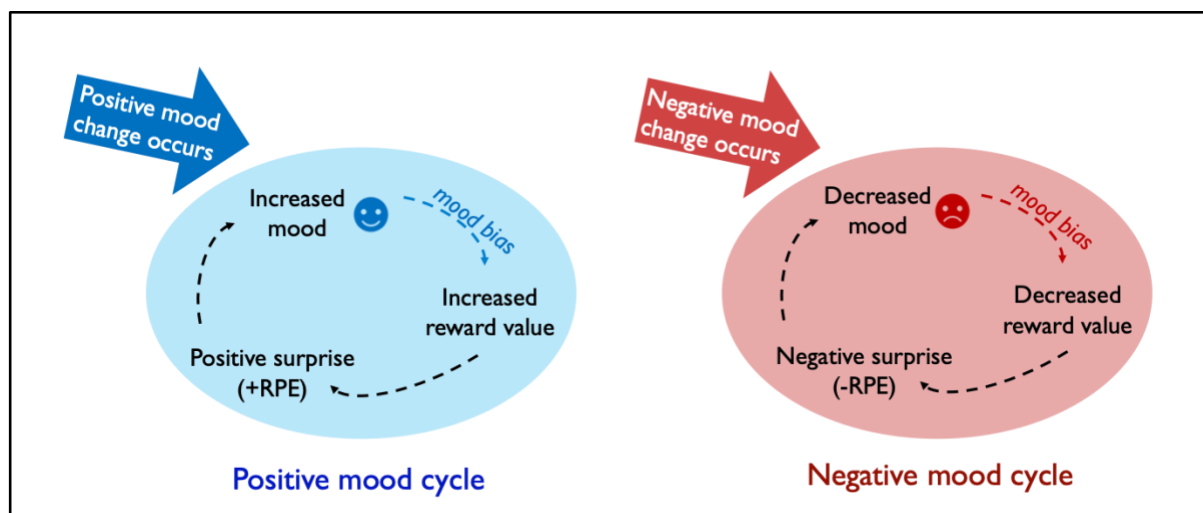


Figure 1. Visual representation of the Neurocomputational Model of Bipolar Disorder (Mason et al., 2017), redesigned with permission from the author.

The present study aimed to empirically test the mood bias theories of Eldar and Niv (2015) and Mason et al. (2017) for the first time, in a group of individuals diagnosed

with bipolar disorder versus a group of controls with no history of mental illness. It used a novel app-based task, the *Wheel of Fortune* game, to quantify the extent of mood bias on reward value (henceforth referred to as 'mood bias'). I hypothesised, in line with previously published work and findings from Chapter 3, that following a mood change, the bipolar group will show a significantly larger mood-biased reward valuation compared to the control group.

2 Methods

2.1 Participants

The study recruited participants who had received a diagnosis of bipolar disorder (type I or II) and controls with no history of mental illness. We defined the following inclusion and exclusion criteria for each group.

Inclusion criteria for participants with mood instability were: ages 16-60; received a bipolar disorder diagnosis (confirmed by clinical diagnostic interview; see section 3.2 below); not in a mood episode for the last 4 weeks prior to enrolment in the study (assessed with a Quick Inventory of Depressive Symptomatology cut-off score of 11 and the Altman Self-rating Mania Scale cut-off score of 12); fluent in English; willing and able to provide written informed consent; unmedicated or receiving stable therapeutic doses of medication (excluding antipsychotics) for at least four weeks.

Inclusion criteria for controls were: ages 16-60; fluent in English; willing and able to provide written informed consent.

Exclusion criteria for both groups included: history of neurological disorders; developmental disorders including learning disability; active treatment with antipsychotic medication; substance dependence in the past 6 months (excluding tobacco) as determined by self-report and/or diagnostic interview; recreational drug

use within 7 days of enrolment in the study; participation in a Clinical Trial of an Investigational Medicinal Product within 1 month before enrolment in the study. Additionally, the control participants were excluded if they had received an Axis I psychiatric disorder diagnosis.

Participants were informed about the study by our collaborating NHS sites and volunteered to take part, or they responded to BIMODAL online and email advertisements. The BIMODAL study is currently ongoing with a recruitment target of 60 participants with mood instability and 60 controls. This chapter includes all data collected from the 29th of April 2022 to the 1st of February 2023.

2.1.1 Power calculation

The study aims to recruit a target sample of 60 patients and 60 healthy controls. This includes an expected (up to) 33% drop-out rate or insufficient time points, leaving 40 patients and 40 controls in total. Previous work by (Eldar & Niv, 2015) found a large effect ($d = 0.8$) in the model parameter of interest (mood bias) that differentiated healthy participants from participants at elevated risk of bipolar disorder. The present study would have 94% power to detect an effect of this size with our projected final sample of $N = 40$ per group.

The final sample size included (16 patients and 13 controls). Therefore, with an effect size of 0.8, a sample size of 29, and a significance level of 0.05, the estimated power is approximately 60.6%.

2.2 Study Design and Procedure

The BIMODAL study employed a case-control design to explore the relationship between mood and decision-making in participants with and without bipolar disorder. The study involved a study session, online or in-person, during which the researcher explained the study, took the participant through all the surveys and games on the app to ensure they understood them and performed a brief clinical interview [MINI DSM 5, (Lecrubier et al., 1997)]. The clinical interview was used to

confirm a diagnosis of bipolar disorder and to ensure no history of mental illness in the control participants. The study session was also used as an opportunity to answer any questions participants may have had about the study or tasks. Following this, participants played the *Wheel of Fortune* game and completed several questionnaire measures.

2.3 Wheel of Fortune game

The Wheel of Fortune game, depicted in Figure 2, was the main task used in this study and each participant played it a minimum of three times and a maximum of five times.

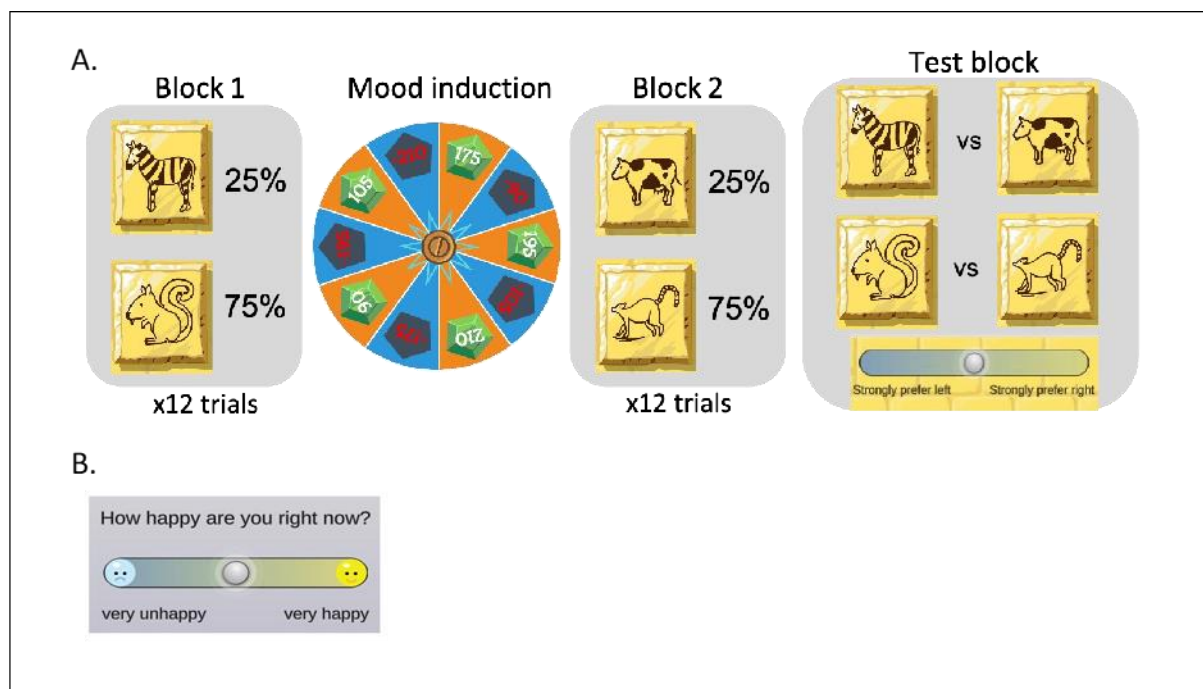


Figure 2. Wheel of Fortune game design schematic. **A)** Participants learned by trial and error about two stimuli in each block, one associated with rewards 75% of the time and the other 25% of the time. Between the learning blocks positive or negative mood was induced by spinning a wheel of fortune. Finally, in the test block trials participants were asked to choose which animal they preferred (left or right) by

binary choice and slider rating. **B)** Momentary mood ratings appeared on the screen every 4-5 trials.

Participants learned about two animals over the course of each learning block. One of the animals had a 75% probability of giving a reward (later referred to 'high prob') while the other had a 25% probability of reward (later referred to as 'low prob').

Between learning blocks participants spun a wheel of fortune which could land on one of the following rewards: ± 175 , ± 195 , ± 210 . During the test block participants had two types of test trials: memory test trials and mood bias test trials. Both types included two binary choices (i.e., select one or the other option) and two slider choices (i.e., indicate preference by dragging a slider). Memory test trials asked participants to choose between the low prob and the high prob animals in each block. Here, the correct response was to select the high prob animal, as this was the more rewarding one. In the mood bias test choices, participants were prompted to select between the low probability animal from block 1 and the one from block 2, as well as between the high probability animal from block 1 and the high probability animal from block 2. It is important to note that there was no objective distinction between the animals from one block compared to the other, as both options offered equal rewards. Any preference for one block over the other was viewed as an effect of mood biasing value of reward.

Pilot testing showed that under game design with 12 trials, participants with bipolar disorder chose the correct high prob animal 59.3% of the time during the learning blocks and 61.4% of times at test. This was under the desired threshold of 70% correct choices and showed that learning was poor and only slightly above chance. Therefore, the number of learning trials was increased from 12 to 15 trials per block, to improve learning and mitigate potential impairments in reinforcement learning which have been documented in participants with bipolar disorder (Ryu et al., 2017). A second pilot study using the new 15 trials design showed improved learning both during the blocks (78.1% correct choices) and at test (77.3%).

I made several other improvements to the WoF game based on insights from the general population study (Chapter 3) and the Social Learning Task study (Chapter 4). One of the changes was to increase the number of trials in each learning block from 12 to 15. This allowed participants more time to learn which animal was more rewarding and reduced the experienced probability discrepancy between the intended probabilities (high probability animal rewards 75% of the time, low probability rewards 25% of the time) and the user's experience. During the learning blocks, participants chose between two animals and saw the outcomes associated with their choice. Depending on the number of times they chose each animal, their experienced reward probabilities could shift from the intended 25/75. It was important to maintain comparable experiences of reward probabilities between the two learning blocks to facilitate accurate mood bias test comparisons. Otherwise, the choices might be driven by reward frequency rather than mood. Finally, to maximize the effect of the mood induction, the wheel was rigged to award only the top three largest outcomes: ± 175 , ± 195 , or ± 210 gems. Additionally, the ratio of in-trial rewards to Wheel of Fortune rewards was increased by making in-trial rewards smaller (reduced from 40 to 10 gems), so the amount won or lost on the wheel had a bigger impact on the total score.

2.4 Questionnaires

The following questionnaires were collected in the study: a trait measure of proneness to strong and changeable moods - the Hypomanic Personality Scale [HPS, (Eckblad & Chapman, 1986)]; a clinical measure of current severity of depression symptoms - Quick Inventory of Depressive Symptomatology [QIDS-SR, (Browning et al., 2015b)]; and a measure of current manic symptoms - Altman Self-rating Mania Scale [ASMR, (Altman et al., 1997)].

3 Results

3.1 Demographic information

The BIMODAL study included 16 participants with a diagnosis of bipolar disorder and 13 controls with no mental health diagnoses. Participants in the BPD group were medicated with a mix of antidepressants ($N = 5$), anticonvulsants ($N = 3$), lithium ($N = 6$), or were unmedicated ($N = 6$). There were no significant differences in age [$p = 0.57$] or gender between groups [$p = 0.48$], as shown in Table 1. All participants with a diagnosis were recruited to the study while in a euthymic mood state. There were no differences between groups in current mania symptoms [$p = 0.54$], or in current depressive symptoms [$p = 0.18$]. As expected, participants in the BPD group scored significantly higher in trait mood instability, as measured with the HPS questionnaire [$p = 0.01$].

Table 1. Demographic information of all participants in the BIMODAL study.

| | BPD (N = 16) | | CTRL (N = 13) | | |
|------------------------|---------------|---------|---------------|---------|--|
| | Mean (SD) | Range | Mean (SD) | Range | |
| Age (years) | 37.25 (10.27) | 22 – 60 | 34.69 (13.84) | 22 – 59 | $t(27) = 0.57, p = 0.57,$ $CI = [-6.63, 11.74]$ |
| Gender (% male) | 12.5 % | | 30.76 % | | $Z = 0.70, p = 0.48$ |
| Depression (QIDS) | 4.81 (2.16) | 2 – 9 | 3.46 (1.89) | 0 – 7 | $t(27) = 1.76, p = 0.18,$ $CI = [-0.22, 2.92]$ |
| Mania (ASMR) | 3.50 (2.80) | 0 – 10 | 2.76 (3.56) | 0 – 8 | $t(27) = 0.61, p = 0.54,$ $CI = [-1.69, 3.15]$ |
| Mood instability (HPS) | 25.37 (8.34) | 10 – 40 | 17.23 (7.98) | 4 – 32 | $t(27) = 2.66, p = 0.01,$ $CI = [1.87, 14.41]$ |

3.2 Learning blocks

Participants quickly learned which animal was more rewarding and proceeded to choose it over the less rewarding one (see Figure 3). Performance started at chance level (50%) and by trial 4 most participants learned which animal was more rewarding,

as evidenced by their choices. By the end of the learning blocks, over 75% of participants were choosing correctly. On average, across both blocks, participants chose the more rewarding animal 80.43% of the time.

An ANOVA confirmed that learning performance was not impacted by group [BPD vs CTRL: $F(1, 234) = 0.12$, $p = 0.61$], by learning block [block 1 vs block 2: $F(1, 234) = 0.01$, $p = 0.89$], or by WoF outcome [won vs lost: $F(1, 122) = 0.04$, $p = 0.33$], or any interactions between these factors [$p \geq 0.36$].

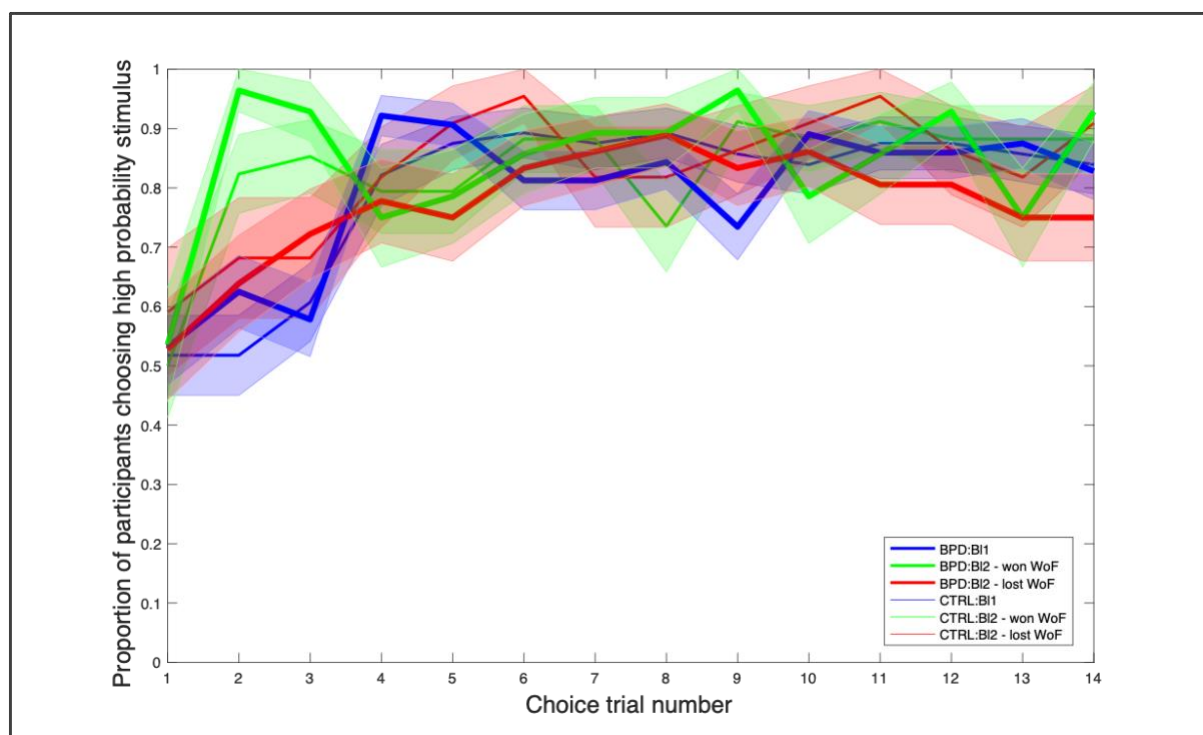


Figure 3. Learning curves split by participant group, mood induction condition, and block. Performance did not differ between the BPD and CTRL groups [$p = 0.61$] or mood conditions [$p = 0.89$].

For each participant, an average memory test preference score was computed by adding the two binary memory test choices (low prob versus high prob block 1 and low prob versus high prob block 2) and the two slider ratings. Here, the scale went from -4 (always chose the less frequently rewarded animal) to 4 (always selected the more frequently rewarded animal). All participants performed significantly above chance (an

average of 0) on the memory test with an average preference score between 2.5 and 3.36 out of 4, depending on group and mood condition (see Figure 4). Overall, 84.71% of all participants correctly chose the more rewarding animal on at least three out of four test choices, indicating they learned which stimulus was better.

The normality assumption was tested using the Kolmogorov-Smirnov test, which revealed a significant deviation from the normal distribution for the memory test preference variable [$p = 0.003$]. Non-parametric Mann-Whitney showed there were no differences in accuracy between participant groups [$U = 255.5$, $p = 0.25$] or between mood induction conditions [$U = 302.5$, $p = 0.64$; see Figure 4].

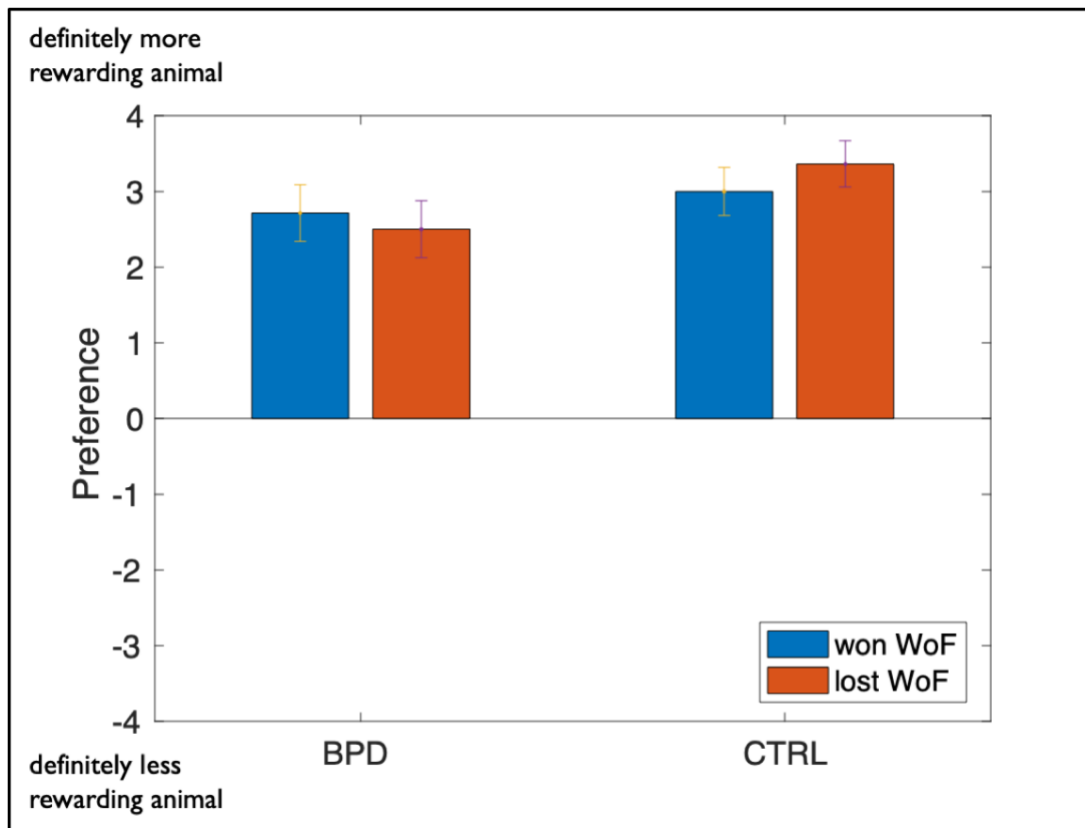


Figure 4. During test trials, participants performed significantly above chance when asked to identify the more frequently rewarding animal. There was no difference in accuracy between groups [$p = 0.25$] or mood induction conditions [$p = 0.64$].

3.3 Mood induction

The mood induction was successful, as demonstrated by a significant main effect of WoF outcome [wins vs loss: $F(1,19) = 15.86$, $p = 0.001$]. There was no significant main effect of group [BPD vs CTRL: $F(1,19) = 0.31$, $p = 0.56$], nor a group and WoF outcome interaction [$F(1,19) = 1.01$, $p = 0.33$].

As seen in Figure 5, further t-tests confirmed that there were no significant differences in mood change between groups, following the positive mood induction [won WoF: $t(24) = -1.17$, $p = 0.09$, $CI = [-0.09, 0.025]$, $d = 0.07$], or following the negative mood induction [lost WoF: $t(22) = 0.36$, $p = 0.71$, $CI = [-0.05, 0.081]$, $d = 0.08$]. However, as seen in Figure 5B, the positive mood induction did not significantly improve mood in the control group [$p = 0.87$].

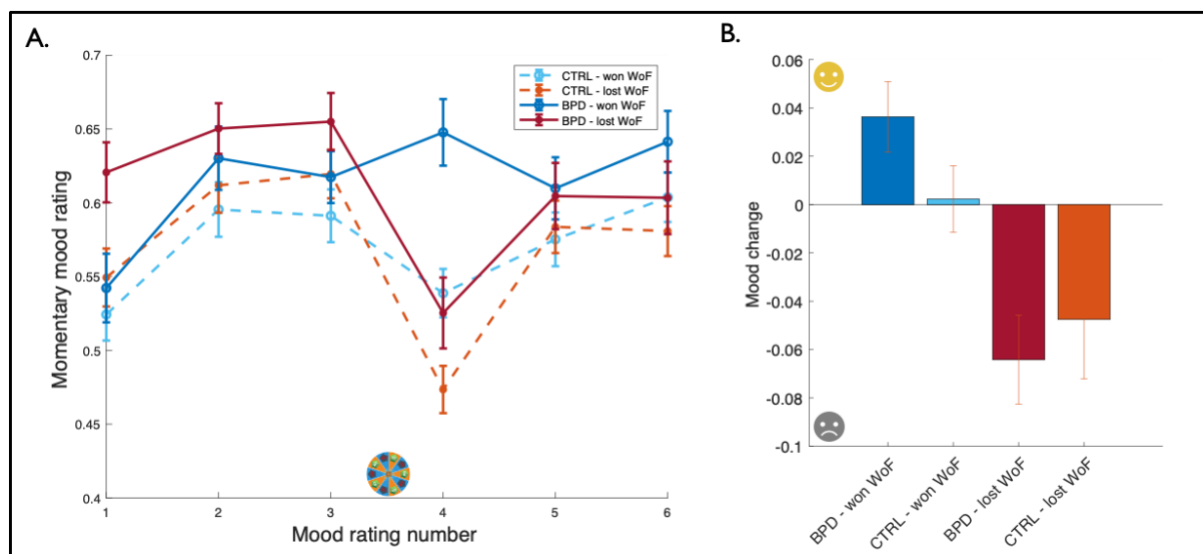


Figure 5. Average momentary mood self-reports during the WoF game. A) Average mood ratings before and after the mood induction manipulation split by WoF outcome (reds - lost WoF, blues – won WoF) and group (dotted lines – controls; continuous lines – bipolar group). **B)** Mood change (defined as block 2 mood minus block 1) split by outcome and group. There were no significant differences in mood change between groups after wins [$p = 0.09$] nor after losses [$p = 0.71$].

3.4 Mood bias on reward valuation

The overall mood bias preference score for each participant was determined by adding up the results of the two binary choice trials (low prob block 1 versus low prob block 2; high prob block 1 versus high prob block 2) and the two corresponding slider ratings. Mood bias preference scores ranged from -4 (definitely preferred block 1 stimuli) to +4 (definitely preferred block 2 stimuli).

For each participant, I calculated an average 'win' mood bias test preference score by averaging mood bias test preferences in games where they won on the WoF draw. Similarly, I computed the average 'loss' mood bias test preference score by averaging their preferences following losses on the WoF. Mood bias test preference was normally distributed for both wins [$p = 0.43$] and losses [$p = 0.77$], as assessed with the Kolmogorov-Smirnov test.

A 2 (group: BPD vs CTRL) x 2 (WoF: won vs lost) repeated measures ANOVA was used to determine if participants showed a mood bias on reward perception during the mood bias test trials. It revealed there was no main effect of group [BPD vs CTRL: $F(1,19) = 3.81$, $p = 0.14$], a trend level main effect of WoF outcome [won vs lost: $F(1,19) = 6.31$, $p = 0.08$], and no WoF and group interaction [$F(1,19) = 3.08$, $p = 0.21$].

Although the overall interaction in the RM ANOVA wasn't significant, we conducted post hoc tests to delve deeper into the significant WoF main effect. This approach aimed to uncover subtle patterns or differences within specific conditions that might not have been apparent initially due to the small sample size generating insufficient power for this type of analysis. By examining contrasts and pairwise comparisons, we sought to provide a more detailed understanding of preferences.

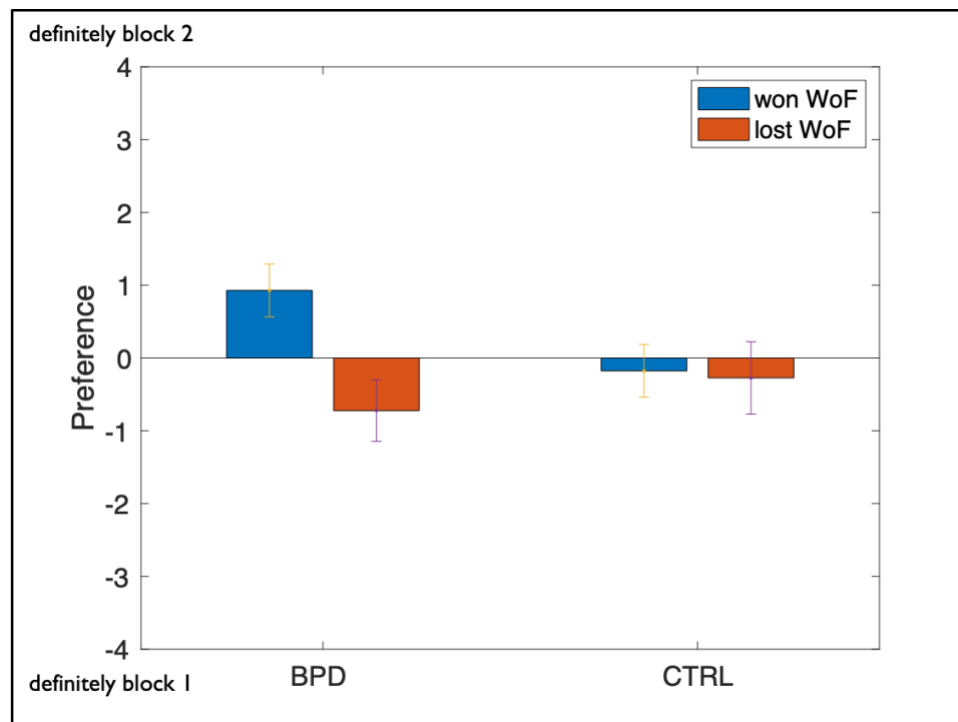


Figure 6. The BPD group showed a mood bias, preferring the block they were happier in [$p = 0.03$], while the CTRL did not have a preference for either blocks [$p = 0.72$].

When splitting mood bias test preference by group as shown in Figure 6 above, t-tests revealed that the BPD group displayed a significant mood bias on test preference selecting block 2 following wins and block 1 following losses on the WoF [$t(10) = 2.43$, $p = 0.03$], while the CTRL group did not show a mood bias block preference [$t(9) = 0.35$, $p = 0.72$]. This suggested that the observed main effect of WoF was mostly driven by the BPD group and was not present in the CTRL group.

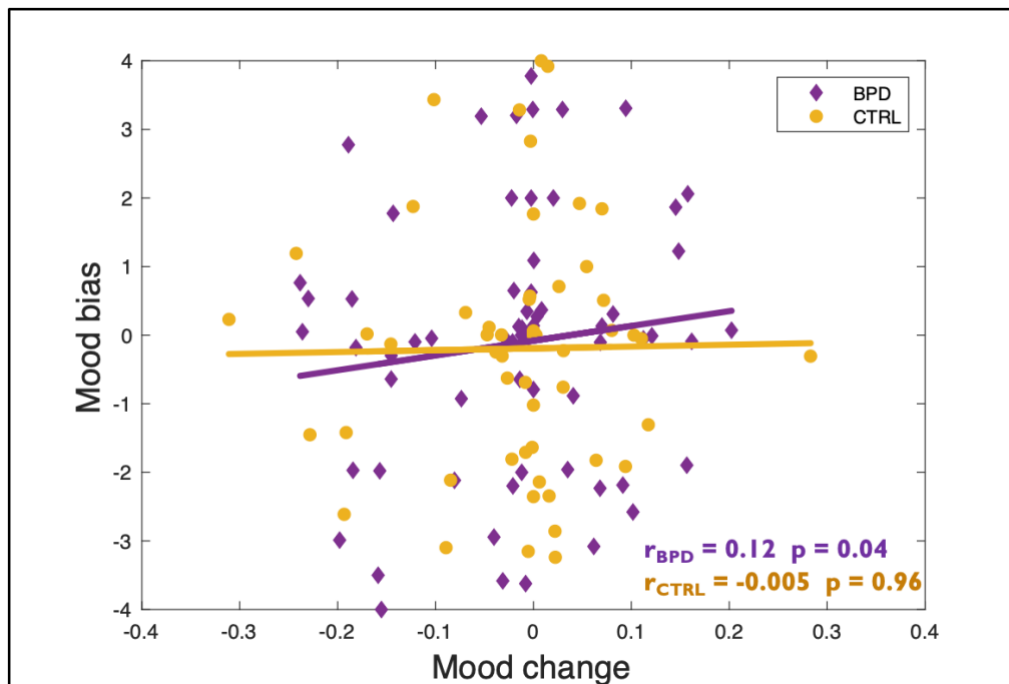


Figure 7. Mood-biased reward value scaled with the amount of mood change in the BPD group [$p = 0.04$], but not in the CTRL group [$p = 0.96$].

In order to understand what the role of mood change was in biasing participants' choices, I explored the association between mood bias and mood change using Pearson's correlations. This was done separately in each group, following on from the previous analysis, where only the BPD group showed a mood bias. In the BPD group, the amount of mood bias on test preference scaled positively with the amount of mood changed experienced by participants [$r = 0.12$, $p = 0.04$]. As expected, this correlation was absent in the CTRL group [$r = -0.005$, $p = 0.96$, see Figure 7].

3.4.1 Mood bias association with symptoms

Overall, mood bias was not significantly correlated with age [BPD: $r = -0.11$, $p = 0.36$; CTRL: $r = 0.04$, $p = 0.74$], residual depression symptoms measured with the QIDS [BPD: $r = -0.04$, $p = 0.71$; CTRL: $r = -0.08$, $p = 0.55$] or trait mood instability measured with HPS [BPD: $r = -0.01$, $p = 0.92$; CTRL: $r = -0.07$, $p = 0.57$], as shown in Figure 8. Pearson's correlations were used to examine these linear relationships.

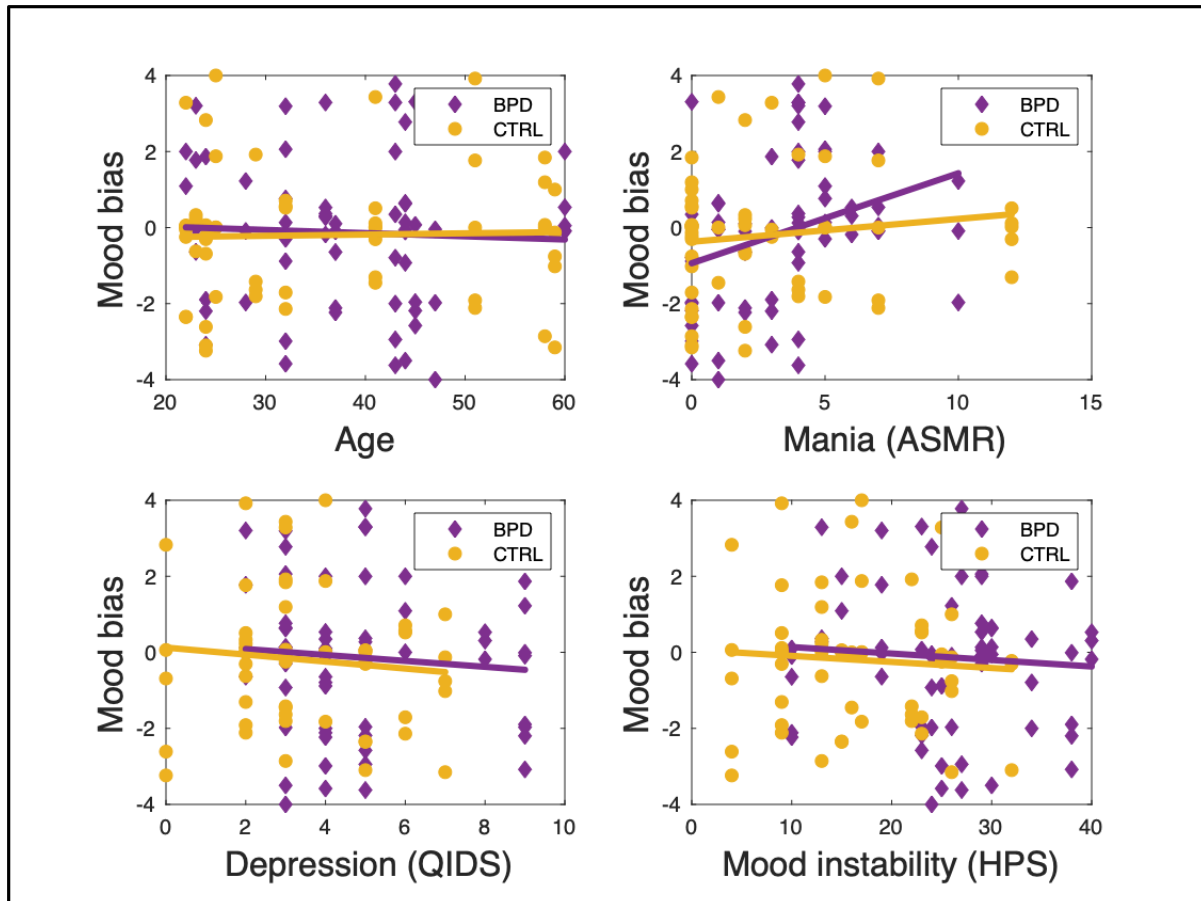


Figure 8. Correlations between mood bias and with age, current self-rated mania (ASMR) and depression symptoms (QIDS), and trait mood instability (HPS), split by group.

In the BPD group, there was a notable increase in mood bias in those with higher levels of residual manic symptoms, as evidenced by the ASMR measure [BPD: $r = 0.37$, $p = 0.002$]. In contrast, the control group did not display any correlation between mood bias and mania symptoms [CTRL: $r = 0.12$, $p = 0.34$].

4 Discussion

The BIMODAL study examined the relationship between mood and reward valuation in individuals with bipolar disorder (type I or II) and controls with no history of mental

ill-health. Results showed that (1) learning was comparably good between the two participant groups and the two induced mood states; (2) participants in the BPD group were no more changeable in their moods following WoF mood induction compared to controls; (3) the BPD group showed a mood bias on reward valuation, while the CTRL group did not; (4) only the BPD group show an association between the amount of mood change reported and strength mood bias experienced; (5) only the BPD group demonstrated an increase in mood bias associated with increased residual manic symptoms.

The BIMODAL study extends previous work in several significant ways. Confirming predictions, the study showed for the first time that euthymic individuals with a bipolar disorder diagnosis show a mood bias on reward valuation per unit of mood change, while healthy controls do not show any association between mood and biased reward perception. This result provides support for the model developed by Eldar and Niv (2015) which conceptualised mood bias as a fixed quantity which amplifies or reduces the value of reward in the direction of current mood (i.e., if mood is higher reward becomes more valuable, mood is lower reward becomes less valuable). The finding of linear increase in mood bias on reward perception per unit of mood change supports the conceptual view of this stable mood bias parameter, specific for each individual. However, the BIMODAL study only measured a proxy of the mood bias parameter by computing how much it biased preference during test. More work employing modelling approaches is needed to quantify the mood bias parameter directly for each individual and compare it between the bipolar and control groups.

Additionally, the study found that mood bias on reward value increased with residual manic symptom severity in individuals with bipolar disorder but not in controls. Previous work has found a similar correlation between mood bias and predisposition to mood instability and developing bipolar disorder, as measured with the HPS questionnaire [Chapter 3, (Eldar & Niv, 2015)]. This suggests that mood bias may be on spectrum and its severity may be a factor in the development and/or maintenance of manic and hypomanic symptoms. Taken together, these findings bring empirical support to the theoretical work of Mason et al. (2017) that explains how the bidirectional interaction between mood and reward valuation can cause and maintain the mania cycles of bipolar disorder. Manic mood cycles are triggered by a shift in

mood (like the BIMODAL mood induction) that then biases rewards to seem more valuable than they are (i.e., amplified by mood bias). Perceiving rewards as better than they actually are leads the individual to pursue those rewards more vigorously, increasing motivation and triggering an increase in the Behavioural Activation System. The process is similar for negative mood, with low mood leading to outcomes being perceived as less valuable than they are, further lowering mood and decreasing the BAS. In other words, the moment-to-moment fluctuations in emotional state may act as precursors or triggers for the onset of more sustained episodes of mania or depression. For example, a series of intense positive emotions (caused by one positive surprise which then biased the next outcomes), if not effectively regulated, may eventually escalate into a manic episode. Conversely, a momentary negative outcome could trigger a belief that 'nothing is going as planned', decreasing the perceived value of future rewards, and contribute to the onset of a depressive episode. Furthermore, moment-to-moment emotional instability can influence decision-making processes and coping strategies. Individuals with bipolar may be more prone to making risky and impulsive decisions during periods of emotional instability, potentially contributing to the longer-term shifts in affect observed clinically. However, the BIMODAL study did not find any direct association between mood bias on reward valuation and depression symptoms. It did find that participants with bipolar disorder overvalued the rewards learned in a more positive mood and undervalued those learned in a more negative mood, in line with the model predictions (Mason et al., 2017).

Finally, in the previous study by Eldar and Niv (2015), participants with greater mood instability also displayed more pronounced mood changes, leaving uncertainty as to whether the observed mood bias was solely driven by the magnitude of mood changes. The present study clarified that only in the bipolar group there was a distinct mood bias on reward valuation per unit of mood change. In other words, even if the mood induction procedure was much more powerful, the control group would likely still not show a mood bias on reward value. Furthermore, in the BIMODAL study there were minimal differences between groups in responsiveness to the mood induction procedure. This finding did not support the notion that bipolar disorder is associated with a heightened sensitivity to rewards (Nusslock et al., 2019). The mood induction

effects were small which may be due to the type of rewards given in the task being of no real value to participants.

4.1 Limitations

A main limitation of the BIMODAL study was that the positive mood induction was not successful in eliciting significant mood changes in some of the control participants. This aligns with previous findings indicating an asymmetry in mood induction, where negative outcomes have a stronger impact on mood compared to positive outcomes [Chapter 3, Chapter 4, (Eldar & Niv, 2015; Michely et al., 2022)]. This result resonates with the concept of loss aversion, which posits that losses have a stronger psychological impact than equivalent gains (Kahneman & Tversky, 1979). However, the control group did not exhibit any mood bias in either positive or negative conditions, nor was there an association between mood change and mood bias. Therefore, even if the mood induction had been more potent, it is unlikely that the control group would have shown a mood bias. This limitation highlights the need for further exploration of other mood induction techniques to effectively elicit positive mood changes in control participants (Joseph et al., 2020).

The number of participants in each group was relatively small which may have resulted in underpowered analyses. The limited sample size was primarily due to time constraints during data collection for this study. It is important to acknowledge that the BIMODAL study is still ongoing, with the aim of recruiting a larger sample of 70 patients and 70 matched controls. The inclusion of a larger and well-matched sample in future research would enhance the statistical power and generalizability of the findings.

Finally, some participants played the *Wheel of Fortune* game more times than others. The experimental design included three plays per participant. Some participants downloaded and installed the app before the initial study session and played the game against explicit instructions (once or twice). All plays were included in this dataset. The inclusion of these plays was based on the anticipation that the mood induction effects would be most pronounced during the initial plays of the game, drawing from prior research findings (Eldar & Niv, 2015). The last plays were included because I wanted

to ensure each participant had a minimum of three plays after participants had received clear instructions from the researcher and had a thorough understanding of the task.

4.2 Implications

The current study provides novel insights into the mood biases that individuals with bipolar disorder experience, which have been largely overlooked in previous research. These results will help researchers better understand the underlying neural mechanisms of bipolar disorder. If proven to be robust across participants, mood bias could potentially be added as an additional diagnostic feature to improve the accuracy of bipolar disorder diagnosis. Currently, up to 69% of patients are misdiagnosed initially, most as having unipolar depression leading to inappropriate treatments, and more than a third remained misdiagnosed for 10 years (Singh & Rajput, 2006). Additionally, it may assist clinicians to designing more effective treatment plans by targeting mood biases through cognitive-behavioural therapy or other interventions. Further research exploring the neural mechanisms underlying these mood biases and their relationship with bipolar disorder symptoms may ultimately lead to the development of more precise and effective treatments for this complex and often debilitating disorder.

New technologies are playing a significant role in advancing the understanding and management of bipolar disorder. Traditional psychiatric assessments for bipolar disorder rely on retrospective measures and are subject to biases and unreliability. However, the emergence of digital psychiatry is revolutionizing the field (Hauser et al., 2022). The concept of "digital phenotyping" (Insel, 2017) is gaining prominence, with bipolar disorder being at the forefront of this development (Nicholas et al., 2015). Connected and wearable devices such as smartphones enable patients to provide real-time self-reporting of symptoms, as well as capture behavioural, cognitive, and physiological data (Faurholt-Jepsen et al., 2015; Grünerbl et al., 2015; McIntyre et al., 2014; Shou et al., 2017). These digital methods offer the potential to move from subjective symptom-based characterizations of bipolar disorder towards a more comprehensive, ecologically valid approach (Stanislaus et al., 2020). By integrating

these diverse data streams, there is the potential to achieve more accurate diagnoses and personalized predictions of illness course and treatment response.

The *Wheel of Fortune* (WoF) game used in the BIMODAL study has the potential to be a valuable tool for digital phenotyping. Not only is it a fun and engaging game that can be played anytime, anywhere and on any smartphone, but it also has several other advantages. It is a short task that takes under 4 minutes to complete and requires minimal training or instructions. It does not include any clinical or personal questions about the participant's mood, which makes it a less intrusive measure than clinical questionnaire measures or clinical interviews. Moreover, it does not rely on self-evaluation or a personal account of mood symptoms, which may make it more accurate in the case of individuals who lack insight into their current state or do not feel comfortable disclosing the full truth. These features of the WoF game suggest that it has great potential as a measure of mood biases and could be a useful tool for clinicians and researchers in the future.

4.3 Future work

Considering the findings from the present study and the potential implications for understanding mood biases in bipolar disorder, several future directions can be pursued. Firstly, it would be interesting to take a computational approach to further explore this dataset. This analysis would be able to directly investigate the mood bias parameter in each participant, as opposed to the mood bias on reward value which is what BIMODAL measured. It could explore whether the model-based mood bias predicts clinical features such as illness severity, number of episodes and current mood state, providing further insights into the relationship between mood biases and clinical outcomes. This will however require extensive work to adapt pre-existing computational models to the current multiple-play dataset. Furthermore, only a longitudinal study would be able to answer the question of what came first, the mood bias or the mood instability.

Secondly, it remains unknown whether mood bias is stable over time. The findings from Chapter 3 suggest that memory for the mood biased stimuli remained constant

over time, but a repeated-measures longitudinal study is needed to definitively answer this question. Future work might benefit from using *the Happiness Project* app framework and specifically our *Wheel of Fortune* game to measure mood bias in the same participants at different time points throughout a longer period (i.e., over a few months or a year). Using a computational modelling analysis, a mood bias parameter could be estimated for each participant at each time point, indicating whether mood bias remained stable or fluctuated over time. Furthermore, such a design would allow researchers to investigate if mood bias predicts future symptom severity.

Finally, exploring interventions aimed at modifying mood bias and their potential impact on both reducing bias and alleviating mood symptoms would be of great interest. Treatments for bipolar disorder fall under psychiatric medication or psychological therapies. Both approaches have some efficacy, but medication is associated with undesirable side effects while talking therapies can be expensive or difficult to access. Even on treatment about 37% of patients relapse into depression or mania within one year, and 60% within two years (Gitlin et al., 1995). A review of existing treatments for bipolar has suggested new approaches should focus on early identification, supportive self-management, and targeted therapy, while also being standardised to serve a high volume of patients and require minimal training resources for staff (Gliddon et al., 2017). Technology-based approaches, like the app-based *Wheel of Fortune* game, may hold the answer to these problems. Measuring and then targeting mood bias reductions with interventions such as meditation, relaxation techniques, and mindfulness could prove beneficial (Marchand, 2015; Perich et al., 2013; Ritvo et al., 2021). Furthermore, *The Happiness Project* app offers a convenient and accessible platform for developing and delivering interventions remotely to individuals, enabling wider reach and potential impact on mental health outcomes. By leveraging smartphone technology, interventions can be tailored and personalized to suit individual needs and preferences, enhancing engagement and adherence to the intervention protocols (Wahle et al., 2016).

4.4 Conclusion

The BIMODAL study was the first study to show that individuals with bipolar disorder exhibit a mood bias on reward valuation, such that outcomes are perceived as better when in a good mood and worse in a bad mood. Healthy controls did not exhibit this bias. Mood bias increased with mania symptom severity in the clinical group, suggesting it may be a key factor in maintaining the (hypo)manic symptoms characteristic of this bipolar disorder. Overall, the BIMODAL study has advanced our understanding of cognitive mechanisms in bipolar disorder, providing evidence of a biased reward perception which may cause the increased goal pursuit seen in bipolar disorder. I hope these findings will inspire other research studies in this field and contribute to the development of more effective assessment strategies and personalized interventions, ultimately improving the lives of individuals affected by bipolar spectrum disorders.

CHAPTER 6. General Discussion

1 Summary of PhD findings

This doctoral thesis has focused on investigating the relationship between mood and rewards, shedding light on its impact on mood instability and bipolar spectrum disorders. Through a large general population study using the smartphone-based app "The Happiness Project," it was discovered that mood bias influences reward perception in a non-monetary context. Notably, this effect was more pronounced in individuals with higher levels of mood instability and scaled with their amount of experienced mood change. This replicated and extended previous findings (Eldar & Niv, 2015; Mason et al., 2017) in a larger, more diverse sample of the population. The study also showed that while memory for the rewarding stimuli faded over time, the preference for the mood biased stimuli remained constant. This finding provides insight into how mood biases during learning then bias memory and later decision-making and how this impact can last over time. Using computational modelling, I showed that participants' choices and momentary mood ratings were best explained by a model that included rewards influencing mood as well as mood-biasing reward valuation confirming the bidirectional effect of mood in reward was a robust effect, which was not specific to monetary contexts.

Furthermore, the investigation of mood bias in a social context revealed intriguing insights. The study showed that negative mood reduced expectations of being liked by others (trend level), while positive mood did not impact expectations. Although conclusive evidence of social mood bias was not found, alternative heuristics were identified that may have influenced participants' choices. In addition, the study replicated and extended previous work (Will et al., 2020; Will et al., 2017) to show that momentary self-esteem tracked both social prediction errors and outcomes and this relationship was not modulated by mood. The study confirmed the cognitive bias of

individuals to see themselves positively and expect more positive than negative feedback, which has been associated with higher levels of well-being and better mental health outcomes. However, some methodological limitations need to be considered. Limitations included reduced effects of the mood induction for positive mood, poor learning as confirmed by a preference for the less rewarding groups (instead of the more rewarding ones), and possible issues with the participants believing the feedback they received was indeed given by other real participants. Future research would benefit from exploring alternative mood induction procedures as well as different types of social feedback to increase the believability of the task and gain a more comprehensive understanding of these complex relationships.

Finally, the BIMODAL clinical study compared patients diagnosed with bipolar disorder and healthy controls to uncover a mood bias on reward valuation specific to the bipolar group, which intensified with the severity of residual manic symptoms. This bias was absent in the control group. A positive association between the amount of mood bias and the degree of mood change experienced by the bipolar participants but absent in the control group, further showed that mood bias on reward perception was specific to the bipolar group and not simply caused by more sensitivity to the mood induction procedure. These findings suggested that mood bias may play a role in maintaining symptoms associated with bipolar spectrum disorders. Future work using longitudinal designs could use the *Wheel of Fortune* app task to explore if over time mood bias can predict the onset of future symptoms of mania.

In summary, this research highlights the presence of mood bias on reward perception, its association with mood instability, and its relevance to bipolar spectrum disorders. The findings contribute to a deeper understanding of the intricate interplay between mood and rewards, paving the way for potential implications in clinical interventions and therapeutic approaches. Additionally, this PhD research emphasizes the significance of leveraging online and smartphone-based methodologies, such as *The Happiness Project*, for gathering extensive and diverse datasets. By incorporating these approaches, we can attain samples that are more representative of the general population, allowing for more comprehensive and generalizable insights into the dynamics of mood, learning, and decision-making processes.

2 Mood bias: is it context specific?

The generalizability of mood bias on reward valuation, particularly its context specificity, remains a relevant area of investigation in cognitive research. Evidence from Chapters 3, 4 and 5 and other work (Eldar & Niv, 2015) suggests that mood bias effects may be more pronounced in non-social and monetary contexts as compared to social contexts. The *Wheel of Fortune* task offered rewards in the form of gems that had no real monetary value to participants. Yet, both in the large general population study (Chapter 3) and in the BIMODAL study, (Chapter 5) participants showed a mood bias on reward valuation. Eldar and Niv (2015) used monetary rewards to elicit these biases. While The Social Learning Task did not capture any clear effects of mood biasing reward valuation, it did show that negative mood impacted expectations of social reward (i.e., participants expected less social reward when in a lower mood).

Regarding the generalisability of mood bias to social contexts, it is important to acknowledge several methodological limitations associated with SLT study which limit drawing a definitive conclusion. These include concerns related to task believability, memory test inaccuracy, and the relatively small mood induction effects observed, together with the predominantly young participant samples. Thus, while the current evidence points to the presence of mood bias in non-social and monetary contexts, it does not preclude the existence of social mood bias in reward valuation. It is plausible that the SLT paradigm may not have been sensitive enough to capture the full range of social mood bias, indicating the need for further investigation using more refined measures and diverse participant samples.

Another possibility is that the impact of mood on different types of rewards may differ from person to person, depending on their values or circumstances. For example, an extroverted individual will likely value social interactions and social feedback more than an introverted one and may experience a stronger mood bias on these types of rewards. While monetary rewards may be ubiquitously understood, the amount

received will have a different impact depending on the individual's socio-economic status (White et al., 2022). Receiving £5 will be valued differently by an unemployed person and a multi-billionaire. A recent meta-analysis has shown that socio-economic status might influence how social rewards are perceived (Hao & Farah, 2020). Thus, it may be that mood will exert a stronger bias on domains relevant to the individual. Future work may benefit from gaining a deeper understanding of participants' values and personality traits, to understand how these individual differences impact mood bias and provide a more comprehensive understanding of how mood bias relates to people and in different contexts. *The Happiness Project* app is well suited for such an investigation, allowing the collection of large datasets to explore individual differences in mood bias on reward perception.

3 Mood bias: is specific to bipolar disorder?

Bipolar disorder and borderline personality disorder share some symptomatic similarities, such as mood instability and impulsivity (McGowan et al., 2020). However, a growing body of scientific research has found significant differences between these two disorders, underscoring their distinct nature. Bipolar disorder is characterized by discrete episodes of hypomania/mania and depression that persist for weeks to months, interspersed with mixed mood episodes (Tohen et al., 2009). On the other hand, borderline personality disorder is characterised by pervasive mood, self-image, and relationship instability, often leading to impulsive and self-destructive behaviours (Gunderson, 2009). One key distinction between the two is that interpersonal dysfunction is central to the emotional reactivity seen in borderline personality disorder (Lazarus et al., 2014), whereas in bipolar disorder mood fluctuations are more related to goal pursuit and goal attainment (Fulford et al., 2015; Johnson, Fulford, et al., 2012; Nusslock et al., 2009).

Neurobiological investigations have also revealed disparities in brain functioning and structure between bipolar disorder and borderline personality disorder, suggesting distinct underlying mechanisms (Macritchie & Blackwood, 2013). Genetic studies further support the differentiation, with bipolar disorder exhibiting a stronger genetic component compared to borderline personality disorder (Skodol et al., 2002).

The measures of mood bias on reward perception in this thesis were shown to correlate with hypomanic symptoms, as measured by the hypomanic personality scale [HPS, (Eckblad & Chapman, 1986)]. Previous research has demonstrated that the HPS not only predicts the development of bipolar disorder but also distinguishes between borderline personality disorder and bipolar disorder (Fulford et al., 2015). These findings suggest that the observed increase in mood bias on reward perception reported in Chapters 3 (general population study) and Chapter 5 (BIMODAL) are likely specific to mood spectrum disorders. The Wheel of Fortune task was purposefully developed to evaluate mood bias on reward perception in a reinforcement learning setting, with the primary aim of maximizing rewards. This task was designed to capture the characteristic intense goal pursuit often observed in individuals with bipolar disorder. By engaging participants in a context where they strive to achieve maximum rewards, the task allows for the examination of mood bias and its impact on reward perception within the framework of bipolar disorder.

On the other hand, it is possible that individuals with borderline personality disorder experiencing a large change in mood due to an interpersonal event (similar to the WoF mood induction procedure) may also exhibit a similar mood bias on future reward perception. The *Social Learning Task* may provide a better context for mood bias to occur in this group, as it involves social rewards instead of monetary rewards. Future work explicitly measuring differences between individuals diagnosed with bipolar disorder and individuals diagnosed with borderline personality disorder on these social and non-social tasks would be able to definitively answer this question.

4 Is mood bias a trait or state?

The question of whether mood bias is a trait or state characteristic remains. The present findings from the general population study (Chapter 3) and the BIMODAL study (Chapter 5) indicate that mood bias is associated with both trait (Hypomanic Personality Scale) and state measures (current mania symptom severity). However, these state and trait measures correlate with each other (Meyer, 2002). A positive correlation between symptom severity and mood bias suggests that mood bias could serve as an indicator of current symptom severity. On the other hand, it is plausible that a trait-level predisposition to hypomania leads to more mood bias which then contributes to increased symptom severity.

Previous computational modelling studies have conceptualised mood bias as a unique parameter that interacts multiplicatively or additively with current mood state (Eldar & Niv, 2015; Mason et al., 2017; Michely et al., 2020). The mood bias parameter is viewed as a stable characteristic, remaining constant across different mood states, including euthymic, depressed, and manic phases. By incorporating the amplification of regular mood fluctuations, the model accounts for the mood instability observed during episodes as well as the residual fluctuations between episodes. In other words, mood bias acts as an intensity dial, turning the volume of current mood up or down, and leading to a larger or smaller bias on reward perception.

To gain a comprehensive understanding of the trait-state dichotomy of mood bias, further longitudinal research is warranted. Only longitudinal studies can help elucidate whether mood bias represents a stable trait that influences symptom severity or if it dynamically fluctuates along with the states of bipolar disorder. Additionally, exploring the temporal dynamics of mood bias and its relationship with symptomatology over an extended period can provide valuable insights into the causal and directional nature of this association. Longitudinal investigations can also shed light on the potential mechanisms underlying mood bias, such as the influence of social and environmental factors.

5 Methodological limitations

5.1 Mood induction

The main methodological difficulty of this project was the mood induction procedure. Across all three empirical studies, the effects of the mood induction were small, and in some cases did not reach the significance threshold for positive mood.

The choice of procedure being a wheel of fortune spin was motivated by previous work (Eldar & Niv, 2015), as well as a need for the procedure to work well when remotely administered on a smartphone. The procedure needed to be quick and engaging for participants and to ensure that if their attention was drawn away from the screen, it would still have an effect. A video-based mood induction may not have been appropriate, given that the videos last a few minutes and if distracted participants might miss the relevant part of the story. For these reasons we chose a wheel of fortune gamble that would reward participants a large number of points compared to the size of the in-trial rewards.

In the general populations study described in Chapter 3, I wanted to extend the work of Eldar and Niv (2015) by allowing a fair wheel of fortune draw, as opposed to using only the largest outcomes. This design choice allowed for more variance in the amount of mood change experienced by participants and showed that the amount participants won on the wheel predicted how much their mood would change. Secondly, this design choice increased believability permitting multiple plays of the game without participants suspecting that the wheel gave predetermined outcomes (which it did). While successful in inducing both positive and negative moods, the effect sizes were small.

When designing the *Social Learning Task*, to ensure that the effect of the mood induction was sufficiently strong while remaining believable, the wheel was rigged to give participants the second largest possible prize (\pm £5). This was consistent to previous work (Eldar & Niv, 2015) and based on insights from Chapter 3. Here, all participants only played the game one time. The mood manipulation was successful in inducing negative mood. The positive mood induction was found to be weaker than

the negative mood induction and not significant, in line with previous findings [Chapter 3, Chapter 5, (Joseph et al., 2020)].

These results are consistent with the concept of loss aversion in prospect theory (Kahneman & Tversky, 1979), which proposes that people are more affected by losses than gains of equal magnitude. A recent meta-analysis has also confirmed that positive mood is more difficult to induce than negative mood (Joseph et al., 2020). The effect sizes for negative mood induction were twice as strong than for positive mood induction. Furthermore, different types of mood induction procedures generate widely different results. The most effective mood induction procedure is showing a film with instructions. This method was approximately eight times more effective than the least effective method (jokes/cartoons).

Another reason for the asymmetrical mood induction results could be due to the 'Mood Drift Over Time' effect (Jangraw et al., 2023). This effect shows that participants' mood declines gradually as they complete tasks or rest during psychology experiments. The effect has been found to occur both in longer lab-based tasks and in more-engaging, shorter app-based tasks. Interestingly, mood did not drift when participants completed chosen activities, suggesting that experimenters may be subjecting participants to stressors that are not accounted for in analyses (Jangraw et al., 2023). The presence of the Mood Drift Over Time effect implies that as participants' mood gradually declines over the duration of the task, a negative mood induction would exacerbate this decline, while a positive mood induction would counteract it. In the context of an equivalent positive-negative mood induction procedure, this would result in a more substantial change in negative mood and a relatively smaller change in positive mood. This finding shed light on the differential impact of mood induction methods on mood and highlights the need to consider and possibly control for mood drift when studying mood changes over time. Future work might benefit from employing other types of mood induction that were shown to be more potent for inducing positive moods and perhaps consider different procedures for positive versus negative mood induction to account for the asymmetry observed.

5.2 Experimenter control

One significant challenge of conducting studies remotely and online is the limited experimenter control, which can result in increased noise in the collected data and potentially poorer performance, compared to lab-based experiments (Gillan & Rutledge, 2021). To mitigate these limitations, larger datasets are often necessary to compensate for the reduced control. For instance, in the study conducted with the general population (Chapter 3), over 4000 participants were recruited to overcome this limitation.

When it comes to studying specific populations such as individuals with mental health diagnoses, the task of identifying and recruiting participants poses significant challenges. The patient study conducted in Chapter 5, faced difficulties in recruiting a large sample of individuals with a bipolar disorder diagnosis. These challenges could be attributed to various factors, including the stigma associated with mental health, privacy concerns, and logistical constraints of working with NHS services and reaching out to the target population. To minimise data noise and participant confusion, those enrolled in the BIMODAL study attended an online session, during which the research team thoroughly explained the study requirements, each game and survey. This ensured each participant fully understood the tasks and this is likely reflected in the larger effect sizes and reduced noise seen in the BIMODAL study compared to the general population study. Thus while the sample size may be smaller compared to the general population study, the insights gained from this investigation provided valuable contributions to the understanding of mood bias on reward perception in bipolar disorder.

6 Theoretical and clinical implications

6.1 Theory

The main theoretical finding of this PhD thesis is that mood bias exists on a spectrum. This aligns with the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) classification of mood disorders which acknowledges the spectrum of mood disorders, highlighting the heterogeneity and varying degrees of symptom severity within these conditions [DSM-5, (APA, 2013)]. The current findings place mood bias on a similar spectrum, ranging from no mood bias – seen in participants with no hypomanic traits, to a moderate mood bias – seen in those with more mood instability, to a clear mood bias in participants with a diagnosis of bipolar disorder. While this thesis showed that mood bias increased with manic symptoms, more longitudinal research is needed to fully understand the causal relationship between mood bias and symptoms of mania and mood instability. Simulations of data based on higher mood bias parameters have been shown to lead to mood cycles seen in bipolar disorder, while a low mood bias promotes more stable mood dynamics (Mason et al., 2017). The manic cycle begins with positive surprises (or positive prediction errors) that improve mood, which biases reward perception making outcomes appear better than they actually are. This then leads to more positive surprises which restart the cycle. Eventually, expectations diverge from reality and negative surprises appear (or negative prediction errors) that lower mood, causing rewards to be perceived as worse than they actually are, leading to more negative surprises and maintaining the depressive cycle.

The concept of mood bias has provided valuable insights into the understanding of bipolar disorder and decision-making processes. Extending the BAS model which focuses on the role of reward responsiveness in motivation and behaviour, the inclusion of mood bias acknowledges the impact of mood fluctuations on decision-making dynamics (Eldar & Niv, 2015). Unlike the previous assumption of global processing biases or rewards, mood bias highlights that even small changes in mood can significantly influence perception, lead to the amplification of mood states and development and maintenance of symptoms of mania. The BAS model alone falls short in explaining the switches between these states, as it does not account for the nuanced role of mood. However, by considering mood bias as a contributing factor, a

more nuanced perspective emerges, providing insights into the intricate dynamics of bipolar spectrum disorders.

While the proposed model for bipolar disorder offers a strong foundation in understanding the relationship between mood and reward processing leading to manic or depressive mood cycles, there is a notable omission regarding how negative life events can also trigger manic episodes, as seen in clinical practice. One possible explanation stems from the nature of manic episodes which can be euphoric episodes but can also be characterised by irritability or anger. On the emotional scale of valence and arousal, manic episodes can be described by increased arousal and positive valence (euphoria) or increased arousal and negative valence (irritability). It is thus possible that a negative prediction error causes higher arousal (perceived as irritability) which then biases reward perception or drives reward pursuit in a similar way to positive affect does in the model, leading to a manic cycle. Ultimately, mood is a complex and multifaceted construct and current existing paradigms have not yet attempted to parse that. This highlights the need for a more comprehensive understanding of how negative life events, arousal, and reward dynamics intersect in the context of bipolar disorder.

6.2 Clinical practice

The theoretical insights into mood biases and their impact on daily decision-making processes hold significant relevance for clinical practice. Recognizing the spectrum of mood biases in individuals with mood instability allows for the customisation of interventions, enabling clinicians to address the unique dynamics of each individual's mood cycles. Personalised strategies, tailored to early warning signs, can be developed, along with specific coping mechanisms to prevent the escalation of manic or depressive episodes.

It's crucial to acknowledge that several of the interventions proposed, such as personalized coping strategies and addressing decision-making during mood shifts, align with standard Cognitive-Behavioural Therapy (CBT) and mindfulness practices for bipolar disorder (Costa et al., 2010; Lovas & Schuman-Olivier, 2018). This

underscores the consistency between the findings of this thesis and established clinical practices. Moreover, the present findings emphasize the nuanced dynamics of mood biases, potentially offering a distinctive emphasis within therapy. For example, CBT is commonly used to help individuals recognize and change thought patterns and behaviours that may contribute to manic episodes. CBT teaches coping strategies for dealing with stress and triggers that may precipitate mood episodes. Bringing awareness to how unexpected outcomes can boost happiness/ sadness and because of mood bias inadvertently escalate to a manic/ depressive episode, could help ground these CBT principles more in each person's day-to-day experiences. For example, after receiving a large prediction error, practicing CBT techniques such as recording thoughts, cognitive reappraisal, behavioural activation, or mindfulness meditation could have a key impact in defusing the situation and preventing the start of a new mood episode.

Meta-analyses of psychotherapy interventions for bipolar disorder have shown that they are effective in reducing symptoms severity, improving disease management and reducing relapse (Swartz & Swanson, 2014; Szentagotai & David, 2010). Cognitive Behavioural Therapy for bipolar disorder has its unique place among psychosocial interventions due to features such as being empirical and flexible, and it is recommended as an evidence-based therapy usually accompanied by pharmacological treatments (Jauhar et al., 2016). Overall, CBT has been shown to significantly lower the relapse rate (pooled OR = 0.506) and improve depressive symptoms ($g = -0.494$), lower mania severity ($g = -0.581$), and increase psychosocial functioning ($g = 0.457$; (Chiang et al., 2017). All CBT processes are fundamentally based on four steps: assessment, psychoeducation, implementation of interventions, and relapse prevention. Evidence suggests that psychoeducation is crucial and the most evidence-based module in this process, used both at the beginning of the therapy and at the stage of relapse prevention (Özdel et al., 2021). Incorporating information about how mood biases can arise even from small surprises and impact future decision making could enrich this module even more.

Conventional psychiatric evaluations are limited as they rely on scales administered during in-person visits with clinicians, and mental state examinations asking patients about their subjective experiences in the past. This approach lacks the ability to

assess patients during crucial moments such as "bad days" or relapse situations. It paints a biased picture of the patient's mood fluctuations, as people tend to give more weighting to recent events and less weighting to ones further in the past. If such an assessment occurs every few weeks or months, it would be near impossible to objectively relate all the fluctuations of mood experienced in that time.

The integration of gamified tasks as an indirect clinical measure, accessible via smartphones, holds the potential to enhance the assessment process and address these limitations. By utilizing gamified tasks, clinicians can gather data in a more convenient and frequent manner, allowing for a more comprehensive understanding of patients' experiences and treatment progress in various contexts. This approach has the potential to provide valuable insights and improve the accuracy and objectivity of psychiatric evaluations, ultimately leading to more effective and patient-centred care. Furthermore, adding a mood tracking component either active (by prompting the person to rate their mood) or passive (though passive physical data collected like steps or sleep) would help paint a clearer picture of what the person has been feeling over a certain period and uncover more subtle mood dynamics.

Incorporating computational models and machine learning algorithms into clinical practice holds promise for predicting and monitoring the time course of illness and treatment response (Gillan & Rutledge, 2021). Interestingly, studies have shown that classifier performance improves when trained on parameters estimated from computational models rather than relying solely on observed data (Huys et al., 2016b). Computational models can also generate testable hypotheses that can be later explored empirically leading to more insights.

By leveraging multivariate data sets collected with app-based tasks, and advanced modelling techniques (which can be automated), clinicians can gain deeper insights into the complex interplay between mood biases, reward processing, and symptom severity in bipolar spectrum disorders. Such approaches have the potential to enhance personalized treatment strategies and improve outcomes for individuals on the bipolar spectrum.

7 The future of cognitive neuroscience research

The usefulness of smartphone-based tools in cognitive science and computational psychiatry has been extensively discussed in the literature [for a recent review, see Gillan and Rutledge (2021)]. One key advantage is the ability to recruit a more diverse pool of participants, as smartphone-based and online samples tend to exhibit greater diversity compared to traditional in-lab testing conducted in Western university settings (Buhrmester et al., 2011) which tends to recruit participants that are western, highly educated, coming from industrialized, rich, and democratic societies (Henrich et al., 2010). Furthermore, it allows the collection of very large datasets, including thousands of participants and multiple time points which allows for the study of individual differences, as well as increasing the generalisability of findings (Gillan & Rutledge, 2021). The use of other gamified smartphone apps has proven to have vast uses from neuroscience studies to smoking-cessation interventions and management of chronic conditions such as asthma (Coughlin et al., 2016; Edwards et al., 2018; Real et al., 2019; Teki et al., 2016).

There is endless untapped potential in fully exploring multivariate datasets, that combine experimental tasks with real-life metrics such as experience sampling methods (ESM). Phenotyping approaches that leverage machine learning algorithms and integrate demographics, ESM, and gamified task data have the potential to predict the time course of illness or treatment response (Gillan & Whelan, 2017) moving towards predictive models (Yarkoni & Westfall, 2017). In addition, combining assessments with passive data collection of physiological data, such as pupillometry, heart rate or step count, might provide additional crucial information (Chan et al., 2017; Seppälä et al., 2019; Valliappan et al., 2020). Data from wearable sensors were indeed associated with certain psychiatric disorders such as schizophrenia and bipolar disorder (Seppälä et al., 2019).

One caveat is that while participant costs are often negligible, the development of smartphone applications can be expensive and labour-intensive, depending on whether it is kept in-house or outsourced to external app developers or companies (Teki et al., 2016). Online testing platforms such as Amazon Mechanical Turk have gained popularity and may present greater cost-benefit trade-offs, particularly if they can incentivize repeated engagement and allow for flexible task updates based on initial insights. However, it is important to note that within the same platform, it may not be feasible to collect a significantly large sample size required for certain studies. Large samples are often driven by online publicity during the app's release, and subsequent attempts to gather additional data for follow-up studies may be limited and require a different approach (example: The Happiness Project app, released in January 2021, which received substantial media attention and downloads in its first month, making it challenging to collect a similar-sized sample for future investigations).

7.1 The promise of Artificial Intelligence

The rapid advancements in Artificial Intelligence (AI) tools, coupled with their increasing accessibility to researchers, hold great promise for psychology and neuroscience research (e.g., Chat GPT, Google Bard). AI tools offer several advantages that can significantly enhance the field. They enable the analysis of vast amounts of data with greater efficiency and accuracy, allowing researchers to extract meaningful patterns and insights that may have otherwise gone unnoticed. AI algorithms can detect complex relationships and uncover hidden associations within large datasets, providing researchers with valuable information for hypothesis generation and testing. Furthermore, AI tools offer the potential for automated data collection and processing, reducing the burden on researchers and increasing the scalability of studies, while saving time and resources. This not only facilitates larger-scale research but also enhances the reproducibility and transparency of studies as AI algorithms can provide standardized and consistent methodologies.

AI algorithms can aid in the development of predictive models and personalized interventions. By leveraging machine learning techniques, AI tools can identify patterns and predictors of various psychological phenomena, leading to more accurate

predictions and tailored interventions for individuals. These models can assist in identifying at-risk populations, optimizing treatment strategies, and informing clinical decision-making. Moreover, AI-based technologies, such as natural language processing and computer vision, have the potential to revolutionize psychological assessment and diagnostics. These tools can analyse and interpret unstructured data, such as text and images, providing valuable insights into individuals' cognitive and emotional states.

Overall, the integration of AI tools in psychology research coupled with large online or app-based studies, offers numerous benefits, including enhanced data analysis, automated processes, personalized interventions, and advanced assessment techniques. By harnessing the power of AI, researchers can unlock new avenues of inquiry, accelerate scientific progress, and ultimately improve our understanding of the human mind and behaviour.

8 Conclusion

This doctoral research delved into the relationship between mood and rewards, shedding light on its implications for mood instability and bipolar spectrum disorders. A large-scale study using the smartphone-based app "*The Happiness Project*" revealed that mood can significantly influence how rewards are perceived, even when the rewards are inconsequential. This mood bias was particularly pronounced in individuals with higher levels of mood instability, suggesting mood bias may play a role in developing or maintaining mood instability. The study demonstrated the enduring nature of mood bias, persistently impacting decision-making processes even as memory for specific rewarding stimuli diminished. This showed how a small mood bias during learning can impact behaviour and choices a week later. The investigation also explored the influence of mood biases in social contexts, but conclusive evidence of social mood bias was not found. In a clinical study comparing bipolar disorder patients and healthy controls, a distinct mood bias on reward valuation was observed

exclusively in the bipolar group. This bias intensified with the severity of manic symptoms, emphasizing its role in maintaining bipolar spectrum disorders.

Overall, these findings offer valuable insights into the intricate interplay between mood and rewards, supporting the view that mood bias on reward perception may be on a spectrum. Lower mood bias serves adaptive functions of guiding behaviour towards maximising rewards, while higher mood biases can lead to mood instability and in more extreme cases bipolar spectrum disorders. The implications of these findings extend to clinical interventions and therapeutic approaches, providing avenues for managing mood instability and addressing bipolar spectrum disorders. Additionally, this thesis highlights the significance of employing online and smartphone-based methodologies, such as "The Happiness Project," for collecting comprehensive and diverse datasets that better represent the general population, facilitating broader insights into the dynamics of mood and its impact on human behaviour.

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