Mechanisms behind Worry and their Role in Anxiety

Alexis An Yee Low

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I, Alexis An Yee Low, confirm that the work presented in my thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Abstract

Worry is central to anxiety and causes key physical and psychological symptoms, including functional impairment. However, it is perceived by some to be helpful in problem-solving and avoiding aversive outcomes. To explore the hypothesis that worry occurs due to a lack of optimum stopping, becoming maladaptive when it persists beyond usefulness, a series of studies were undertaken. The overarching aim was to produce a computational model of worry as computational modelling is uniquely suited to reveal underlying mechanisms. First, a systematic scoping review revealed that evidence accumulation models are the best way to address the current lack of computational models of worry. Next, a novel experimental paradigm tested on 306 participants showed that sampling within it functions as a proxy for worry, successfully quantifying and externalising the process of worry, a process required for model-fitting. Sampling ('re-lookings') was predicted by both within-subject trial-to-trial state worry ($p < .001$) and between-subject trait worry ($p = 0.0178$). This sampling behaviour was shown to be maladaptive in high worriers, driven by a tendency to sample even with low success probability, supporting the hypothesis that maladaptive worry occurs due to sampling persisting beyond usefulness. Furthermore, momentary worry and trial-specific information ratio completely mediated the effect of other factors on sampling upon multivariate analysis; this suggests that psychological and biological constructs associated with worry may act on it via the sampling processes identified. Lastly, an evidence accumulation model in the reinforcement learning framework was proposed and was able produce synthetic data similar to collected data, suggesting a new and useful model for both adaptive and maladaptive worry.

Impact statement

Academic

This thesis has contributed a novel experimental paradigm which captures worry successfully as well novel computational model of worry. Both contribute significantly to the understanding of the underlying mechanisms of worry by enabling testing of the hypothesis that worry is the sampling of thoughts and memories aimed at avoiding aversive outcomes, which becomes maladaptive when it persists beyond usefulness. Data collected via the experimental paradigm was sufficient to identify some individual differences, and can be used to test computational models not just within this project but in potential future work even by other academics.

Clinical

First, the finding that perfectionism plays a key role in between-subject differences in worry has psychoeducational and therapeutic implications, as this suggests that targeting perfectionism can reduce worry. CBT for perfectionism has been shown to be efficacious in reducing symptoms of anxiety in a recent meta-analysis. Therefore, this supports findings which show that perfectionism-focused therapy can be an avenue for reducing worry.

Second, the fact that high worriers but not low worriers respond to a lower chance of success by sampling more suggests a possible driver for worry on the level of the individual. Specifically, responding to worry not producing a satisfactory solution is responded to with 'this means I need to search harder' rather than 'this means I need to stop worrying'. This is a belief that can be targeted in talking therapies such as cognitive behavioural therapy.

Lastly, parameters in the model can, upon being fitted with empirical data, differentiate between different forms of worry, as it may manifest differently in different disorders, as a transdiagnostic symptom present in many disorders from Generalised Anxiety Disorder to Post-Traumatic Stress Disorder (PTSD) and Obsessive Compulsive Disorder (OCD). For example, worry that occurs due to increase in a parameter related to the 'favourite number' bonus could be associated with OCD, due to the repetitive behaviour in OCD sometimes being characterized by rigid rules. This can shed light on the key mechanisms behind different types of worry, whether in different disorder types or in maladaptive compared to adaptive worry especially, allowing treatment to be targeted to specific types of worry.

Outreach

This increased understanding of the mechanisms behind worry can be shared in publications such as The Mental Elf, which the author has published with in the past and which aims to facilitate conversations between clinicians, patients, researchers, and policy makers. It can also be shared in press releases both by UCL and by the Agency for Science, Technology and Research, which funded this work.

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This thesis is dedicated to, and inspired by, the people who suffer from mental health problems worldwide, the neurodivergent, and everyone who is struggling – may you continue to fight, and may you get the support you deserve.

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Main Body of Thesis

1. Introduction

The lifetime prevalence of anxiety disorders is 33.7% (Bandelow & Michaelis, 2015). This high prevalence suggests a substantial societal burden, confirmed by epidemiological evaluations (Baxter et al., 2014; Yang et al., 2021). Notably, excessive anxiety is present in a range of mental health conditions such as social anxiety disorder, obsessive compulsive disorder and paranoid schizophrenia. The ubiquity of anxiety in a large range of disorders suggests that its psychopathological mechanisms are present across diagnostic categories, and that understanding anxiety is crucial to a full understanding of mental health.

Indeed, the concept of a transdiagnostic element – underlying mental disorders – has been established to the point of forming the basis of treatments (Newby et al., 2015), and is reflected in concepts such as the p-factor, which posits that many psychiatric disorders share a single psychopathology dimension representing greater-to-lesser severity of psychopathology. Given the commonness of anxiety, it is likely that it is a key element of mechanisms that underlie mental disorders as a whole; especially since the p-factor is already linked to anxiety specifically, such as in predicting long term outcomes (Carhart-Harris et al., 2023; Cervin et al., 2021).

1.1. The Problem of Worry

Worry is central to anxiety. It is phenomenologically defined as uncontrollable distressing thoughts due to concern about an impending threat (Hirsch & Mathews, 2012; see Box 1 below).

Box 1.

Phenomenological Definition of Worry.

Phenomenological Definition of Worry:
Uncontrollable distressing thoughts due to concern about an impending threat (Hirsch & Matthews, 2012)

Note that this is a descriptive, rather than mechanistic definition. A more mechanistic definition of worry, suitable for interrogating its functional underpinnings, will be discussed later in this section.

What is the significance of worry? Worry is the central diagnostic criterion for Generalised Anxiety Disorder, which is diagnosed by ‘excessive anxiety and worry, occurring more days than not for at least 6 months, about a number of events or activities’, with worry being difficult to control, and causing distress, but also functional impairment. Furthermore, it is not simply a symptom but the root of other distressing aspects of anxiety, because it is thought to contribute to several physical and psychological symptoms, such as muscle tension, irritability and impaired sleep. On the other hand, when employed in measure, worrying may help problem-solving, or feeling more in control in a stressful situation (Davey, 1994; Llera & Newman, 2010); in a study of naturally occurring worry episodes, the largest category of thoughts was “reflecting a problem-solving process” (Szabó & Lovibond, 2002). Some studies have shown that aspects of anxiety — such as increased threat perception — are adaptive, increasing when problems *can* be solved, and decreasing when they cannot be resolved (Notebaert et al., 2017). Hence, worry may be seen not just as a pathological phenomenon, but a state of mind, which is adaptive in certain circumstances and harmful in others.

1.2. When is Worry Adaptive?

Following this, there is a need to discuss what exactly it means for worry to be adaptive.

Tinbergen’s (1963) landmark paper in behavioural sciences proposed that, when studying behaviour, adaptive significance is key. Adaptive significance is defined as ‘how does the behaviour affect the organism’s fitness’ (Tinbergen, 1963). This is particularly so in human behaviour, where it is well-established that both thoughts and behaviours are adapted to the environment (Brunswik, 2023). Indeed, ‘[t]he view of Homo sapiens as an adaptive decision maker has continued to receive support’ (Glöckner et al., 2014; Weber & Johnson, 2009).

Broadly, there are two approaches to determining what is adaptive: the nomothetic and the idiographic approach, concepts which are present not just in psychology but in law and in scientific study in general. The nomothetic approach seeks a general law which explains a large group of people; the idiographic approach seeks understanding of specific, or particular, groups of people (Robinson, 2011; Windelband, 1998). In the past decade or so, there has been a push towards personalised medicine, including in psychiatry, owing to the shortcomings of using the same treatment approaches across an entire population (de Leon, 2014; Vieta, 2015). However, it is important to note that these approaches are complementary, not antagonistic (Robinson, 2011). The nomothetic approach to science is what enables clinical trials to test the efficacy of a treatment in general; the idiographic approach allows for studying of how this treatment may interact with people with particular characteristics. A general rule may also enable specific modifications on top of it to improve it; for example, a clinical trial may show the effectiveness of talking therapies in general, and personalised research can add to this general 'rule' of talking therapies being effective by specifying which ones are more effective for particular groups of people e.g. dialectical behaviour therapy for those with severe emotional regulation problems (Neacsiu et al., 2014).

In the context of adaptiveness, the two differing approaches mean that behaviour which is maladaptive in a general context may well be adaptive in the specific niche, or context, the agent is in. For example, a bias against exploration may not be adaptive in most environments, but it may be adaptive for an abused child who often has to hide in their room to avoid punishment. The use of the label 'maladaptive' must therefore have careful consideration and is certainly not a simple label to apply.

Indeed, as discussed in the previous section, it has been noted that worrying may help with feeling in control during a stressful situation. Other studies have discussed a possible role of worry in emotional regulation; the contrast avoidance model of worry (Newman & Llera, 2011) states that worry helps to avoid unexpected large changes in emotions felt e.g. from happiness to sadness. This means that whether worry is adaptive is highly dependant on each individual and their relationship with worry, e.g. positive and negative beliefs they may have e.g. 'worry helps me problem-solve'.

Using caution when applying the labels of adaptive or maladaptive in worry is particularly important in the clinical approach to anxiety and worry, as labelling a patient's behaviour maladaptive has certain implications. Firstly, crucially, it fails to recognize that not all patients are in the 'after' stage of trauma and may still be experiencing adverse events where their maladaptive coping mechanisms are helpful in some way. Complex PTSD, for instance, is caused by long-term or recurring traumatic events, which may still be ongoing when encountering a clinician e.g. domestic abuse or housing instability. While behaviours and schemas start being built at an early age, these continue to change and adapt to life events, and every person's psychology could be arguably said to be how they adapt to – and survive – each moment in their lives, including the present. This is especially important in the current world we live in, where socioeconomic causes of poor mental health are aplenty, from housing crises to war and conflict and political instability (Çalıyurt, 2022; Macintyre et al., 2018); research cannot be done completely in a vacuum. Therefore, removing these coping mechanisms simply because they would be maladaptive in an ideal world – which may be far from the world one actually is in – could be very dangerous, and is indeed a possible way psychotherapy can cause harm (Lilienfeld, 2007).

In addition, negative labels when applied to someone can have a significant impact on their well-being. Much research has been done on the effect of mental health labels. For instance, common derogatory terms used to describe people with mental health problems such as "nuts" or "psycho" lead to increases in stigma and social distance (Szeto et al., 2013). This is not limited to colloquial terms, but includes some formal psychiatric diagnoses, such as Borderline Personality Disorder, where unfortunately even clinicians show stigma towards people with the diagnosis (Ociskova et al., 2017). Even if others are not aware of their label, self-labellers have been shown to have more internalized stigma, though it must be noted that it has some benefits, such as increasing the likelihood of seeking help from health services (A. B. Fox & Earnshaw, 2023; Horsfield et al., 2020). Given how complex and potentially harmful the issue of labelling is, one would be recommended to tread with caution.

Lastly, to label as maladaptive is – inherently – act of judgment. Therefore, it is not impossible for biases to creep into how and to whom this label is applied to, as indeed clinicians are human with their own prior experiences. For instance, having a tendency to overwork may well not be labelled as maladaptive – even if it should be – if the patient is a fellow clinician with a busy work schedule, even if the patient is experiencing negative effects due to their behaviour.

How, then, can adaptiveness be assessed, as it is key to supporting behaviours which enable one to thrive in their world? The most important approach is arguably to consider each individual's self-determined goals as they are naturally already shaped by the context they are in. In many talking therapies, this simply involves asking the person in question what their goals are. However, in research, it is different as the goals of the general population one hopes to shed light on by studying a representative sample are unknown. Indeed, this means that they have an unknown utility function, in the context of cognitive neuroscience and computational psychiatry.

Given that the utility function is unknown, there needs to be a different way to assess adaptiveness. The economically adaptive utility function, where one is maximizing objective returns, will therefore be used for the following reasons.

First, taking into account the definition of adaptiveness as fitness to an environment, behaviour is best defined in terms of obtaining reward and avoiding punishment from this environment. Second, this approach allows for quantification of the benefit of worry, which can then be further analysed and modelled. Lastly, it is difficult and complex to assess each factor's importance to each individual, and accurately capturing the relationship an individual has with worry would be a separate project which deserves time and attention separate from this study. This means, for example, while feelings of control may provide some benefit, it will not be included in analyses as it is not as relevant to obtaining the best possible outcome from an environment.

Drawing a link back to the discussion about nomothetic or idiographic approaches, this means that in the context of this study, given that it explores worry in a computational context where utility needs to be calculated, the nomothetic definition of adaptiveness will be used. In terms of a cost-benefit approach, since worry concerns an impending threat (as defined in Box 1), what is gained is the avoidance of aversive stimuli, i.e. the impending threat. The cost, then, is the psychological and physical distress caused by the act of worry (as discussed in Section 1.1.). Therefore, worry can be considered adaptive when what is gained outweighs the cost of gaining it. Note that this approach is used without claiming that it is the only, or best, approach, and a discussion will be conducted about the limits of this approach in the overall discussion section.

Correspondingly, worry can be considered *maladaptive* if the outcome was not worth the myriad costs of physical and psychological distress and functional impairment – in other words, when the cost outweighs the benefit. In sum, for the purposes of this study, the below definition of maladaptive worry (Box 2) is used:

Box 2.

Defining maladaptive worry.

Definition of Maladaptive Worry:
Maladaptive worry is when the cost of worry (distress and functional impairment) outweighs the benefit (avoidance of aversive outcomes).

1.3. Worry as Problem Solving

Now that it has been discussed that worry can be adaptive, how exactly does it do so?

First, worry is key to a bigger picture in anxiety, which is that of motivation. Anxiety, despite being framed as something that paralyses, has an element of trying to achieve a goal, which may include approach, avoidance, or maintaining one's current state. There is an element of trying, over and over and over again, to try to think of a solution, or something you can do, something you can understand about the situation. Fundamental to this is also the assumption that the more one tries, the more likely one is to succeed, whether by increased preparation or increased problem-solving. This has links to vigour in reinforcement learning, which is the energy or effort one invests in pursuing a strategy; arguably, anxiety and worry is the motivated channelling of this effort, whether it is successful or not. This is a key difference between worry and its cousin rumination; conventionally, while rumination considers the past, worry considers the future (Hirsch & Mathews, 2012).

This leads to an interesting paradox which may, in fact, only be an apparent paradox: while anxiety makes one appear stuck action-wise, due to behavioural inhibition (Clauss, 2019; Lyyra & Parviainen, 2018; Svihra & Katzman, 2004; White et al., 2011), one is exploring thinking-wise. One is 'curious' but does not look like it because they do not externally explore; all the exploration is internal. In one's mind, this manifests as constantly exploring one's thoughts, ideas or perspectives, trying to bump into a solution to one's problems, like continually pacing around a room looking for a misplaced object in hope of finding it, while on the outside, the person appears stuck inside their room. This exploration often comes with much vigour, such that energy and effort can be said to be channelled disproportionally into thought instead of action.

In order to explain anxiety and worry, we need to understand this desire to problem-solve, where preoccupations persist even when this is no longer effective. This is a concept which has been explored in the past, for example by Davey (1994), who describes pathological worry as a problem-solving attempt which is unsuccessful (Davey, 1994). However, although existing literature has explored the links between worry and anxiety, accounts of worry as problem-solving lacked a clear, well-evidenced mechanism.

1.4. Models of Worry

To further address this, an overview of existing definitions and theories of worry will be presented. There are several models of worry in a psychological context.

Wells' cognitive model of generalised anxiety disorder, also known as the metacognitive theory of worry, first established in 1999, posits that anxiety is an abnormal worry state (Wells, 2006). It asserts that generalised anxiety results from using worry as a coping strategy, and is reinforced by negative meta-beliefs about worry (worry about worry) as well as positive meta-beliefs about the usefulness of worry. Similarly, in Dugas' model of generalised anxiety disorder, updated in 2019, anxiety is maintained by positive beliefs about the function of worry (Robichaud et al., 2019). It suggests that when people perform common safety behaviours — such as attempts to gather information or avoidance — they are doing so in hope of reducing uncertainty. However, the process of worry in fact increases uncertainty: the process of generating "what if" questions increases the number of available possibilities, not to mention the emotional impact of repeated negative thoughts.

The contrast avoidance model by Newman & Llera (2011), on the other hand, states that worry is used to avoid a sudden shift in emotional state due to unexpected negative occurrences: the 'contrast avoidance' (Newman & Llera, 2011). It argues that because individuals with generalised anxiety are more sensitive to feeling emotionally distressed by negative events, they use worry to maintain a negative emotional state, thus avoiding the sudden shift that comes with transitioning from a positive or neutral to negative state. This, again, positions worry as a coping mechanism, though in a different form — it is a form of emotional regulation rather than a problem-solving technique.

Next, according to Hirsch & Matthews' cognitive model of pathological worry (2012), worry results from a combination of a 'bottom up' automatic bias towards threat and impaired 'top down' cognitive control processes, leading to the intrusive thoughts which characterise worry. Worry, and thus anxiety, is then further reinforced by an inability to intentionally disengage from these negative intrusions once they have come to one's attention, something which has also been characterised in other models. Indeed, it is described as 'the tendency of worry to grow over time', leading to the maintenance of processes which cause anxiety to take root.

All these models posit that worry has the following characteristics. One, it acts as a coping mechanism, whether to problem-solve or to regulate emotion. Two, it persists longer than is warranted; likely because of this strategy being perceived as helpful in some way, especially in people with generalised anxiety. However, while there is evidence for individual assumptions, the models have not been tested as a conceptual or functional whole. This is crucial as worry could have interactions with other elements of anxiety such as perceptions of uncertainty or threat, and these may be key elements in understanding how exactly worry persists so strongly in people who struggle with it. These models also lack clear mechanistic backing where there is a clear characterisation of the parts that cause worry and how they interact with each other, limiting understanding and certainty about what worry *is*. This will be further discussed in the scoping review section.

1.5. Key hypotheses regarding Worry

My hypothesis builds on these ideas, formalising the concept that worry is a problem-solving mechanism in the context of information-seeking. More precisely, it is a cognitive search strategy to obtain more information to solve a problem or to provide emotional relief (e.g. when one feels like one has sufficient information, one may be no longer anxious). To illustrate, information is often searched for in one's own mind; someone worried about an upcoming interview may continually consider many possible questions, such that they can be prepared for any eventuality. This occurs to the point of distress in maladaptive worry as one presses on with the search strategy even when they have exhausted most realistic possibilities.

This is consistent with theories that worry is maintained by positive beliefs that it is helpful (Davey, 2008; Hebert et al., 2014; Wells, 2006) and is further supported by how targeting these beliefs can reduce worry (Laberge et al., 2000). It also allows for a formal explanation of why worry persists. Meta-beliefs about worry being useful — beliefs about beliefs — can be modelled by the idea that a higher level of processing compels one to keep on exploring in the mind: 'I cannot stop worrying yet, I have not found a solution that feels right', as opposed to 'I am not sure how this will go, but I have done enough'. If this is true, it can then be demonstrated by constructing an ecologically valid paradigm which shows avoidance of action in an effort to reduce uncertainty via worry.

To sum up thus far, this thesis aims to test this novel hypothesis — that worry is a problem-solving mechanism based on sampling for information – and that this can be considered maladaptive if it persists despite the costs outweighing the benefits.

1.6. Operationalising Worry

Operationalisation refers to redefining an abstract concept such that it can be measured or studied, and is critical to experimental psychology (Pfister, 2022). In the context of this study, which will employ multiple methods to capture worry, it can be operationalised in several key ways which differ but complement each other.

First, the phenomenological experience of worry can be captured by a validated questionnaire such as the Penn State Worry Questionnaire (Meyer et al., 1990), as well as trial-to-trial self-reports of worry. Comparing this to the other operationalisations of worry will allow for checking of whether the others do, in fact, capture worry.

Second, behaviourally, it is operationalised as persistent search for information – i.e. sampling – in order to avoid an aversive outcome. This is to test the hypothesis in 1.3. that worry is a problem-solving mechanism in the form of information-seeking. This renders the internal processes of worry external and measurable within the context of an experimental paradigm – the purpose of operationalism. Within an experimental paradigm, the persistence of sampling behaviour can be measured by the number of samples one makes, which can then be analysed quantitatively alongside the phenomenological measures of worry. 'Aversive outcome(s)' to avoid can also built into an experimental paradigm, such as in the form of shocks.

Lastly, for mathematical modelling, worry can be similarly operationalised via simulating the number of samples the agent will take given a certain set of parameters. Model-fitting will again enable aligning this with behavioural and phenomenological measures of worry by fitting it to these sources of data. Modelling will add mechanistic depth to the measured behaviour by showing which parameters causally produce this behaviour. For example, a high magnitude of a certain parameter may indicate that the agent has a prior which predisposes them to heightened sampling behaviour.

The key operationalisations of worry at each level of analysis and measurement will now be summed up below.

Box 3.

Operationalisations of worry.

Phenomological

- Definition: Uncontrollable distressing thoughts due to concern about an impending threat (Hirsch & Matthews, 2012)
- Measurement: Validated questionnaire (Penn State Worry Questionnaire) and trial-to-trial self-report

Behavioural (Quantified)

- Definition: Persistent internal search for information - i.e. sampling - to avoid an aversive outcome.
- Measurement: Number of samples participant makes in a trial

Computational

- Definition: Persistent internal search for information - i.e. sampling - to avoid an aversive outcome (same as behavioural)
- Measurement: Number of samples agent makes in a trial, generated by a model, given a specific set of parameters

Note. For ease of comparison, the phenomenological definition is repeated from Box 1.

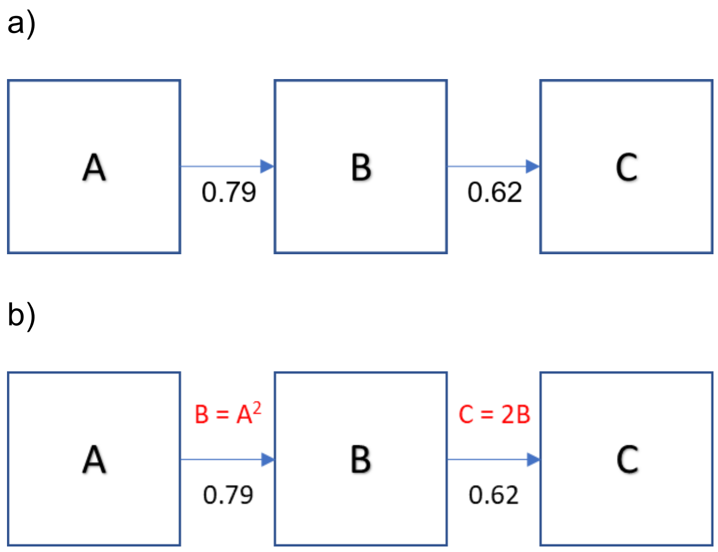
1.7. Modelling Worry

Why computational modelling? As we have seen, various models have been proposed in an attempt to explain worry, but a clear mechanistic answer remains elusive. An initial literature search suggested that while cognitive models of worry have been established, they do not have sufficient information to provide a full picture mechanistically. These models follow a box-and-arrow structure which draws casual relationships between constructs to form an overall picture, such as that of anxiety. However, indicating the existence or even the strength of a relationship is insufficient detail: to truly understand how the moving parts relate to each other, the exact computations that lead from one part to another must be known.

To illustrate, Figure 1a) is a possible cognitive model. While it shows that A is the basis of B which correspondingly is the basis of C, it is unknown how exactly this happens. Figure 1b), on the other hand, provides a much fuller picture by including both the existence of the relationships and how they are computed. These equations are computations which represent processes, thus making a model computational rather than suggesting a mechanism alone.

Figure 1.

A schematic of a possible computational model.



Why is a computational account, characterised by crafting hypotheses in the form of a mathematical model that includes mathematical computations, important?

First, computational models can compare and contrast very specific mechanistic hypotheses, which would not be comparable without foregrounding the exact mechanisms that occur under the surface (Adams et al., 2016). In the context of worry, this may mean comparing and contrasting different hypotheses for why worry happens; especially useful for worry, as there have been many ideas entertained in the literature. For example, models can help arbitrate on whether worry happens because of bottom-up value placed on the potential information that will be gained, or whether it happens due to top-down favouring of a policy of searching for information to deal with a threat when one is encountered. As an example, for this particular comparison (bottom-up vs top-down), two models would be constructed, one representing the 'bottom up' and one the 'top down' hypothesis, and then both models would be fit to the same dataset; e.g., quantitative online experiment data of people responding to threatening stimuli. Each model would then be evaluated quantitatively by estimating how likely it is that each model would produce the exact observations obtained: i.e. Model Evidence or marginal likelihood, usually approximated by a criterion such as the Bayesian Information Criterion (BIC). Importantly, this allows for these two models to be quantitatively compared e.g. a lower BIC indicates higher model evidence, i.e. a better fit.

This offers an efficient and principled way to compare models which may even come from different philosophies, fields or schools of thought; e.g., cognitive therapy compared to exposure therapy – with more objectivity as well, as although mathematical analyses may incorporate human biases, they still produce a quantitative score of evidence for a hypothesis or model, which can be used for clear comparison. In other words, it allows for a clean answer to simple and yet elusive and crucial questions such as 'which model is better?'; sidestepping the difficulty of comparing apples with oranges, due to the large diversity of models and viewpoints available. This does not entail any loss of nuance, as it is perfectly possible for one model to explain a particular group, while a different model may explain the data from a different context better; e.g., social anxiety compared to post-traumatic stress disorder — providing different insights into different areas of mental health. Furthermore, of course, these mathematical results themselves and the techniques that gave rise to them can be discussed and evaluated for scientific merit.

Another scientific benefit is that when models are compared, the relative success of models can be used to gain knowledge. Simply, if a model containing a term for baseline anxiety levels performs significantly better than a model without it, one may conclude that baseline anxiety levels are important. Thanks to the mathematical nature of the models, findings can be extremely precise. For example, in Low et al (2022), the model for self-esteem which performed the best, was based on the rate of change of social approval, which provides evidence that self-esteem is based on social momentum — whether one's status is currently going up or down — rather than simply one's position in a social group (Low et al., 2022). There, the difference between a stance of 'social position determines self-esteem' and a stance of '*changes* in social position determines self-esteem' was simply and definitively pulled apart by using a set of mathematical equations — i.e. a model — to represent each theoretical position.

In the context of worry, this means that one would, in principle, be able to model the difference between similar concepts such as 'worry is caused by trait anxiety' and 'worry is caused by state anxiety' given a set of experimental data. In terms of the knowledge gained, cognitive models differ from models such as growth-curve or change-score models, as there is an explicit focus on what information the brain processes, and how exactly it is processed — unlike the latter models, which tend to be more descriptive. They focus on capturing how dynamics change over time, rather than how dynamics change over different conditions or how a change in one 'moving part' affects the rest of the system, which is what cognitive computational models are built for.

Furthermore, while mathematical models are evidently useful in a large range of applications from weather prediction to spacecraft, it is in understanding the mind that they are uniquely illuminating. Mathematical models provide a way to 'see' inside someone's mind, because psychological processes are inherently hidden: with them, one can capture intuitively simple and yet difficult to measure core concepts such as 'mood', 'vigour' and 'uncertainty'. While psychological questionnaires are helpful, they ask about the thoughts and behaviours that psychological processes cause, rather than the dynamics of the process itself. Furthermore, the act of self-awareness induced by answering a question can influence these dynamics by itself. Having a way to capture inner psychological processes is particularly important in mental health, where it is well-documented that the exact same symptoms can be caused by very different psychological processes, leading to treatment difficulties. For example, social anxiety may be caused by catastrophising potential negative outcomes e.g. ‘I will make a social faux pas that destroys my life’ or, alternatively, strong intolerance of the uncertainty of social situations rather than simply being certain of negative outcomes. In other words, mathematical models provide a way to track and analyse what is happening in one’s mind, and evaluate the accuracy of any assessment.

The ability to quantify psychological processes further provides the foundation for testing another hypothesis: the ‘Goldilocks’ evolutionary account of psychology, where for every psychological process, there is an optimum point where it is the most helpful. This is grounded in the concept that for phenomena such as worry, too much worry causes destructive anxiety, and is widely studied, but too little worry can also cause harm; e.g., if someone makes inadequate safety precautions for danger. This is similar to the effect of stress, where some amount of pressure is motivating, but too much causes one to collapse, which has been characterised with an inverse U-shaped curve (Salehi et al., 2010), Evolutionarily, some amount of tendency to worry may be selected for, as it would have maintained alertness in the face of potential threat to individuals and community; e.g., worrying about dangerous enemies means building more barriers to keep them out, suggesting that this characteristic was meant to be helpful. In the present day, this still applies: for example, worrying about one’s health causes one to take precautions such as vaccinations and eating healthily, resulting in a lower overall rate of illness. In other words, the issue with worry is not simply that it happens, but that it happens *too much*, suggesting a new avenue for research and potential treatment. This is the key link to the hypothesis proposed earlier.

Mathematical modelling allows for not just calculating this optimal point, but the underlying calculations the mind makes to attempt to reach it. For example, it may shed light on the cognitive process of calculating a trade-off between the potential distress caused by worry, e.g., the stress of worrying about one’s keys every time one leave their home and potential reward obtained e.g. a reduced chance of being locked out of one’s home. This decision-making trade-off is computed differently in different people, resulting in varying perceived ‘perfect’ levels of worry, an area which is ripe for targeting personalised interventions and capturing neurodiversity. The same person may also behave differently in different contexts, and this context sensitivity can be dissected mathematically; for example, the learning rate that informs how much to worry on a moment-to-moment basis may be significantly larger numerically in a context of lower social position e.g. subordinate rather than superior. Precise, individual characteristics captured via mathematical modelling, e.g., volatility of worry, adaptiveness of worry can also be compared to an ideal value or a population norm and analysed in relation to questionnaire data, allowing for further exploration of their psychological and psychiatric implications. For example, one may find that people with a higher 'worry adaptiveness' value are less likely to have generalised anxiety disorder for a given value of trait worry.

Furthermore, mathematical models are uniquely useful in decision-making research as the best decisions to make in an experiment are objective – not something we can easily determine in real life. The 'distance' between optimum decision-making and participant behaviour can then be evaluated. A crucial point to make is that optimum behaviour within an experiment does not necessarily parallel conventional health, and sub-optimum behaviour does not necessarily parallel a disorder. For example, in an experiment where there is no explicit cost to trying to obtain new information, the optimum policy would be to search for as much information as possible, but in real life this policy would lead too much time and energy wasted. This is an example of how experiment-optimal behaviour may not be real world optimum behaviour. This allows for the fascinating hypothesis that certain behaviours may not be optimized for the present world, but may very well be perfectly optimal in other contexts, such as a more volatile environment, possibly one where these very behaviours were forged by fire. In other words, there is no 'perfect' set of behaviours or psychological processes – it simply depends on the environment, and the fit between the behaviour and the environment.

Models can also hold predictive power in a way that is not just descriptive but mechanistic. Unlike, for example, some neural networks which can predict outcomes but have opaque rationales (a 'black box'), cognitive computational models are constructed with a clear rationale behind each component. This means that, in the event of a successful prediction, one can analyse how exactly the prediction was made, resulting in an increase in scientific understanding. For example, previous research, e.g., a regression model, may suggest that level of uncertainty is a key predictor of worry, A computational cognitive model can then provide a hypothesis for *how* exactly uncertainty predicts worry, moving beyond a correlative relationship. For example, it can mathematically posit that it is the interaction between uncertainty and a person's baseline trait anxiety level that results in state worry. This is done by crafting a model consisting of the equation *state worry* = *uncertainty* × *baseline anxiety*, and then modifying it by adding terms to increased accuracy such as decay rates, a scaling constant, etc.

The predictions themselves — in terms of projected data into the future — can also be potentially useful in clinical practice. For example, mechanistic mathematical models of time series e.g. ecological momentary assessments can be used to not only predict downturns in mood or upticks in anxiety, triggering advice to seek help, but can also determine why exactly this negative emotional state is happening e.g. an increase in the stress parameter suggests that this happened due to a recent stressful event.

All in all, it is clear that computational models are key to the exploration and determination of psychological processes, and studying these processes would be incomplete without their use.

2. Scoping Review

2.1. Methods

As we saw in the previous chapter, computational modelling has the potential to provide insights into ‘worry’ due to the way it captures psychological processes. The study of worry is not only a pertinent area of research but also one that attracts a large literature: a search for ‘worry’ on Google Scholar currently returns 2,670,000 results. Worry itself also has many aspects, from decision-making to emotional to linguistic facets. How, then can one select the aspects to focus on?

To address this question, a scoping review was conducted. A scoping review aims to map key concepts, research, and gaps in a defined area of study to identify an exploratory question (Colquhoun et al., 2014), and does so in a systematic way, making it ideal for guiding a new project. In the context of this thesis, the following scoping review aims to do the following:

1. Provide a comprehensive account of computational models of worry.
2. Identify and analyse key themes in modelling worry.
3. Determine key gaps in the field, and therefore priorities for modelling research, with an eye on translational potential.

The following databases were searched in pursuit of finding models of worry, with the following search terms. Search terms were based on “worry”, “computational”, and MeSH terms for “model”, as well as known terms both within and outside the field of computational psychiatry which could describe computational models, such as “mathematical”, “simulation”, “Bayesian inference”, “neurocomputation” and “active inference". Where available as advanced search options, studies which are explicitly not modelling studies – e.g. clinical trials, case studies, field studies, as well as non-human studies, were excluded. References were exported in .ris format and compiled in EndNote.

Table 1. Search terms for each database.

Database	Search terms
OVID MEDLINE, EMBASE, all other OVID journals	((model* or simulation* or neurocomputation* or computational* or bayesian inference* or active inference* or mathematical*) and worry).af. not (case study or clinical trial or followup or longitudinal or prospective or retrospective or field study or interview or focus group or trial).pt. Search limited to human studies only
PUBMED	((model* or simulation* or neurocomputation* or computational* or bayesian inference* or active inference* or mathematical*) and worry) NOT (case study or clinical trial or followup or longitudinal or prospective or retrospective or field study or interview or focus group or trial) NOT (animals[MeSH Terms] NOT humans[MeSH Terms])
CINAHL Plus	(model* or simulation* or neurocomputation* or computational* or bayesian inference* or active inference* or mathematical*) AND worry NOT PT (case study or clinical trial or followup or longitudinal or prospective or retrospective or field study or interview or focus group or trial)

	Search limited to human studies only
Web of Science	((model* or simulation* or neurocomputation* or computational* or bayesian inference* or active inference* or mathematical*) and worry) NOT (case study or clinical trial or followup or longitudinal or prospective or retrospective or field study or interview or focus group or trial)
SCOPUS	(ALL (model* OR simulation* OR neurocomputation* OR computational* OR bayesian AND inference* OR active AND inference* OR mathematical*) AND ALL (worry))
psychINFO	(cognitive) models Computational Modelling/ OR Affective Computing/ OR Computer Simulation/ OR Simulation/ OR Cognitive Modelling/ OR Computational Neuroscience/ OR Machine Learning/ OR Artificial Intelligence/ OR Computational Reinforcement Learning/ OR Machine Learning Algorithms/ OR Unsupervised Learning/ OR Cognitive Computing/ OR Bayesian Analysis/ OR Mathematical Modelling/ OR Artificial Neural Networks/ OR (simulation* OR neurocomputation* OR computational* OR bayesian inference* OR active inference* OR interpersonal inference*).ti,ab,id.

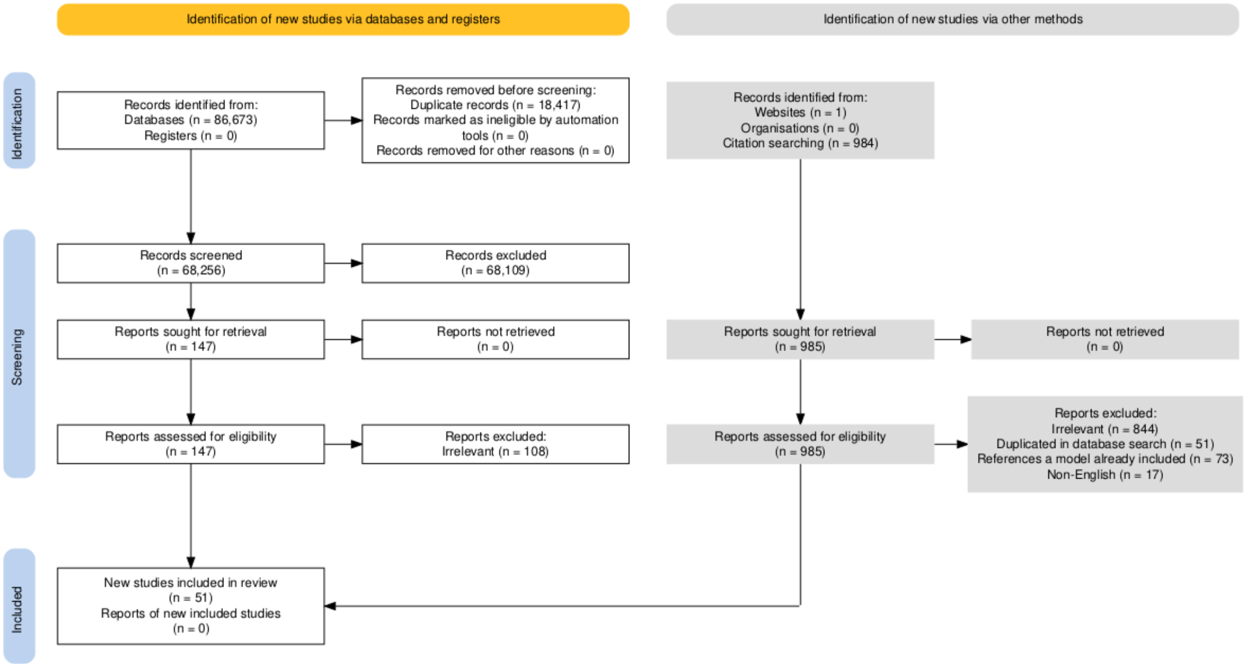
	Study type (exclusion) (clinical case study OR clinical trial OR field study OR interview OR focus group OR nonclinical case study OR treatment outcome OR longitudinal study OR followup study OR prospective study OR retrospective study).md.

Citation-tracing based on key papers (n = 3) was also conducted (inputs: 10.5127/jep.007910, 10.1016/j.cpr.2011.01.008, 10.1016/j.brat.2012.06.007) (Hirsch & Mathews, 2012; Newman & Llera, 2011; Wells, 2010), resulting in n = 304 items for backward tracing and n = 680 items for forward tracing. A recently established journal —that is highly relevant in our field, but which is not reliably indexed in databases: Computational Psychiatry — was also hand-searched for relevant papers, and yielded a single result as of 11^{th} June 2023 (Kazinka et al., 2022).

In total, before deduplication, 86,673 records were retrieved. After deduplication, 68,256 records remained. The artificial intelligence review tool ASReview (Haddaway et al., 2022) was then used to retrieve the most relevant records, based on hand-selected relevant records as training data. Using this tool, 147 records were reviewed before discontinuing as per the protocol for ASReview. 51 records were selected for retrieval (39 from databases and 12 from citation tracking). See Figure 2 for details and the Appendix for the full list of articles.

Figure 2.

PRISMA diagram of systematic review.



Note. Generated using software by Haddaway et al., 2022.

The models were evaluated based on the following criteria:

1. Is the model computational?
2. How specific is the model to worry?
3. How widely applicable is the model?

The last two criteria were included after an initial review. It was evident that many models examined anxiety as a whole rather than specifically focusing on worry; such as by including ‘anxiety symptoms’ as a component of the model rather than specifically ‘worry’. Many were also limited in applicability, focusing on specific populations such as patients with a specific physical disease and their health worries rather than crafting models for underlying processes present in every person and context. This is important for several reasons. First, having a general model enables worry to be understood regardless of what condition it manifests in; from obsessive compulsive disorder to generalised anxiety disorder. Second, if the model can adapt to both high and low worry, e.g., by varying the value of a parameter, it can smoothly measure variation both within and between individuals. Third, niche models — e.g., worries about ovarian cancer — may contain components or relationships which are simply not present in other contexts, limiting their usefulness in understanding the underlying principles of worry. They have, however, been included, as comparing and contrasting niche models may shed light on commonalities which could be useful. Elements of the models were also identified and categorised.

2.2. Systematic Review Results

Below are tables summarising the results of the systematic review. The full list of articles, as well as the identification of which elements of worry are present in each of them, are present in the Appendix.

Table 2.

Evaluating the specificity of each model

Specificity of Model	
Worry	21
GAD	10
Worry but part of GAD model	4
Illness worry	3
Anxiety (various)	4
Worry (and repetitive negative thinking)	2
Anxiety and depression	3
Anxiety (trait)	1
Climate anxiety	1

Note. Specificity refers to what the model is aiming to describe or explain. Also note that worry was used as a search term and anxiety was not.

Most of the models (30/51) were not specific to worry.

Table 3.

Populations captured by the models.

Population	
General	25
Adolescents	2
Clinical (GAD)	4
Children	4
Children & adolescents	1
Non-clinical	2
People with specific physical health conditions	2
General vs Clinical	4
Clinical (anxiety disorders which are not just GAD)	2
People at risk of specific physical health conditions	1

Only a minority of models were applicable to the general population. Many had limited applicability, e.g., concerning ovarian cancer worries, or being only about children.

Table 4.

Whether models were computational.

Computational	
Yes	0
No	51

There were no papers which involved computational models. While there were mathematical models, e.g., a mediation model (Yıldırım & Bahtiyar, 2022), they were not computational. Specifically, the models were statistical models of correlations between components, rather than mechanistic models of how worry manifests in the brain, or how components of the model causatively relate to each other.

Table 5.

Overview of number of models which have the given element within the model

Elements	
Metacognition	30
Beliefs	27
Intolerance of Uncertainty	20
Experiential avoidance	8
Neuroticism	6
Control	4
Emotion dysregulation	4
Attentional bias to threat	4
Anxiety sensitivity	2
Psychological distress	2

Note. Some models have multiple of these elements, so the numbers do not add up to 51).

2.3. Computational processes relevant to worry

From the preceding results, computational processes which may be relevant to worry were identified as follows.

2.3.1. Metacognitions

Metacognitive processes were the most represented element in models of worry, present in 30 out of 51 papers found.

They were operationalised with a variety of methods, including questionnaires, single questions and experimental methods. Of particular note is the self-reported Metacognitions Questionnaire (MCQ), which was used in a majority of metacognition papers, and the Meta-Worry Scale, which was found in fewer papers but was still often used. For example, in Penney, Dwight & Rudanycz (2013), positive and negative beliefs about worry are assessed using a self-report questionnaire based on the Metacognitions Questionnaire (MCQ), which measures both the positive and negative beliefs that individuals hold about worry. The MCQ was used in many of the papers found, including Wells (2005), van der Heiden et al. (2010), and Ruggiero et al. (2012). The Meta-Worry Scale, on the other hand, was used specifically to measure worry about worry, and was similarly used in many papers, including Wells (2005), Ruggiero et al. (2012), and Esbjørn et al. (2014).

A few papers also used Ecological Momentary Assessments (EMA), an experimental method which captures metacognitions in real time in daily life (Rist et al 2015, LaFreniere & Newman 2019, Thielsch, Andor & Ehring 2015). These involved participants using their mobile phones to provide data about their metacognitive thoughts, worries and beliefs, and via repeated assessments over time, captured their relationship with worry.

As can be seen above, a key metacognitive element often present was beliefs – specifically, positive and negative beliefs about worry. It was present in 27 out of 51 papers found. Positive beliefs about worry refer to the belief that worry is helpful, whereas negative beliefs refer to 'worrying about worrying', i.e., convictions that worry is damaging or unhelpful, and thus something to be avoided. Both have been found to be predictors of worry (Penney et al., 2013). Metacognitive beliefs about worry can be modelled computationally; for example, by modelling a minimum amount of certainty a subject believes they need before they commit to a decision or action.

The second metacognitive element often present was the desire to maintain certain mental states or avoid certain thoughts. Of note is the contrast avoidance model discussed in the introduction (Newman & Llera, 2011), where worriers seek to maintain an emotional state of negative affect to avoid the contrast that occurs from transitioning suddenly — or unexpectedly — from a positive or neutral to negative state. This is an example of experiential avoidance, an element present in 9 out of 51 models, defined as "the unwillingness to remain in contact with distressing internal experiences along with the attempts to control or avoid distressing internal experiences" – positioning worry as a metacognitive coping mechanism. This is intertwined with the beliefs element above, as according to these models, a key positive belief held by worriers is that that worry is useful in this way.

2.3.2. Intolerance of Uncertainty

Intolerance of uncertainty is another process which is strongly associated with worry (Yook et al., 2010), and was found in 20 out of 51 papers. It is defined as “a trait-like disposition reflecting the tendency to fear unpredictable and uncertain future events and in the belief that feeling uncertain is undesirable” (Bottesi et al., 2020; Buhr & Dugas, 2002). It is primarily operationalised using the self-reported Intolerance of Uncertainty Scale (IUS), which assesses discomfort with ambiguous situations both cognitively and emotionally (Carleton et al., 2007; Freeston et al., 1994). This scale was used in all papers which had intolerance of uncertainty as an element of their model of worry (e.g. Kusec, Tallon & Koerner 2016, Norton et al 2005, and Chen, Yao & Qian, 2018). Uncertainty itself was also a model element in a single paper (Chen, Yao & Qian, 2018), in addition to intolerance of uncertainty.

The fact that worry increases with intolerance of uncertainty suggests that it is meant to manage, or resolve it; in other words, worry is a problem-solving mechanism to reduce uncertainty. Beyond this literature review, there is much work on the interaction between intolerance of uncertainty and anxiety. There is evidence for uncertainty being perceived differently between anxious and non-anxious people: people with various anxiety disorders e.g., GAD (Dugas et al., 1997) and panic disorder (Carleton et al., 2014) also show greater intolerance to uncertainty, finding uncertainty more threatening (S. Milne et al., 2019). However, recent evidence is coming to light that uncertainty itself, apart from intolerance of uncertainty as a trait, may not necessarily affect decision-making (Hopkins, 2021). Given the current open questions in the literature about how uncertainty or intolerance of uncertainty affects worry, it can be included as a factor in developing a model of worry, but does not hold as much importance as other factors with a more well-established role in worry.

2.3.3. Attentional Bias to Threat

4 out of 51 papers had attentional bias to threat as an element in the model of worry (Eysenck et al. 2007, Riskind 2024 et al., Hirsch & Matthews 2012, and Songco, Hudson and Fox 2020). A further 2 have anxiety sensitivity as an element (Sexton et al. 2003, Kertz et al 2013), which may have links to attentional bias to threat, as it suggests an amplified perception of feelings of anxiety which are likely to be caused by, or related to, threat stimuli. In these studies, attentional bias to threat is

operationalized using tasks that demonstrate how people with high anxiety or worry direct their attention preferentially towards threatening instead of neutral stimuli. They are, specifically, the dot-probe (in Eysenck et al. 2007, Riskind 2024 et al., Hirsch & Matthews 2012, and Songco, Hudson and Fox 2020), visual search (in Hirsch & Matthews 2012 and Songco, Hudson and Fox 2020), looming stimuli paradigm (in Riskind et al 2024) and emotion recognition tasks (Songco, Hudson and Fox 2020).

Attentional bias to threat has been a major theme in anxiety research for decades (Cisler & Koster, 2010; McNally, 2019). It refers to attention being allocated more towards threatening compared to neutral stimuli (Bar-Haim et al., 2007). Anxious individuals – across different diagnoses and including high-anxiety non-clinical populations – display this attentional bias, whereas non-anxious individuals typically do not (Bar-Haim et al., 2007). The phenomenon has been observed across several tasks, including the modified Stroop task (Hadwin et al., 2009; McNally et al., 1990), the dot probe task (Cisler et al., 2009), and the visual search task (Rinck et al., 2005), suggesting its robustness. Correspondingly, high trait worriers also display this bias strongly (Goodwin et al., 2017), and this was particularly evident in verbal stimuli i.e. words compared to images e.g. faces. As such, attentional bias to threat could be argued to be essential to a model of worry.

However, in the context of computational modelling and given that there has not yet been a computational model of worry, we need to start with a single, discrete process which can be validated, rather than attempting to incorporate every possible element of worry immediately. Complexity can lead to problems such as overfitting, which increases with the number of parameters and amount of noise (Ying, 2019). Incorporating both top-down and bottom-up aspects of worry would increase both noise and number of parameters, as well as require the operationalization of both threat and worry separately, making the model much more complex and overfitting more likely. Instead, discrete processes can be tested for validity, then be used as building blocks for a more complex model in future.

This study will focus on the cognitive aspects of worry. Firstly, this is because a majority of models had metacognition or beliefs as an element (30 and 27 respectively), whereas only 4 had attentional bias to threat as a model element. Secondly, as worry is fundamentally a quasi-verbal phenomenon; although threat bias may drive it, hold importance, cognitions are what would represent it best phenomenologically. This would make for a more ecologically valid and intuitive model. Importantly, this will also make the future model useful in clinical applications. Specifically, as CBT infers and analyses cognitions that cause disordered mental states, a belief-based model would also be useful in cognitive behavioural therapy (CBT) (Moutoussis et al., 2018; Nair et al., 2020). Furthermore, extensive studies have already been conducted on threat bias and appraisal, given its long history in anxiety research, while much fewer studies focus on repetitive negative thinking.

Notably, this focus on the cognitive aspect of worry does not mean the complete exclusion of other aspects. First, as discussed in the introduction, worry causes somatic symptoms such as muscle tension (and vice versa), such that any quantitative self-report of worry would naturally include its somatic aspects. Indeed, there are suggestions of mechanistic links between the top-down metacognitive and bottom-up attentional bias to threat, such as attentional bias being due to a top-down inability to disengage from threatening stimuli (Cisler & Koster, 2010; Hirsch & Mathews, 2012). Therefore, it is impossible to study one aspect of worry while completely excluding others, even if there is a need to focus on one for purposes of focusing on one at a time. Second, the effect of attentional bias to threat can still be accounted for in an empirical study, to control for its effects as much as possible. This is important as, without doing so, the robustness of the effect of attentional bias to threat in literature means that will be likely to occur. For example, if stimuli used in an experiment includes a variety of stimuli valences, the effect of different valences on behaviour can be quantitatively analysed for bias.

2.3.4. Control

The 4 papers which have control as an element of their model of worry operationalize it in two distinct ways. Chapman, Kertz & Woodruff-Borden (2009) and Ruggerio et al (2012) operationalise it using the self-reported Anxiety Control Questionnaire (ACQ) which assesses perceived control over both internal and external anxiety-related stimuli and events. Anderson et al (2019) and LaFreniere & Newman (2019) examine control as part of the larger framework of held metacognitive beliefs, capturing it using the subscale ‘beliefs concerning the uncontrollability and danger of worry’ within the Metacognitions Questionnaire.

Given that the uncontrollability of worry is one of the key diagnostic criteria for GAD in the DSM-5, it is arguable that control, or lack thereof, could be a key aspect of worry. Indeed, having an external locus of control – where one believes that events randomly happen to one and cannot be affected by one's behaviour – has been associated with anxiety for decades (Hoehn-Saric & McLeod, 1985; Molinari & Khanna, 1981; Ryon & Gleason, 2014). However, interestingly, worry has also been reported to increase feelings of control (Llera and Newman, 2010). Indeed, there is some evidence suggesting that there is increased perception of threat specifically when the threat can be mitigated – i.e. can be controlled – suggesting that worry may occur in response to threat when one feels that actions can be done to resolve it. In Notebaert et al (2017), participants showed a greater difference in reaction time between threat and non-threat cues when the threat cue could be mitigated by solving a math problem quickly, showing upregulation of a threat response due to increased perceived control.

However, while control is an element worth exploring, fewer models have included it in comparison to other elements such as metacognitions and intolerance of uncertainty. Furthermore, importantly, perceived control and beliefs about control fall neatly under the existing umbrella of metacognitions, and can be considered part of metacognitions; therefore, focusing on metacognition more broadly will provide a foundation for more detailed exploration of control specifically in future.

2.3.5. Other Elements

Neuroticism was identified as a model element in 6 papers out of 51, but was not included due to the fact that it is a disposition, not a process, and this thesis aims to use computational modelling to capture the processes behind worry. Emotion dysregulation and psychological distress appeared in 4 and 2 papers respectively; while they are clearly key aspects of worry which may lead to vicious cycles as they are both caused by worry and cause worry, they are too non-specific to be processes which can be captured by a model.

Next, the following model elements only appeared once and are therefore not included in the table. This is especially since some are highly specific to a limited context, and are therefore not relevant to a cognitive model of worry intended to be applicable to any situation – such aspects related to cancer, aspects related to cognitive development, and aspects related to climate change. The index of the paper in the list in the Appendix in which the element appeared is indicated in brackets afterwards.

1. Sleep (2)
2. Casual importance and self-concept clarity (5)
3. Age (19)
4. Extraversion (24)
5. Danger (28)
6. Aspects related to cancer (31)
7. Aspects related to cognitive development (34)
8. Aspects related to climate change (51)
9. Worry itself (51)

2.3.6. Optimal stopping

Optimal stopping is a key concept in decision-making literature. While it is not represented in the worry models found so far, this construct represents an opportunity; as a clear link can be drawn between stopping criteria and worry. It also draws links with the metacognitive element of worry which is so prominent. Worry, if considered in the light of exploration, can be stopped at some point such that the information gained during the search can be used – in the real world. However, one has to decide when to make a decision after some amount of worrying. This moment can be affected by many factors, e.g., a time constraint ("the bus is coming, we need to leave now!") or some level of certainty ("well, I've worried enough, let's move on"). In this sense, optimal stopping interacts with all the key elements above, and can be considered an action-adjacent element, into which other elements are funnelled. Many experimental paradigms decide the moment of information use on behalf of the agent, e.g., displaying information for 3 seconds, and then shifting to a decision-making screen. However, if one allows the agent to decide when the moment is, optimal stopping can be examined empirically.

This is reflected in models of planning under aversive circumstances; which, while not models of worry specifically, often draw strong links to worry. For example, both Gagne & Dayan (2021) and Wise et al (2021) connect their models to worry by stating that the problem-solving methods their agents choose may reflect the mechanisms behind worry (Gagne & Dayan, 2022; Wise et al., 2021). In the first study, worry is discussed as a meta-level problem of optimisation, where the agent has to trade-off between planning and action. In the- second study, worry is discussed as a simulation of both actual and hypothetical outcomes in one's mind which helps the agent avoid harm. This fits neatly with the concept of an optimum amount of worry, where worry begins as helpful and may only become maladaptive if prolonged to a point where distress outweighs helpfulness.

The persistence of worry is also a key aspect of a recent computational model of rumination (Bedder et al., 2023), which is closely linked to worry. The model formalises rumination as the process of sequentially sampling thoughts or memories to infer the hidden state of the world these experiences belong to. At each timestep, the agent either performance a sampling action or two terminating actions that lead to reward, if the agent infers correctly, and punishment otherwise. This sampling causes the update of beliefs, which are then used to compute values of choices and therefore the best decision to make. Notably, simulations showed that rumination-like behaviour is optimum in conditions where negative outcomes are likely or large in magnitude and when samples are more varied than expected. This demonstrates the importance of incorporating the concept of optimum stopping, where factors in the environment affect what behaviour is considered optimum.

Conceptually, this model has strong links to worry as problem-solving, despite being about rumination. As seen from the above, rumination is framed as "think(ing) through" a situation — a process which resolves uncertainty about the consequences of choices or actions. Furthermore, simulations showed that rumination, although increasing with pessimism, is only initiated if not entirely futile.

However, rumination and worry are qualitatively different, even if the structure of the models share some similarities. In the rumination model, sampling is conducted in order to infer the underlying state in terms of a general rule about the world, e.g., 'everyone is in a bad mood on Mondays'; however, worry is often about specific issues such as illness (Price et al., 2007). Worry is also more preventative and aimed at avoiding a negative outcome, whereas rumination is more reflective and less goal oriented. These distinctions speak to how worry should be modelled, such as highlighting the avoidance of punishment.

Another key computational model which involves optimum stopping is the Hauser et al information sampling model (Hauser et al., 2017, 2017). Here, the experimental paradigm involved the participant, or agent, being presented 25 facedown cards which were either blue or yellow on the other side. They then could uncover cards, without an explicit cost, until they were certain what colour the majority of the cards were. The winning computational model modelled actions based on whether the inferred sequence generator was more likely to deal blue or yellow next, as well as a subjective sampling cost which resembled an increasing urgency signal. The decision threshold for no longer sampling was calculated using both the sampling cost described above and the objective component of there being only 25 cards.

While this evidently has an optimum stopping and information-seeking element in that sampling no longer occurs when the decision threshold is reached, there are a few reasons why it would not be an appropriate model for worry.

First, worry aims to avoid an aversive outcome, and while this can be done *via* inferring an underlying state, this model stops at state inference, without making the link to avoiding punishment. This element is crucial as worry is phenomenologically thoughts avoid a potential outcome one does not wish to happen. Second, worry is most often social; the most frequent content category is family and interpersonal issues across both people with and without GAD (Diefenbach et al., 2001; Roemer et al., 1997). This paradigm, though elegant for the purpose of capturing information seeking, would therefore be unlikely to capture information seeking in the context of worry; it lacks ecological validity for this purpose. Lastly, it does not include some factors which would be desirable to study about worry, such as the effect of uncertainty (of which its importance was discussed above) and the emotional valence of any stimuli presented.

However, the model does demonstrate that sequential information sampling models can capture behaviour, and that is it a viable way to study optimum stopping. Aspects of the models could also be considered as potential models of worry if adapted, e.g. the mathematical function for impatience used. As can be seen, concepts can be drawn from existing models, even if these models are not direct or specific models of worry. Taking existing concepts into account therefore allows a new model of worry to be linked to the wealth of scientific knowledge in the decision-making literature.

2.3.7. Interim Summary

Below is a table which summarises the key elements of worry as discussed above.

Table 6.

Key components of worry models, operationalisations, context within current literature, and recommendation for inclusion.

Component	Operationalisation in Existing Models	Number of Papers	Recommended to include in model to be developed?
Metacognition	Self-reported questionnaires: Metacognitions Questionnaire (MCQ), Meta-Worry Scale Ecological Momentary Assessment diary entries	30	Yes
Intolerance of Uncertainty	Self-reported Intolerance of Uncertainty Scale (IUS)	20	Yes
Attentional Bias to Threat	Experimental tasks – dot-probe task, visual search task, looming stimuli paradigm, emotional recognition task	4	No
Control	Anxiety Control Questionnaire (ACQ) and control-related subscale of MCQ	4	No
Optimum Stopping	Not directly operationalized in papers found	0	Yes

Note. Reasons as discussed in the previous section.

2.4. Discussion

In sum, the key findings of the scoping review can be summarised as follows, which will be discussed in turn:

1. There are no computational models specific to worry, although there are non-computational (cognitive psychology) models of worry or related to worry.

2. Key components to include in modelling worry are metacognition, intolerance of uncertainty, and optimal stopping (see table above).

2.4.1. The Difficulty of Worry Models

As the search was comprehensive, covering multiple databases and with alternative search terms for the key terms of “worry” and “model”, it is unlikely the above conclusions are entirely inaccurate. While there is a chance that ASReview, being a new method of conducting a systematic review, may have yet unknown flaws, the papers that it suggested during the review process included models which were independently found via a conventional literature search, lending the process validity, in this specific field. ASReview itself is also open-source and has been independently shown to be effective (Campos et al., 2024). Furthermore, exclusions due to access reasons — such as the papers being non-English — were rare (only 17 out of a total of 985 papers screened via non-database methods, about 1.7%).

One possible reason behind the lack of models is reflective of a key challenge in the field; namely, the difficulty in capturing a phenomenon which is somewhat nebulous. Worry — unlike, for example a motor movement — is difficult to measure even though it is clearly observable and experienceable, because by nature it lies in one’s mind in a way which is not immediately accessible via overt expression. This makes it difficult to capture and measure with precision, which impedes modelling, because to fit a model well, data needs to precise. In a similar vein, it is difficult to claim that any measurement is, in fact, of worry *per se*.

How, then, to capture worry the best we can? While advances in technology have brought neuroimaging to the forefront, a well-validated questionnaire remains the one of the most reliable and valid measures of mental states and predispositions. Therefore, there needs to be an external proxy for the internal process of worry which is accurate and quantifiable. The development of such a proxy needs to be considered, and its effectiveness verified empirically, e.g., by linking reported anxiety to the ‘worry representative’ measure statistically. There is a lot of room for development here, as the proxy can be linked to anything from individual, overall levels of worry — as measured by questionnaires — to trial-by-trial feelings of anxiety.

Due to the complexity of these layers — e.g., embedding trial-by-trial anxiety questions — the development and validation of such a paradigm necessarily needs to happen from the ground up; with worry in mind rather than simply using an existing model or paradigm not validated for worry. Anxiety-driven worry needs to be deeply woven through the paradigm, model building, fitting and testing. For example, in order to test the hypothesis that worry reduces anxiety by problem solving but may in fact increase anxiety, one needs to measure anxiety levels not just once per trial but twice, before and after worry, i.e., information search in the form of evidence accumulation and implicit uncertainty reduction (i.e., information gain). The trial-by-trial feature is also important as worry is not a static trait but a phenomenon that varies within a person from moment to moment. Even chronic worriers have brief moments where they do not worry, and even those who consider themselves non-worriers have worried at some point in their lives. This opens up another avenue for differentiating people: if their behaviours can sometimes overlap, what can differentiate them? Is it simply a matter of frequency, or is there a way to distinguish between expressions of worry even in moments where they look exactly the same? In other worlds, the trial-by-trial nature allows for capturing both between and within person variations in worry, rather than simply correlating explorative or information seeking tendencies to worry propensity across a population.

2.4.2. What can we learn the components of models?

From the initial literature search, current models posit that worry may have the following characteristics. First, it acts as a coping mechanism, whether to problem-solve or to regulate emotion: the metacognitive element, potentially related to intolerance of uncertainty. Second, it persists longer than is warranted, likely because this strategy is perceived as helpful in some way, especially in people with generalised anxiety: the issue of optimum stopping. However, while there is evidence for individual assumptions, the models have not been tested as a conceptual or functional whole. This is crucial as worry could have interactions with other elements of anxiety, such as increased perception of threat, and different vulnerabilities may interact within the same individual; something that is missing when analysing individual elements alone. Different elements may also contribute to different extents in different people, creating feedback loops and states that a patient may be stuck in.

From the preceding systematic review, firstly, it is evident that models often do not capture worry specifically, instead focusing on anxiety as a whole. Second, they often focus on specific populations — e.g., children – and may not be suitable as a general model for worry in all contexts. Since worry is present across various mental health disorders, a model of worry would ideally be applicable across the population, and not just to people with a specific disorder; even if it is as ubiquitous as GAD, especially given frequent comorbidity. Third, there is a complete absence of computational models of worry. However, there has been literature which makes links to worry in decision making — to avoid aversive outcomes — and this is what will be pursued now.

It is time to recall the components of worry as operationalised in the introduction. Worry is characterised by:

1. A disposition to problem solve
2. Information seeking, or searching, in one's head
3. Making the decision to keep searching, i.e. decision making
4. In order to avoid an aversive outcome.

For #1, the 'problem' may refer not to an explicit problem but a 'problem' of emotional dysregulation, i.e., feeling emotional discomfort or unbearable anxiety. Some literature, — such as the contrast avoidance model (Newman & Llera, 2011) — suggests that worry occurs in order to reduce sudden negative emotional shifts. Thus, if one was already in a negative emotional state due to worry, any subsequent negative occurrences would be less of a surprise.

The term 'disposition' is used to refer to a motivation to avoid an aversive outcome where worry becomes the way one attempts to do so. 'Disposition' is used instead of more terms that imply more conscious, or explicit, awareness of purpose, such as 'intention' for example, as this desire to problem-solve may not be a conscious one that the person is aware of, especially if worry has become a habit. This aligns with what has been found in the literature about how threat response is upregulated when the threat can be mitigated, with no evidence that this upregulation is conscious or intentional (Notebaert et al. 2017).

In the context of worry being broken down into these key components, the existing literature captures the various components of worry, but not worry as a whole. Many computational models in psychiatry include these elements or closely related ones. For instance, many models address the management of uncertainty (related to #1), evidence accumulation (related to #2), or thresholds and optimum stopping points (related to #3). However, importantly, they are inadequate for the purposes of characterising worry fully, as none of these were crafted with worry in mind – as evidenced by the lack of literature in the results section above. This means that while they may capture some components of worry, such as repetitive thinking, they are not, in fact, fully about worry, and are likely to lack key phenomenological features; e.g., the fact that worry is forward-thinking to avoid a future, potential, aversive outcome.

If a model has a few, but not all, of the components of worry, one may argue that elements can be added to make it complete, e.g., adding a decision threshold (#3) to a leaky evidence accumulation model. However, this would not change the fact that the model was not crafted, tested and evaluated against ecologically valid measures of worry, or built with worry in mind.

To illustrate, in Bedder et al (2023), rumination accumulates evidence which helps to infer the underlying state of the world with the aim of obtaining reward and avoiding punishment. While the model's structure of sampling information to reduce uncertainty could potentially capture worry, worry is only associated with avoiding negative outcomes and not obtaining reward, making that aspect of the model somewhat inaccurate. More importantly, the model has not been tested against real experimental data, nor was it designed for such testing. For instance, it is unclear how inferring an underlying state of the world could occur experimentally in way that is quantifiable and can be validated; indeed, there is also no external validation that the process of rumination is indeed reflected here.

Making a model testable is important as it allows for the verification of the assumptions in the model. For example, inherent to the model above is the assumption that resolving uncertainty is a key motivator of rumination. However, though certainty level is a key factor in decision-making, rumination and worry are far more emotionally charged than simple decision-making, and it may play a different role or even be much less relevant in these complex phenomena. An experimental paradigm specifically crafted for model validation could shed light on this, e.g., by analysing how the ambiguity of stimuli effects the extent of repetitive negative thinking.

2.5. Evidence Accumulation Models

A further analysis of the components of worry above yields a useful insight: an intention to problem-solve (#1) and search persistence (#3) can naturally be included in evidence accumulation models of information seeking (#2). Evidence accumulation as information gathering does not occur in a vacuum, but towards a purpose: the 'problem' to solve which #1 refers to. The component of a decision threshold is even more clearly incorporated in evidence accumulation (EA) models, being one of their key characteristics (N. J. Evans & Wagenmakers, 2019); evidence accumulates towards potential decisions, until a threshold for one of them is reached and becomes the selected decision. In this case, the decision is the decision to stop searching, or stop worrying. EA models are where "evidence accumulates for decision alternatives at some rate, until the evidence for one alternative reaches some threshold that triggers a decision".

From the above, EA models are particularly suitable to model worry, and yet there has not yet been one, revealing a key gap to be explored. With the definition above in mind, there is a large range of EA models, from the most well-known drift diffusion model to models that involve adding to the sufficient statistics of a distribution, e.g., beta models, and can be continuous or discrete. The threshold may come in different forms, e.g., a softmax function producing a binary outcome, rather than a numerical threshold. Interestingly, even in models which are not explicitly evidence accumulation models, the process of obtaining information to make a decision is implied. In models based on experimental paradigms that involve choices, the participant makes choices based on the information they have gathered about the choice.

Similarly, if there is learning in the model, learning clearly involves accumulating relevant evidence. For example, in a review of in reinforcement learning models in people with mood and anxiety disorders, the differing learning rates for punishment and reward can be considered accumulation learning rates and are clearly part of the evidence accumulation (EA) process (Pike & Robinson, 2022). In this case, this involves accumulating different outcomes — punishment or reward — as evidence. This is useful in building hypotheses: for example, threat compared to safety learning rates can be used to consider the difference between worry and information gathering.

Another example of how existing modelling literature can inform new hypotheses can be seen in how McFayden et al (2022) found that stimuli which are both fearful *and* surprising create a novel electroencephalography (EEG) interaction – specifically, that patterns of activity associated with stimulus encoding started earlier (McFadyen et al., 2019). The characterisation of EEG data was done with the assistance of a drift diffusion model: the duration of a specific window of EEG data was significantly inversely correlated with the drift rate parameter, lending credence to the hypothesis that this period is when evidence accumulation and stimuli encoding occurs. If applied to worry, this suggests that unexpected anxiety-inducing environments jumpstart worry, as worry in the form of evidence accumulation would start earlier. This can inform model hypotheses, e.g., in an evidence accumulation model about worry. For example, one might hypothesize that higher state worry results in a lower drift rate towards 'stop sampling', given the same initial bias and boundary separation (such as if these remain constant for a given individual).

Clearly, building an EA model would enable rich links with the existing literature. The flexibility and range of types of EA models allows for many such scientific decisions to be made. Specifically, EA models can be continuous or discrete. The best-known example of a continuous model is the drift diffusion model (DDM) (Pedersen et al., 2017; Ratcliff & Rouder, 1998), where continuous sampling of noisy evidence occurs until one of two decision boundaries is reached, causing one of two alternative choices to be made. In contrast, in a discrete model, sampling occurs at discrete intervals, and evidence is obtained in steps at distinct time-points (Ratcliff, 1988).

Modelling decisions can be informed by empirical knowledge about worry. For example, the decision to characterise worry with a drift rate or learning rate as one of its parameters can be justified by the phenomenon of persistence in worry, and where one may think for a long period of time about a single piece of stimuli, e.g., worries about your boss's angry facial expression. A lower drift rate or learning rate suggests that the agent's thoughts will be 'stuck' on this particular issue for a longer period of time, instead of any decision being reached. While worry can also meander between topics, this provides a good example of how existing literature can be combined with worry-focused specific empirical knowledge to build the best model.

What is missing from current literature to explain worry? While there are robust evidence accumulation models in aversive contexts, they do not capture the cognitively persisting form of worry in one's mind which is phenomenologically central.

For example, Wise et al 2019 captures learning processes in avoiding aversive outcomes, but the link between the learning which occurs in their model and the real process of worry is not explicit. Worry, by nature, is internal and thought-based rather than overt behaviour-based, making capturing the cognitive aspect key. Furthermore, these models are not sufficiently detailed about the process of evidence accumulation itself. For example, in associative learning models, values of states are assigned and used in computing a decision, not evidence or information, and there is no explicit representation of evidence. These models therefore clearly cannot speak fully on processes of accumulating, assessing and processing. Second, these models may lack relevant components such as a participant-determined threshold. A unique threshold is necessary when modelling worry due to the nature of worry being as prolonged as the person wishes it to be, and if the decision point is fixed, it would be unable to capture how decisions are hastened or postponed by low or high worry.

2.6. The Translation Question

Worry is the explicit (i.e., can be verbalised and is observable) manifestation of decision-making processes in one's head. It is the natural visible outcome of inherently internal processes. The translation from internal processes to an observable phenomenon is a key issue in computational psychiatry.

Computational psychiatry — especially when it comes to mechanistic models — has not yet been translated into clinical practice. While some of this is because it is a relatively young field, there are also often questions, especially from clinicians, about whether these models do, in fact, capture psychological phenomena to a useful degree, as clinicians are often sceptical about complex human processes being abstracted and simplified. Focusing on the bridge between decision making (unseen) and worry (seen) is key to bringing models closer to clinically familiar understanding.

This is important as in itself, knowing about decision making is not necessarily useful in the clinical context. Decision-making is an abstract, and broad, concept which is potentially generalisable to many cognitive and emotional phenomena. It therefore necessarily needs to be refined into the specific processes which occur during worry in order to explain it. 'Turning' abstract decision-making concepts into an evidence accumulation model of worry, which in itself has a more intuitive structure than other types of models, is what will allow exploration of symptoms in the clinical context.

Worry is also particularly suitable for modelling as, being an observable phenomenon, it grounds an abstract decision-making model in empirical reality. This also makes it useful for clinicians to understand, who may not wish to engage with theoretical decision-making concepts but would be receptive to an increased understanding of worry: it is what they encounter every day. Therefore, it is a particularly good candidate for looking into the translation question.

2.7. Conclusion

Based on this systematic scoping review, there is a lack of computational models specific to worry. Therefore, non-computational models of worry, as well as computational models which are not specific to worry but which have strong links to it, were examined, and key elements identified: namely, metacognition, intolerance of uncertainty, and optimum stopping.

Taking this into account — as well as the ways in which current models lack the full mechanics of a computational account of worry — there are several key conclusions and recommendations. First, worry is best characterised as a problem-solving mechanism in service of avoiding aversive outcomes. Second, an evidence accumulation model is particularly suitable for capturing worry. All in all, this scoping review furnishes key pointers for modelling, and has done so via a comprehensive synthesis of the literature.

3. Experimental Paradigm and Task Development

3.1. Background

In the previous chapter, it was asserted that due to worry not being directly accessible, there is a need for a proxy which is accurate and measurable, such that data suitable for model-fitting can be generated.

What characteristics should such a proxy have? First, in order for it to be validated, it needs to be measured trial to trial, alongside self-reported worry or anxiety. This is because while trait worry is a measure, state worry is what people experience phenomenologically, which varies with moments in time.

Recall that the key elements identified in worry from the scoping review and subsequent discussion are the following (with reference to table 6 in previous chapter):

Table 7.

Key elements to consider in an experimental paradigm aimed at capturing worry.

Element	Identified in scoping review?	Include in final paradigm?
Metacognition	Yes	Yes
Intolerance of uncertainty	Yes	Yes
Attentional Bias to Threat	Yes	No
Control	Yes	No
Optimum stopping	No	Yes

Note. Reasons for including or excluding in final paradigm were discussed in Chapter 2.

From this, the key elements to include are (i) intolerance of uncertainty, (ii) metacognitions, and (iii) optimum stopping. To address them in order, first, there needs to be an element of uncertainty, which worry aims to resolve. Second, the paradigm needs to include a metacognitive element where people can self-evaluate the actions they take to reduce this uncertainty. Thirdly, optimum stopping can be captured by how each person decides the trade-off between resolving uncertainty compared to worry. This may involve different stopping behaviours for different conditions, as continued search may be more useful in some conditions than others.

The issue of assessing if worry is adaptive or maladaptive can also be addressed within the paradigm. Given the framework decided on in the introduction – that an action is considered maladaptive if the cost outweighs the benefit (see section 1.2) – this can be captured in the following way. The cost is the distress experienced by the agent which can be recorded via a self-reported question. The benefit is the avoidance of aversive outcomes, which can provided via aversive stimuli such as shocks or screams which occur probabilistically. Therefore, determining maladaptive worry within a paradigm would involve calculating how effectively worry-like actions, which cause distress, reduce the chance of encountering an aversive outcome.

Lastly, such a paradigm would need to be ecologically valid. As discussed in Chapter 2, models of decision making under aversive circumstances are aplenty, but were not made with worry specifically in mind. Therefore, it should be as close as possible to worry emotionally, phenomenologically, and experientially, in order to allow the internal processes to be a valid proxy for worrying.

Taking these into account, I have developed a paradigm that renders explicit and measurable the resolution of uncertainty in order to avoid an aversive outcome which occurs during worry.

3.2. Experimental Paradigm – Trials

The basic concept is that the participant has to infer someone's emotions, and if they do so incorrectly, they may suffer adverse consequences. This is ecologically valid as having to navigate emotional uncertainty is stressful and commonly experienced. Avoiding harm by reading emotion correctly is also a feature of certain types of childhood maltreatment (Passardi, 2018), e.g., recognizing anger in physically abusive caretakers (Ardizzi et al., 2013; Gibb et al., 2009; Pollak, 2008). This would naturally correspond with worries such as "is he mad at me?" and "what if they are in a bad mood when I get home?". Worries about other people's feelings often occur (T. Borkovec, 1985; Diefenbach et al., 2001; Roemer et al., 1997), and sometimes even involve imagining their facial expression (Szabó & Lovibond, 2002). In fact, the most frequent content category for worriers was family and interpersonal issues, across both people with and without GAD (Diefenbach et al., 2001; Roemer et al., 1997). Additionally, faces are naturally salient stimuli (Kwon et al., 2016; Santos et al., 2011). Reading emotion via facial expressions is therefore ecologically valid for emulating worry.

In the task itself, which will be described in full detail in the immediate next section, the aim of the participant is to read the overall emotion from a set of facial expression images (see Figure 3 for details). If they are inaccurate, there is a 50% chance that a scream will be heard — i.e., aversive emotional stimuli — based on the threat of scream paradigm (Beaurenaut et al., 2020). In each trial, the participant is first shown 5 images of facial expressions from the same person. This is the *initial information* they are given. They are then asked to provide an initial emotion rating on the basis of this initial information.

Crucially, they are then given an option to gather more information by pressing the spacebar to obtain more images of facial expressions. This captures worry as a process of attempting to avoid aversive outcomes by assessing and re-assessing a situation in one's mind. Each press of the key will most likely reveal one of the facial expressions they have already seen, but has a small chance of revealing a facial expression from the same distribution, but one they have not seen before, i.e., not one of the initial 5.

This is much like what happens in worrying, where searching for relevant clues in our mind leads us to images and memories that we have already considered, but there is a small chance of noticing or realising something useful. A real-life example would be, on the way home to a volatile household, "I wonder what it will be like today – oh yes, dad was upset today – I'd better not make too much noise" or simply a child watching his parents anxiously to decide if he should deliver the news that he failed an exam ("Should I tell them today? Maybe tomorrow, mum looks like she's in a bad mood.").

In each trial, the chance of getting this new piece of information is either 1 in 5 or 1 in 40. This probability is provided explicitly, such that the effect of success chance on worry-like behaviour can be studied directly (without having to learn it). This is a key factor, the <u>information ratio</u> factor. If they do successfully receive the 'new' facial expression image, it is bordered in green, to remove the need to figure out which images are ‘old’ or ‘new’. Then, whenever they feel ready, after however many revisits or openings (of the ‘facedown deck’ of facial expressions) they wish to perform, they can press ‘enter’ to move onward. They then indicate their final decision on the emotion reading, as well as their certainty level and worry level. Then, at the very end of each trial, there is a 50% chance of a scream being played if they are inaccurate by more than one arbitrary unit on the rating scale.

Here is a detailed breakdown of the paradigm (see Fig. 3 for overview), excluding instructions, training, example trials, and checks, which will be discussed shortly after. A graphical overview of the full factorial design will also be provided.

1. 5 images of facial expressions from the same person are presented sequentially, each image displayed for 1.5s, with a fixation cross presented for 0.5s between each image. Generative normal distributions were used to determine which facial expressions are shown (represented by the 1-9 numerical range, where 9 represents extremely upset and 1 extremely happy).

   Specifically, to vary both mean and standard deviation of facial expressions presented, the distributions N(3.75, 0.75), N(3.75, 2.5), N(6.25,0.75) and N(6.25,2.5) were used (low mean and low SD, low mean and high SD, high mean and low SD, high mean and high SD respectively). For each distribution, random samples were drawn using the *rnorm* function in R e.g. *rnorm(5,3.75,0.75)*. This yielded the following sets of numbers, each representing a provided set of facial expressions:

   Low mean, low SD: 4, 4, 3, 4, 5 and 3, 3, 3, 4, 5
   Low mean, high SD: 5, 3, 6, 2, 3 and 2, 4, 7, 2, 1
   High mean, low SD: 7, 6, 6, 5, 6 and 6, 7, 6, 6, 7
   High mean, high SD: 2, 4, 7, 7, 9 and 6, 7, 10, 3, 9
   (two sets were generated for each mean and precision to limit the effect of learning from previous presentations of the exact same stimuli)

These 8 sets of stimuli are presented for each one of the 4 possible persons shown. This forms a total of 4 × 8 = 32 trials.

2. The participant is asked ‘Please select the overall mood you think the person you were just shown is feeling by choosing ONE of the markers below’. A scale with 9 markers is provided and the participant clicks anywhere on the scale to proceed. An example scale image containing a range of facial expressions corresponding to 5 points on the scale between ‘extremely happy’ and ‘extremely upset’ is also provided in order to limit the effect of perceptual bias in emotion-reading. Note that for any part of the experiment which requires participant input, the participant is timed out if they take longer than 10 seconds to decide.
3. Then, the participant is given the following instructions: ‘Think about the range in which you are 80% sure the true emotion lies. Using your mouse, indicate the left (most happy) and right (most upset) boundaries of this range.’ They then press ‘space’ to submit their response.
4. Then, they are asked ‘How worried are you about a possible scream?’ and they indicate their response on a continuous scale using their mouse. This scale has 5 markers with the extremes being ‘extremely calm’ and ‘extremely anxious’.
5. Then, they arrive at the re-looking stage. The instructions are ‘Press ‘space’ to attempt to get more information (additional facial expressions). Press ‘enter’ to state how you think they feel.’ They can choose to press ‘enter’ immediately. The chance of seeing a new facial expression is provided explicitly – either ‘1 to 5’ or ‘1 to 40’. If they press the space bar, a facial expression image is shown for 0.5s. The image has a green border if it is a facial expression they have not seen before. The above instructions continue to be displayed on-screen for reference.
6. Once they press enter, they arrive at a repeat of Step 2, followed by Step 3 and Step 4.
7. This is repeated for 32 trials.

Figure 3.

Screens shown to participant over the course of each trial.

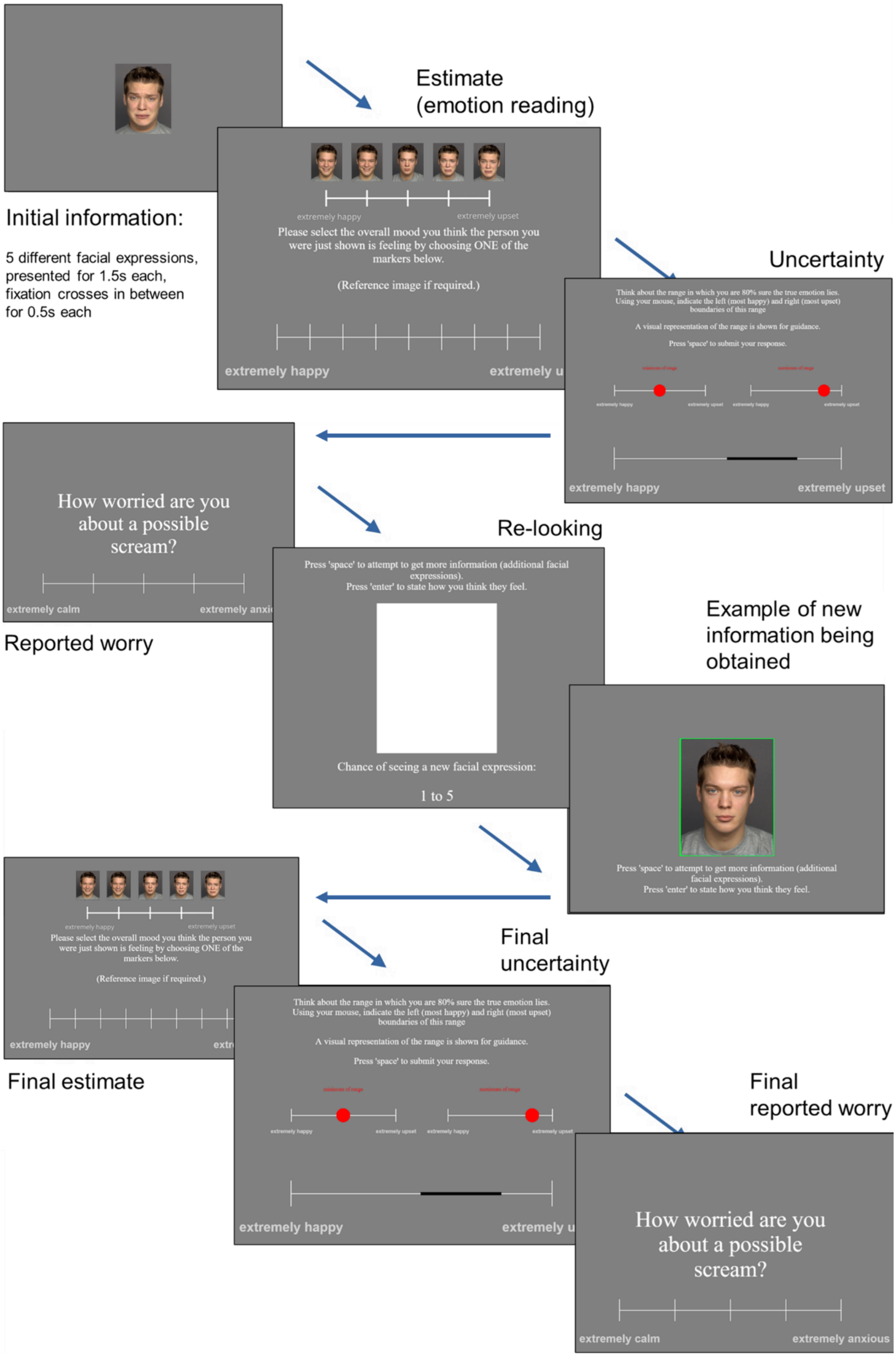
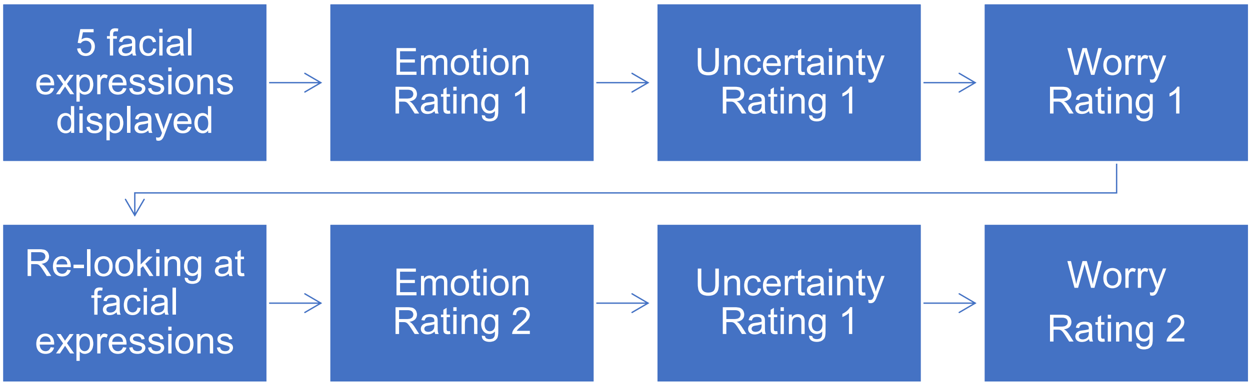


Figure 4.

A summary overview of each trial.



Participants are also given training on the correct emotion ratings for each possible person, in the context of this experiment (to be discussed subsequently in Figure 10). New information may not be available on every trial: most of the time, the information would be a facial expression from the first set of 5.

3.3. Experimental Paradigm – Facial Expressions

Sets of facial expressions were generated in the following way. First, videos from the Dynamic FACES database (Holland et al., 2019) were obtained. These videos portrayed a face shifting from a neutral expression to an angry or happy facial expression. Four people's facial expressions were included: one middle-aged man, one middle-aged woman, one young man, and one young woman, for a total of 12 videos. Then, frames from each video were obtained at regular intervals, providing 5 frames per video. The first frame for both the angry video and happy video were the same, as they both started from a neutral expression. These frames were then used to produce a 1 (extremely happy) to 9 (extremely upset) scale:

Figure 5.

Example of how the facial expressions of one person translates into a numerical scale.

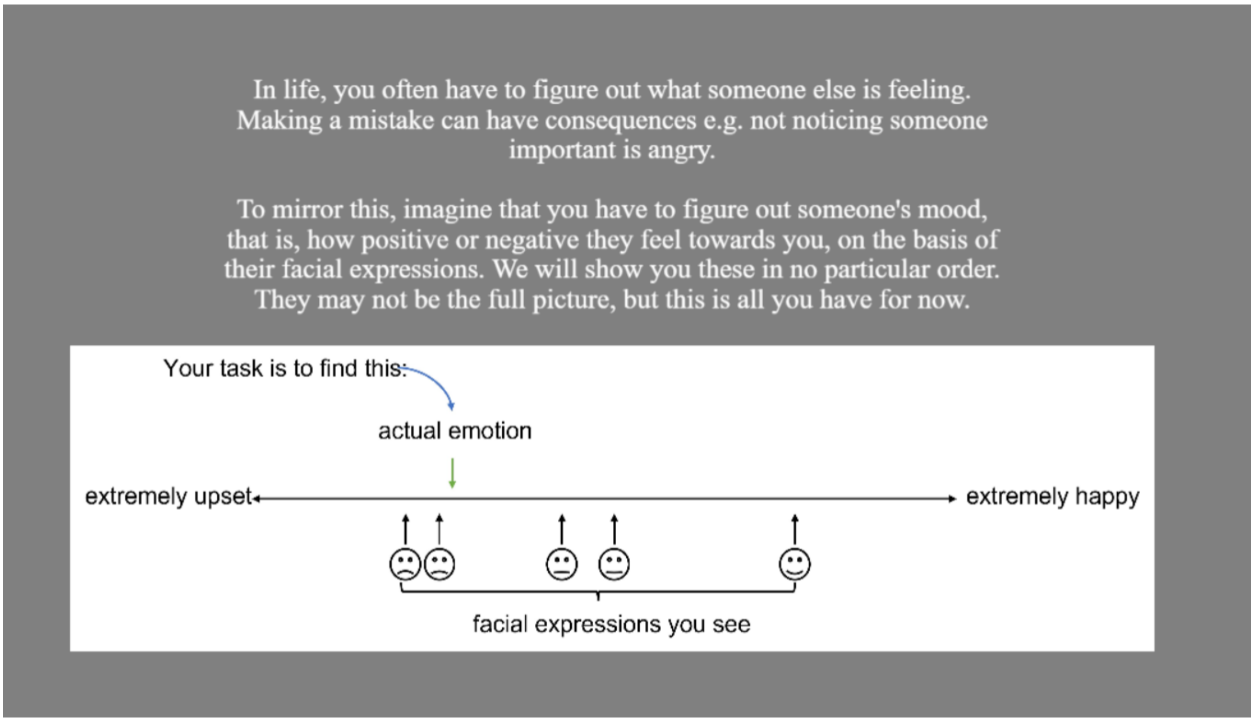
3.4. Experimental Paradigm – Instructions and Checks

At the start of the experiment, participants headphones were checked to ensure that their headphones were functioning and that they did not have hearing issues that would prevent them from reacting appropriately to the threat of scream paradigm (A. E. Milne et al., 2021).

They were also provided with the following instructions and explanation for the task (Figure 6).

Figure 6.

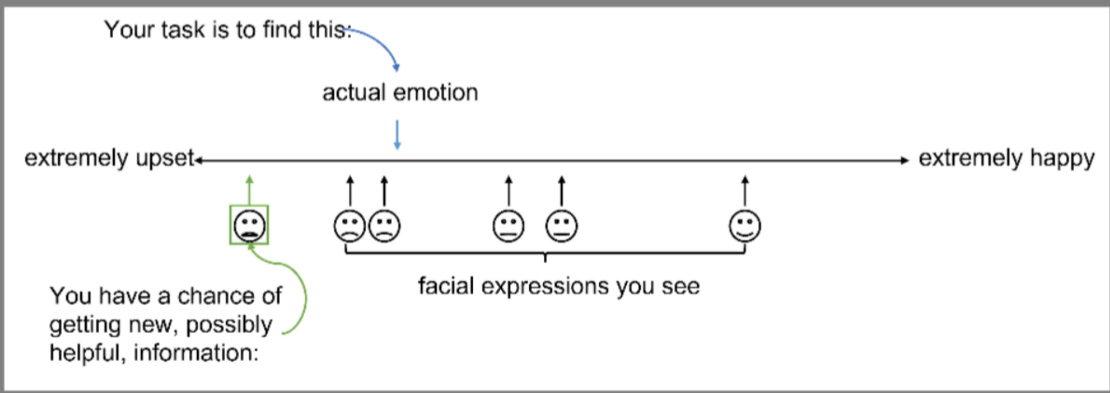
Instructions of the task, with an illustration to aid understanding.



After you have seen the initial few facial expressions, you can:

- immediately state what mood you think they are feeling (by pressing 'enter'), or
- attempt to get more information about their mood, that is, additional facial expressions (by pressing 'space').

Press 'space' to continue.

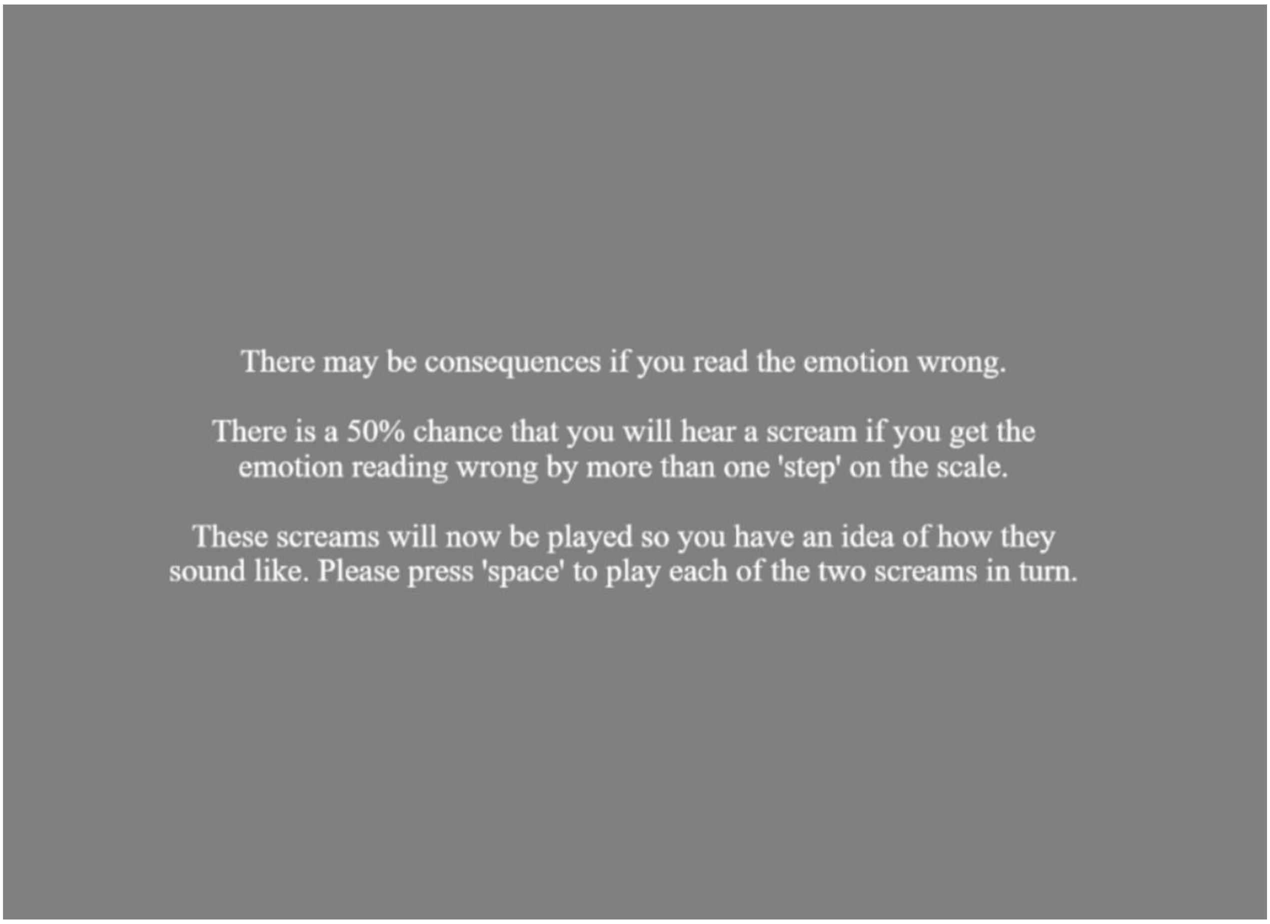


Each press of the 'space' will most likely reveal one of the facial expressions you previously saw, but there is a small chance of revealing a facial expression you have not seen before. This image will be bordered in green.

The chance of you seeing it will be indicated at the bottom of the screen, and will be either '1 to 5' (higher chance) or '1 to 40' (lower chance).

You can do this as many times as you want, until you feel like you can state what mood you think they are feeling.

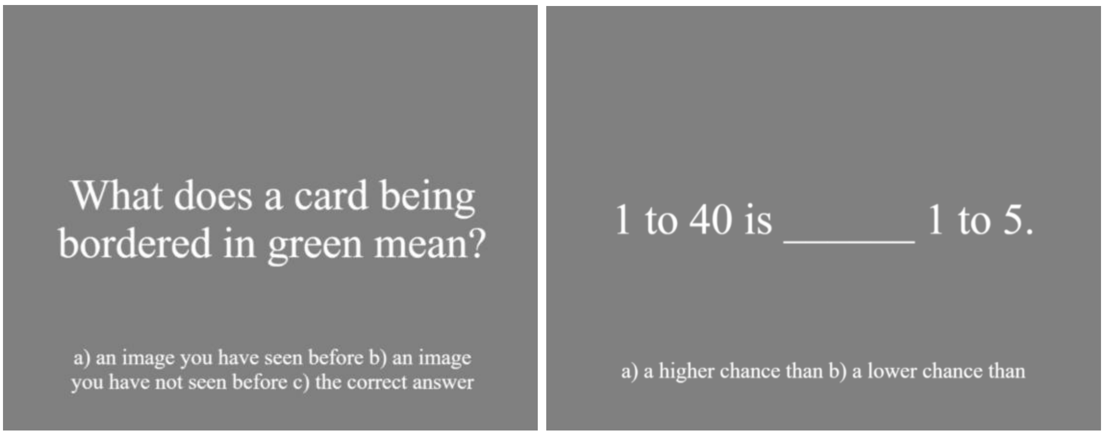
Press 'space' to continue.



Two comprehension check questions were also used to check that the participant had the correct understanding of the task and of ratios (Figure 7).

Figure 7.

Comprehension check questions.



Note. For both, b) is the correct answer. If they did not answer correctly they could not proceed.

Lastly, two example trials are provided to illustrate the experimental paradigm. These involved a person which would not be shown in the final experiment.

3.5. Experimental Paradigm – Trait Worry

The first between-subject factor is trait worry.

The power of the study can be increased by enriching the sample with participants screened with a worry questionnaire and invited if they score in the top and bottom 10% (i.e., increasing the experimental variance in terms of between subject effects). This affords increased sensitivity in detecting between-subject differences. Limiting the study to high and low worriers allows for a structure akin to a case-control study, as the processes of maladaptive compared to adaptive worry can be directly compared.

Therefore, all potential participants were given the Penn State Worry Questionnaire (Meyer et al., 1990), and people who scored in the top and bottom 10% were invited to do the paradigm (exact details such as group numbers to be discussed in Results).

3.6. Experimental Paradigm – Power Manipulation

The second between-subject factor is power manipulation.

A brief experimental manipulation, the Power Manipulation Writing Task (Gruenfeld et al., 2008; Schaerer et al., 2018), was included before the main experiment. This task places participants in a frame of mind of feeling either relatively powerful, powerless or neutral by reminding them of a life experience that evinced these feelings. This allows a better exploration of the mechanisms of worry, as participants are expected to more readily experience worry when in a subjectively less powerful state of mind. Social power not only affects decision making, as low power increases deliberation and decreases tendency to act (Galinsky et al., 2003) as well as impairs executive function (Smith et al., 2008), but also has links to the function of worry. Specifically, low social status provides a functional motivator for anxiety and worry to emerge (Jonason & Perilloux, 2012), providing a further incentive to adapt strategically. A sense of low or high power can be induced via cues (Dubois et al., 2012; Galinsky et al., 2003) and has been shown to influence behaviour predictably and meaningfully.

Participants were randomised to either ‘high power’ or ‘low power’ manipulations prior to the main experiment.

High Power:

Please think of a professional relationship you have, or have had in the past, that is hierarchical. The relationship should be one in which your work partner either reports directly to you or in which you have disproportionate power or control (or both) over him/her. Briefly describe your partner, and the nature of your relationship in the space below.

Low Power:

Please think of a professional relationship you have, or have had in the past, that is hierarchical. The relationship should be one in which you report either directly to your work partner or in which your work partner has disproportionate power or control (or both) over you. Briefly describe your partner, and the nature of your relationship, in the space below.

The participants were also given the Trait Sense of Power questionnaire (Figure 5) (Anderson & Galinsky, 2006) prior to the power manipulation writing exercise. Following Schaerer et al. (2018) — as a manipulation check — the ‘State Sense of Power’ questionnaire was then completed after the power manipulation writing exercise. This was completed after asking participants to reflect on the relationship they described in the writing exercise. They completed similar items from the ‘Trait Sense of Power’ scale, adapted to measure ‘State Sense of Power’. E.g. “In my relationship with this person, I can get him/her to do what I want.”

Figure 8.

The Trait Sense of Power questionnaire.

In rating each of the items below, please use the following scale:

1	2	3	4	5	6	7
Disagree strongly	Disagree	Disagree a little	Neither agree nor disagree	Agree a little	Agree	Agree strongly

In my relationships with others . . .

______I can get people to listen to what I say.
______My wishes do not carry much weight.
______I can get others to do what I want.
______Even if I voice them, my views have little sway.
______I think I have a great deal of power.
______My ideas and opinions are often ignored.
______Even when I try, I am not able to get my way.
______If I want to, I get to make the decisions.

Note. For state sense of power, the sentences were edited to refer specifically to the person they wrote about, e.g. 'I can get this person to listen to what I say.'

Lastly, before the main experiment, they were asked to imagine the facial expressions they would be seeing later are of either a person they report to, or a person who reports to them, depending on the power manipulation they received e.g. Figure 6.

Figure 9.

Power manipulation before main experiment.

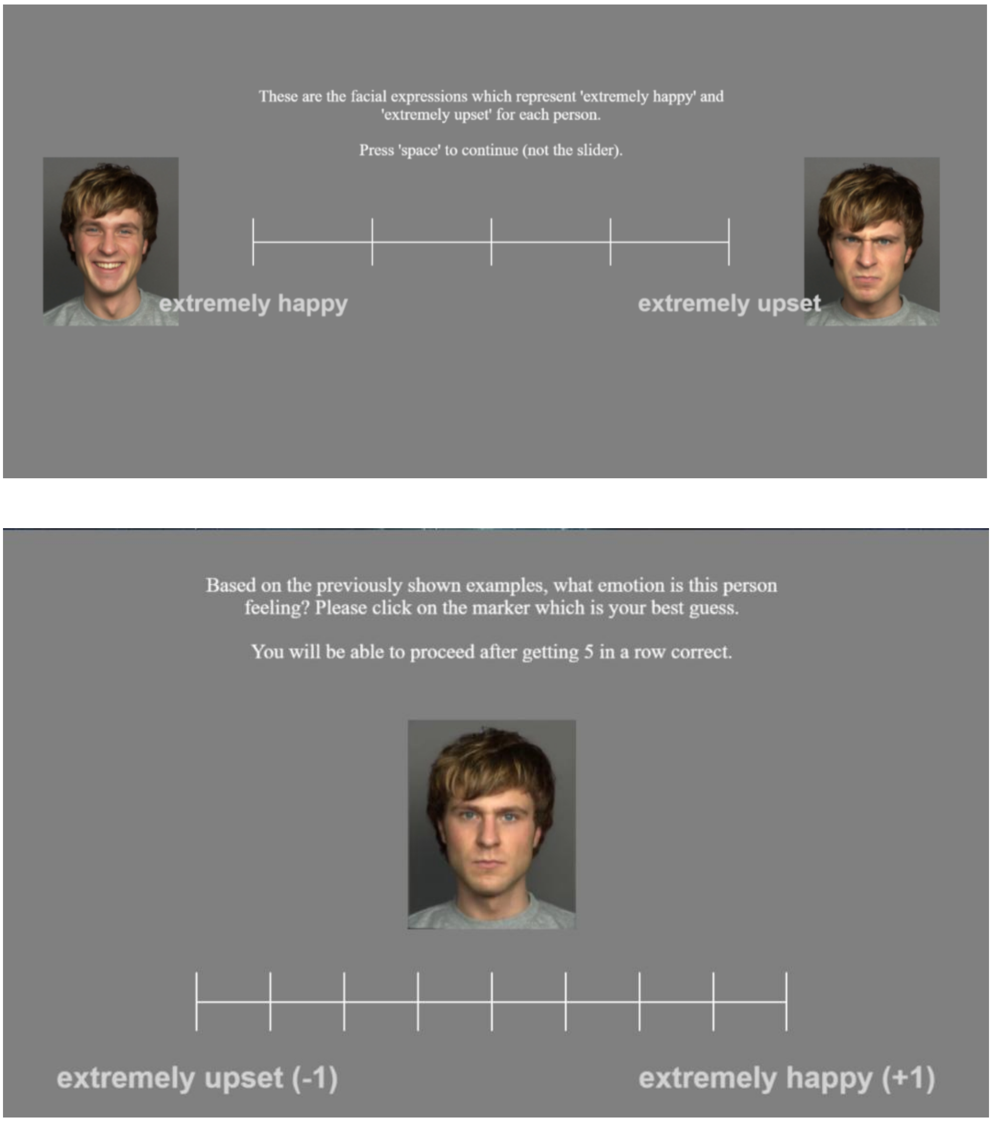
3.7. Experimental Paradigm – Training

Much literature has shown that people with anxiety disorders are more likely to read facial expressions as angry or upset (Bradley et al., 1999; Miloff et al., 2015). To limit the effect of this confounding factor, participants were trained on what the ratings should be in the context of this experiment, and only allowed to proceed after getting

5 ratings in a row correct or after 25 attempts (example in Figure 7). They were given feedback on each attempt.

Figure 10.

Example of training given.



Note. This is repeated 4 times as 4 people’s facial expressions were displayed in this experiment.

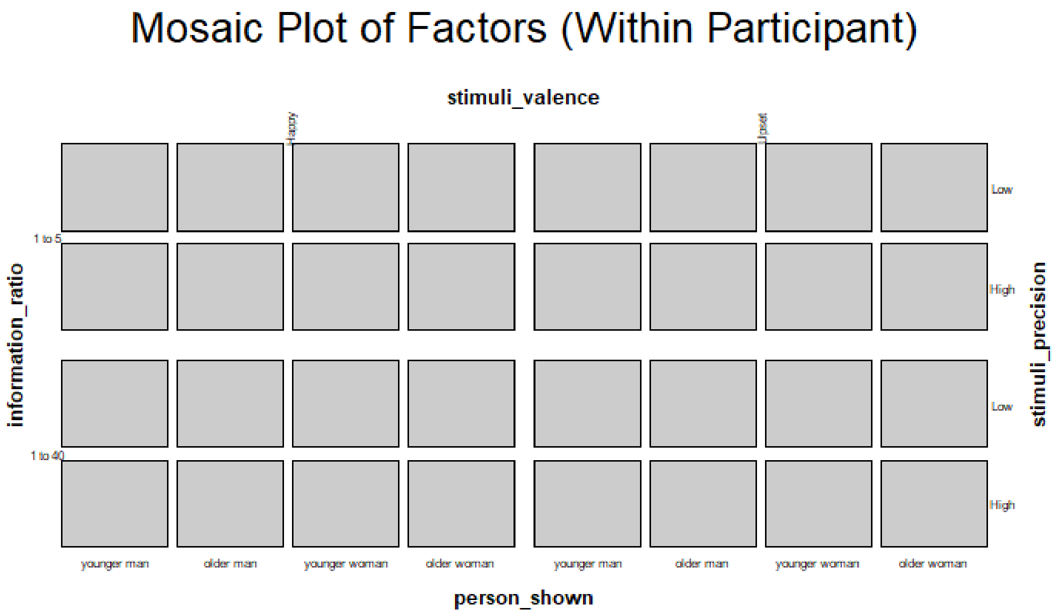
3.8. Overview of Full Factorial Design

The within-participant variables are:

1. Information Ratio: 1 to 5 or 1 to 40
2. Stimuli Valence (initial 5 faces): Happy or Upset
3. Stimuli Precision (initial 5 faces): High or Low
4. Person shown: younger man, younger woman, older man, older woman

Figure 11.

Visualisation of within-participant variables.



Note. Each rectangle represents a trial, forming the full 32 trials per participant.

The first 3 experimental factors (i.e., information ratio, stimuli valence, and stimuli precision), representing the initial sensory information provided in each trial, were chosen to introduce experimental variance in the degree to which subjects continued to search for evidence to resolve uncertainty about the target attribute (i.e., emotional valence). The last factor, person shown, was included to reduce the chance of effects occurring because of the specific person shown and therefore included a variety of ages and genders.

Next, the between participant variables are:

1. Trait Worry (as measured by the Penn State Worry Questionnaire): High or Low
2. Power Manipulation: High or Low

Figure 12.

Visualisation of between participant variables.

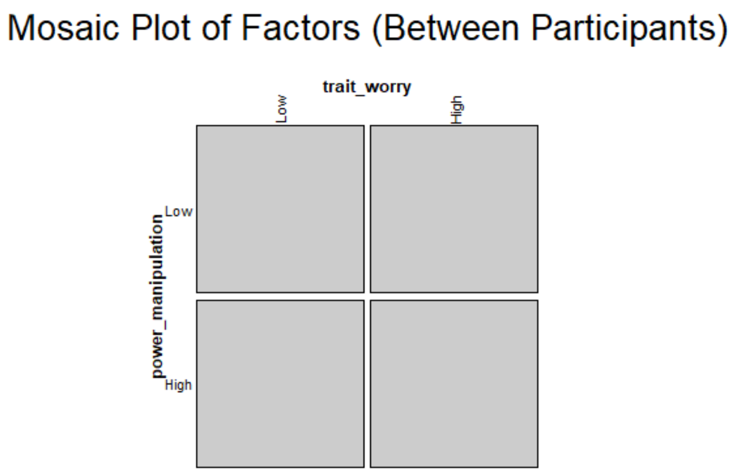
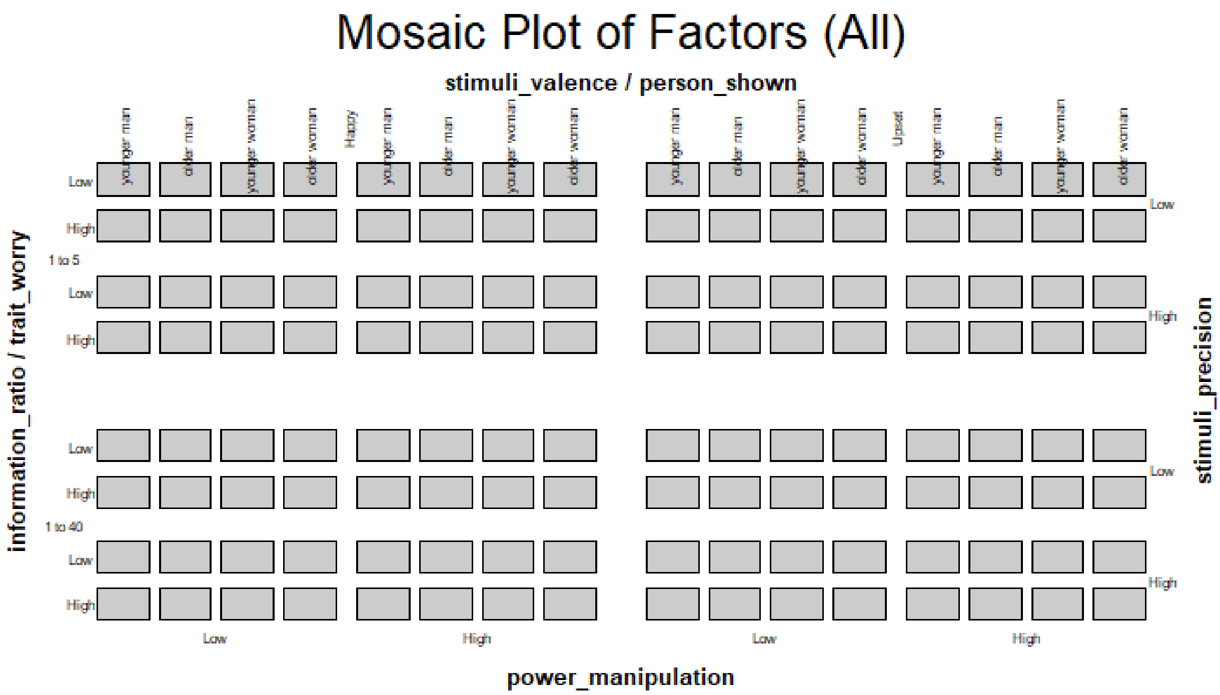


Figure 13.

Visualisation of all variables in a single image.



3.9. Piloting Process

To refine the experimental paradigm, several rounds of piloting were conducted with about 30 participants each. The piloting process and changes that occurred between rounds of piloting are now discussed. First, an overview of the changes across the pilots is provided below. Each set of changes is then explained in detail.

Table 8. Overview of changes to the experimental paradigm over the piloting process.

	Pilot 1	Pilot 2	Pilot 3	Final Paradigm
a) Scenario	Online interview			Power manipulation + superior/subordinate
b) Images of facial expressions	Hand chosen		Generated by sampling from distribution	
	'Happy to angry' scale and 'happy to sad' scale	'Happy to angry' scale only		
c) Initial 5 faces presented…	Together		Together + background of Gabor gratings	Separately and sequentially
d) Uncertainty indicated using…	Arrow keys (slow)			Mouse clicks (immediate)
e) Emotion rating indicated by…	Assumed to be middle of uncertainty bar			Clicking on a scale
f) Information ratio presented as	1 in 6 / 1 in 41	1 to 5 / 1 to 40		
g) Self-reported worry	How anxious would you be about messing up this interview?		How anxious are you feeling?	How worried are you about a possible scream?
h) Aversive stimuli	None	Threat of scream (50% of trials)		Threat of scream (all trials)
i) Comprehension & attentional checks	None	Included		
j) Factors	Information ratio, precision and valence		Information ratio and valence (- precision)	Information ratio, precision and valence

This aims to provide clarity on what is similar and different between pilots. Each row will be discussed in detail subsequently.

a) Scenario

In the pilots, the scenario was that of an online interview where the internet connection was unstable, and the interviewers' facial expressions were provided via the 5 initial images. The participant then had to attempt to read their interviewers' facial expressions as accurately as possible. Qualitative feedback was that the scenario felt too unrealistic and not related to the actual experiment. Initially, this was addressed by the addition of aversive stimuli, but in the end the paradigm was changed to a simpler scenario of imagining that the faces seen are that of a superior or subordinate, depending on the power manipulation participants were randomised to.

b) Images of facial expressions

In the first 2 pilots, the initial 5 faces provided were not drawn from a distribution, but hand selected as below (Figure 14). This was later changed as it was more conducive to future mathematical modelling to have a generative distribution from which samples were drawn. Furthermore, both the ‘happy to sad’ and ‘happy to angry’ scales were used. This was subsequently simplified to focus on the happy to sad emotional valence, as anger is more threatening than sadness, and to reduce the number of experimental factors for analysis.

Figure 14.

Facial expression image selection process in Pilot 1 and 2.

Upset + High precision			x	x	x	x	x	x				
Upset + Low precision	x	x		x		x		x		x		
Happy + High precision					x	X	x	x	x	x		
Happy + Low precision			x		x		x		x		x	x

Note. Black ‘x’s indicate the initial 5 faces, red ‘x’s indicate the possible new face shown.

c) Initial 5 faces presented…

The initial 5 faces were presented as in Figure 15a) in Pilots 1-2, due to concerns that presenting facial expressions sequentially would cause participants to assume a timeline, e.g., someone turning from angry to happy. However, feedback was given that it was particularly difficult for participants to retain all 5 facial expressions when presented in this way.

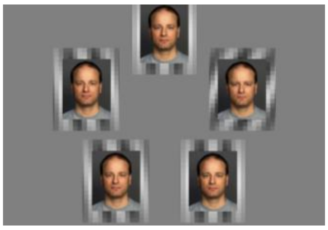
In Pilot 3, Gabor gratings were added as the background (assumed to be helpful in decoding putative neuroimaging data, an assumption which was later corrected), as well as to assist participants in remembering the initial 5 faces. A ‘worry period’ of 6s was also added after the initial presentation of images — to allow the possibility of decoding neural activity during this period in a neuroimaging version of the paradigm.

However, it was found at Pilot 3 that firstly, the main effect of information ratio — which was seen strongly in Pilots 1 and 2 (to be discussed in results section) — was no longer detectable, and secondly, the Gabor gratings distracted from the main focus of the task, which was to read facial expressions. Therefore, the Gabor gratings were removed.

The decision was then made to present the faces sequentially as concerns about the timeline effect could be countered by a clearly illustrated example in the instructions to ensure that the faces were not changing over time. Showing them one by one also allowed a natural evidence accumulation process which could be modelled.

Figure 15.

Example images of how the initial 5 faces were presented across the piloting process.

a) Pilots 1 & 2	b) Pilot 3	c) Final Paradigm
	 + fixation cross for 6s	 x5, with fixation crosses in between

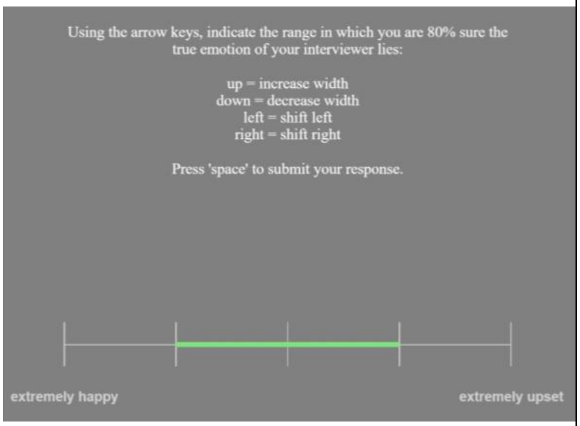
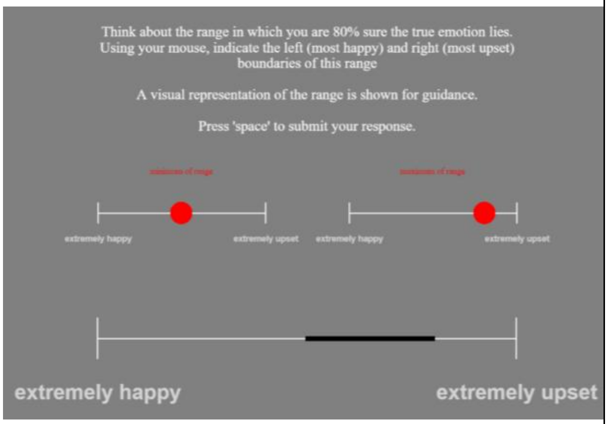
d) Uncertainty indicated using…

The uncertainty rating was measured with arrow keys (Figure 16a), where arrow keys could increase or decrease the size and location of a bar (i.e., range). However, it was found that people often did not shift the bar at all, because many key presses were needed to move it to the desired location, but if each key press were coded to move the bar more, sensitivity would be lost. Therefore, the rating was changed to a simple

2 click system (Figure 16b), where the participant simply has to click to provide the upper and lower boundary of the range they are 80% sure the true value lies in.

Figure 16.

Example images of how uncertainty was indicated.

<table>
<tr><td>a) Pilots 1-3</td><td>b) Final Paradigm</td></tr>
<tr><td>
</td><td>
</td></tr>
</table>

e) Emotion rating indicated by…

In the pilots, there was no direct way for the participant to indicate the emotion rating they chose, and it was simply assumed to be the middle of the uncertainty bar. This was changed to make the rating explicit, via clicking on the estimated emotion rating.

f) Information ratio presented as…

The information ratio was initially presented as ‘1 in 6’ instead of ‘1 to 5’, and ‘1 in 41’ instead of ‘1 to 40’. This was changed after qualitative feedback, since a ratio of 1 in 41 is difficult to conceptualise.

g) Self-reported worry

The wording of the self-reported worry question in Pilots 1 & 2 was ‘How anxious would you be about messing up this interview?’. This was changed in Pilot 3 to be simply ‘How anxious are you feeling?’ due to feedback that participants were not convinced of the connection between the scenario and the experiment, and because aversive motivation rather than the scenario would form a significant part of the anxiety. In the final paradigm, it was changed to 'How worried are you about a possible scream?' to directly capture the use of aversive stimuli, as well as to specifically capture worry rather than anxiety.

h) Aversive element

In Pilot 1, there was no aversive element as it was assumed that the scenario of an online interview was sufficient to induce worry, alongside innate motivation to get a correct answer. However, since feedback was that the scenario was not sufficiently convincing, an aversive element was considered in subsequent pilots. In Pilots 2 & 3, 50% of the trials had a threat of scream if one was inaccurate, and 50% of the trials were safe. In the final paradigm, all trials had a threat of scream. This is because worry is by definition a phenomenon that occurs during circumstances where one needs to avoid an aversive outcome; therefore, trials without aversive motivation may simply be information-seeking, and not underwritten by worry. This is especially so, since the scenario may not be convincing enough to induce worry on its own.

i) Comprehension & attentional checks

Comprehension checks for the instructions and for understanding the information ratio were added from Pilot 2 onwards. These checks were added due to feedback that ratios may be difficult to understand for some participants. The attentional check added was that approximately twice during the experiment, there would be audio asking the participant to press 'x'. If they did not do so, they were excluded from the experiment analysis.

j) Factors

Precision was removed as a factor in Pilot 3 due to needing to reduce the number of trials for a potential neuroimaging study (and there was a failure to detect a main effect of precision). It was reinstated in the final paradigm as the neuroimaging study was pursued and although there was no main effect, analyses might reveal interactions.

3.10. Participant Selection

Participants in the pilots were selected with the following eligibility criteria and without making them aware that the study is focused on worry:

Studies in how healthy people think to overcome problems

[Items appear in succession. Answers in blue result in exclusion and immediate directing to concluding thanking statement. Otherwise, the electronic Consent Form part of the document obtains permission for all Eligibility answers to be recorded]

Are you **between 18 and 65** years of age? [Yes] **[No]**
Do you **speak, read and write English fluently**? [Yes] **[No]**
Do you currently **live in the UK**? [Yes] **[No]**
Are you currently suffering from a **psychiatric condition** diagnosed by a professional? **[Yes]** [No]
Have you ever suffered from **a condition affecting the brain (neurological condition)**, such as serious head injury, epilepsy, or stroke? **[Yes]** [No]
Do you have a recognised learning difficulty [none] [mild] **[moderate]** **[severe]**

Most people that have had a COVID-19 illness will be eligible for our study, but in order to check we need to ask you a few questions. You do not have to be certain of the answers, please answer just to the best of your knowledge.

To the best of your knowledge, **have you been ill with COVID-19 at any time**?
[Yes] [No]
(this is the stem question: If they answer 'yes', the following questions appear:]
.
Did COVID-19 make you **severely out of breath**? **[Yes]** [No]
Did COVID-19 affect **your memory, concentration, or your ability to think clearly ('brain fog')** at any time? **[Yes]** [No]
Are you **completely better from COVID-19** for 6 weeks (1 ½ months) or more? [Yes] **[No]**

[This guidance then appears for everyone who reached the stem question above:]
Please note – our study is not designed to help you with COVID-19 related problems. If you are worried about COVID-19 related health problems, please use the NHS covid-19 App on your phone, or refer to the [COVID-19 NHS website https://www.nhs.uk/conditions/coronavirus-covid-19/]

Participants could also be excluded after their data was collected. Exclusion criteria was:

1. If any one of the attention check questions were answered incorrectly
2. If there were no re-lookings across all 32 trials – suggesting a lack of effort or understanding of instructions.

3.11. Separate Overview of Each Pilot Study

Now, an overview for each pilot study will be presented, in chronological order.

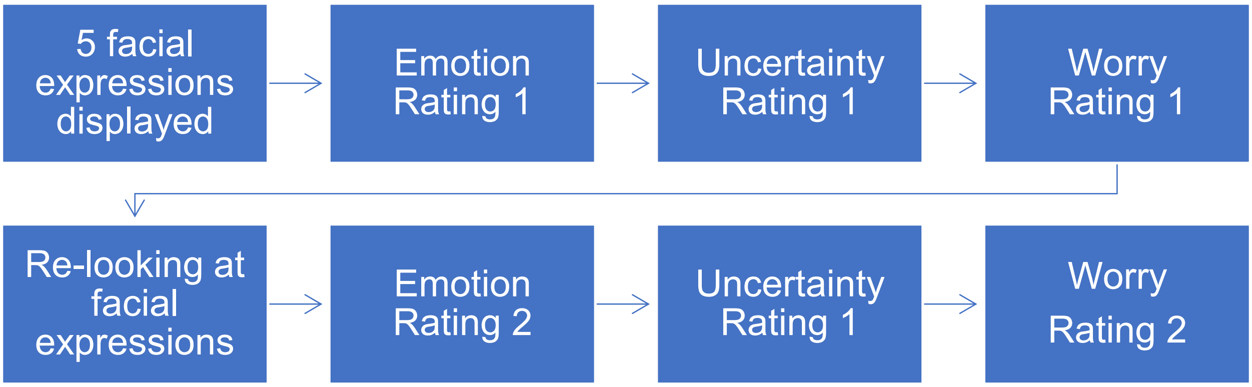
Pilot 1

Overview of Experimental Paradigm:

The core concept of 5 facial expressions being presented and the participant having to read the overall emotion is present throughout all the pilots and the final paradigm. The underlying structure of each trial is also consistent throughout (image below repeated from Figure 4).

Figure 4.

A summary overview of each trial.



In Pilot 1, the scenario presented to the participant was that of an online interview where the Internet connection is faulty, causing the participant to only be able to view random screenshots of their interviewer's face, in no particular chronological order. The experimental factors were information ratio, precision of stimuli and valence of stimuli.

The facial expressions chosen were hand-generated (as opposed to generated from a distribution; see Figure 14 previously provided for details). Two possible scales for the facial expressions were used, happy → angry and happy → sad. The initial 5 faces were presented simultaneously (see Figure 15). Participants then indicate their uncertainty level by using arrow keys (see Figure 16), indicating the range in which they are 80% sure the true emotion lies. Their emotion reading is assumed to be the value in the middle of the range.

The information ratio condition was presented as either a ‘1 in 6’ or ‘1 in 41’ chance of obtaining new information. Self-reported worry was obtained using the question ‘How anxious would you be about messing up this interview?’ given the scenario provided to participants. There was no built-in aversive motivator; the motivation for getting the correct emotion read was the imagined consequences of ‘messing up the interview’. There were also no comprehension of attention checks.

3.12. Key Hypotheses and Results

Pre-Experiment Hypotheses:

Hypothesis 1: Participants re-look more in the ‘1 to 6’ compared to ‘1 to 41’ condition.
Reasoning: Re-lookings are more useful (8 times more likely to yield new information) in the ‘1 to 6’ condition.

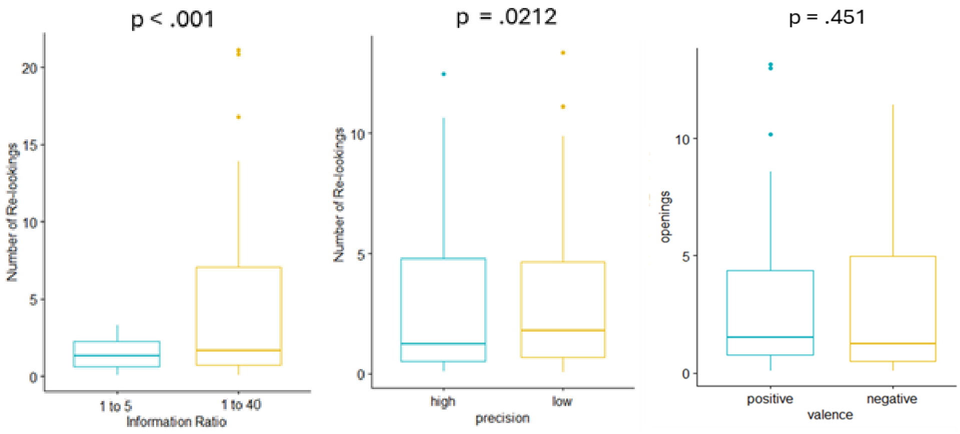
Hypothesis 2: Participants re-look more in the low precision than high precision condition.
Reasoning: More re-lookings are needed to obtain the requisite level of stimuli precision before the participant is confident enough to submit their answer.

Hypothesis 3: Participants re-look more in the negative valence compared to positive valence condition.
Reasoning: Participants experience more state anxiety when perceiving angry faces.

Results:

Figure 17.

Main effects of the 3 key factors in Pilot 1.



Note. A Wilcoxon signed rank test with continuity correction, selected due to non-normality of data distribution, was conducted to examine the main effect of each factor.

<u>Result 1:</u>

Contrary to Hypothesis 1, participants re-looked significantly more in the 1 in 41 condition (labelled here as 1 to 40 to be consistent with the final experimental paradigm).

<u>Result 2:</u>

Participants re-looked significantly more in the low precision condition, supporting Hypothesis 2.

<u>Result 3:</u>

Contrary to Hypothesis 3, there was no significant difference in re-lookings between trials with positive and negatively valenced stimuli.

Discussion

<u>Discussion 1:</u>

There are a few possible explanations for this finding. First, performing a higher number of re-lookings when each re-looking has a lower chance of being useful could be a way of adapting to the environment, as more re-lookings are needed to obtain information. Second, a heuristic such as ‘search until success’, where re-lookings are performed until a green-bordered facial expression appears, could be in use. Third, as the first pilot did not include a comprehension check question for the information ratios, this could indicate that participants had misunderstood the ratios, and thought that there was a higher chance of success in the 1 to 40 condition. With regards to this last possible explanation, as a result, Pilot 2 included comprehension check questions to check that participants understood what the ratios meant. Participants could not proceed unless they answered them correctly.

Discussion 2:

As predicted by Hypothesis 2, participants re-looked more in the low precision condition, likely because more information is needed to resolve uncertainty.

Discussion 3:

There are a few possible reasons why there was no significant difference in re-lookings between the positive and negative valence conditions. First, participants may not have emotionally engaged with the stimuli and focused on the numerical value it represents. Second, the training stage where participants had to learn to rate facial expressions correctly before being able to proceed with the experiment may have sufficiently reduced their biases in processing emotional stimuli. Third, as this is a pilot with only 30 participants, the power may simply have been too low to detect a significant effect.

Pilot 2

Overview of Experimental Paradigm:

Pilot 2 is similar to Pilot 1, except for the following:

1. Instead of facial expression images being drawn from both the ‘happy → angry’ and ‘happy → sad’ ranges, facial expression images were only drawn from the ‘happy → angry’ range.
2. The information ratio presentation was changed from ‘1 in 6 / 1 in 41’ to ‘1 to 5 / 1 to 40’.

3. Pilot 1 provided no external aversive motivation to provide the correct emotion rating; in Pilot 2, the threat of scream paradigm was incoporated for half the trials, such that if the participant is more than one step on the scale inaccurate, there is a 50% chance that a scream will play (aversive stimuli as punishment).
4. Comprehension check and attentional check questions were added.

Pre-Experiment Hypotheses:

Hypothesis 1: Re-lookings are higher in the '1 to 40' than '1 to 5' condition.

Hypothesis 2: Re-lookings are higher in the low precision compared to high precision condition.

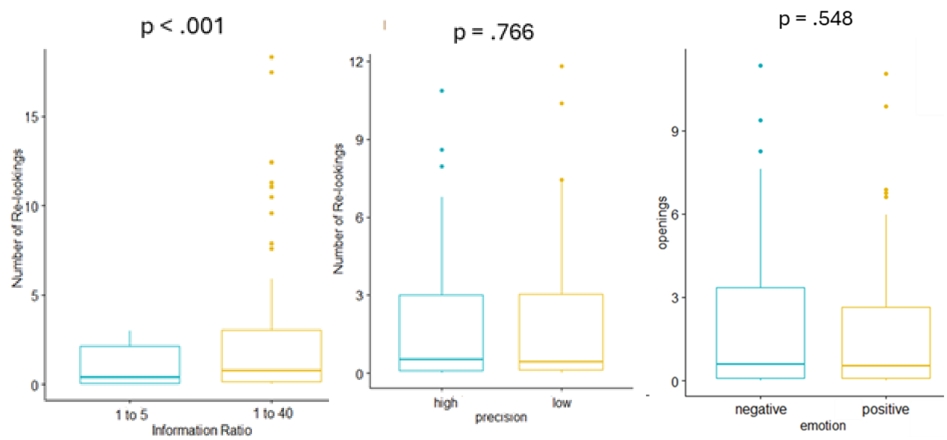
Hypothesis 3: There is no significant difference in re-lookings between the positive valence and negative valence conditions.

Overall Reasoning: This result occurred in Pilot 1 and the pilots are sufficiently similar that the results are not expected to differ greatly.

Results:

Figure 18.

Main effects of the 3 key factors in Pilot 2.



Note. A Wilcoxon signed rank test with continuity correction, selected due to non-normality of data distribution, was conducted to examine the main effect of each factor.

Result 1:

Re-looking numbers were significantly higher in the 1 to 40 compared to the 1 to 5 condition.

Result 2:

There was no significant difference in re-looking numbers between the high and low precision conditions.

Result 3:

There was no significant difference in re-looking numbers between the positive and negative valence conditions.

Discussion:

Discussion 1:

The result from Pilot 1 that participants re-looked significantly more in the 1 to 40 condition was replicated, providing further support for the validity of the result. Importantly, as comprehension questions were included this time, this suggests that the result was not simply due to participants misunderstanding the information ratios. The other possible reasons discussed for Pilot 1 still apply.

Discussion 2:

Unlike in Pilot 2, there was no significant difference in re-lookings between the high and low precision conditions. A possible reason is that since Pilot 2 incorporated external aversive motivation and Pilot 2 did not, the effect of the aversive motivation reduced the effect of precision to the point of non-significance. Another possible conclusion is that the result in Pilot 1 happened by chance, and precision does not in fact have a significant effect on re-lookings.

Discussion 3:

This replicates the result from Pilot 1 that there was no significant difference in re-lookings between positive and negative valence trials, increasing the support for the validity of the result.

Pilot 3

Overview of Experimental Paradigm:

Pilot 3 is similar to Pilot 2, except for the following:

1. The facial expression images were now generated by sampling from a distribution instead of being hand-chosen.
2. Gabor gratings corresponding to the intensity and valence of the facial expression were added as background frames to each image.
3. A 6-second period was added right after the initial 5 facial expressions were shown to have a 'worry period' which could be explored via neuroimaging.
4. The self-reported worry/anxiety question was changed from 'How anxious would you be about messing up this interview?' to 'How anxious are you feeling?'
5. The precision factor was removed as Pilot 2 showed that it did not have a significant effect.

Pre-Experiment Hypotheses:

Hypothesis 1: Re-lookings are higher in the '1 to 40' than '1 to 5' condition.

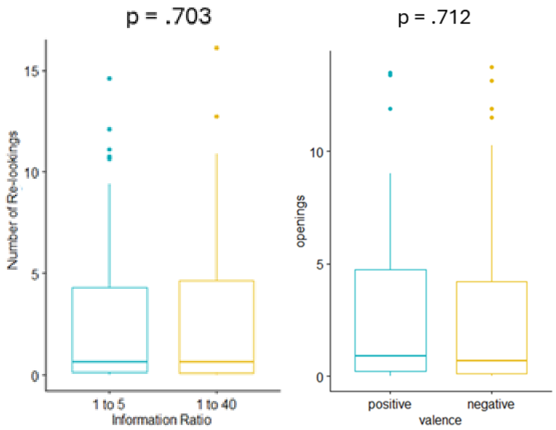
Hypothesis 2: There is no significant difference in re-lookings between the positive valence and negative valence conditions.

Overall Reasoning: Both these results occurred in both Pilots 1 and 2, and the pilots were thought to be sufficiently similar that the results are not expected to differ greatly.

Results:

Figure 19.

Main effects of the 2 key factors in Pilot 3.



Note. A Wilcoxon signed rank test with continuity correction, selected due to non-normality of data distribution, was conducted to examine the main effect of each factor.

<u>Result 1:</u>

There was no significant difference in re-lookings between the ‘1 to 5’ and ‘1 to 40’ information ratio conditions.

<u>Result 2:</u>

There was no significant difference in re-lookings between the positive valence and negative valence conditions.

Discussion

<u>Discussion 1:</u>

This result was at odds with both Pilot 1 and 2, which both showed that participants re-looked significantly more in the ‘1 to 40’ condition. However, while unexpected, there are several possible explanations.

First, given that Gabor gratings were added to the images which corresponded to the numerical value each facial expression represented, this could have made the task too easy, such that participants felt no need to re-look overall. This floor effect can be seen by the very low median in Figure 19.

Second, the addition of the 6-second worry period after the initial 5 facial expressions were shown could have reduced the necessity of re-looking, as it allowed participants to process the images they had just seen and compute an overall emotion. Interestingly, this also suggests that the re-lookings behaviour recorded in Pilots 1 and 2 may reflect what the participant would have done in the 6-second worry period, as including this period caused the pattern in Pilots 1 and 2 to be no longer present.

Discussion 2:

As this result replicates the findings in Pilots 1 and 2, this provides further support for the hypothesis that valence of stimuli does not have a significant effect on number of re-lookings.

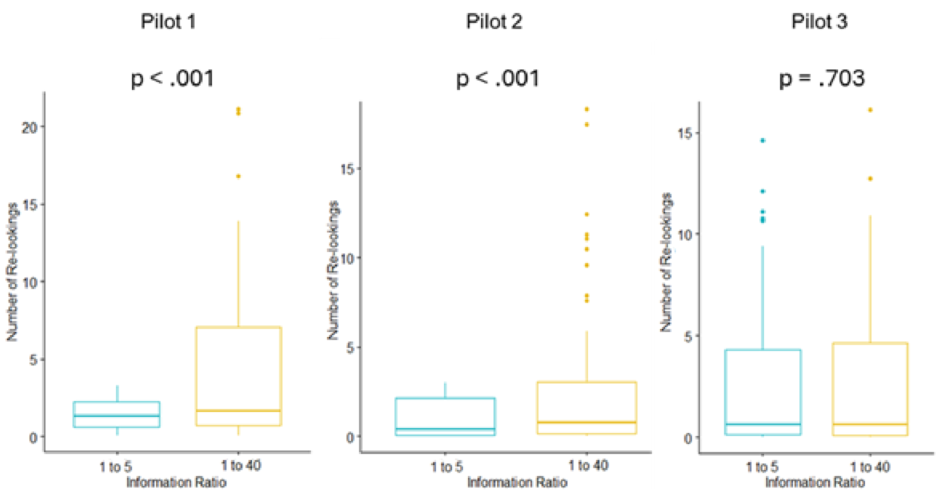
Overall Results

The key results across all 3 pilots are now presented for compare and contrast.

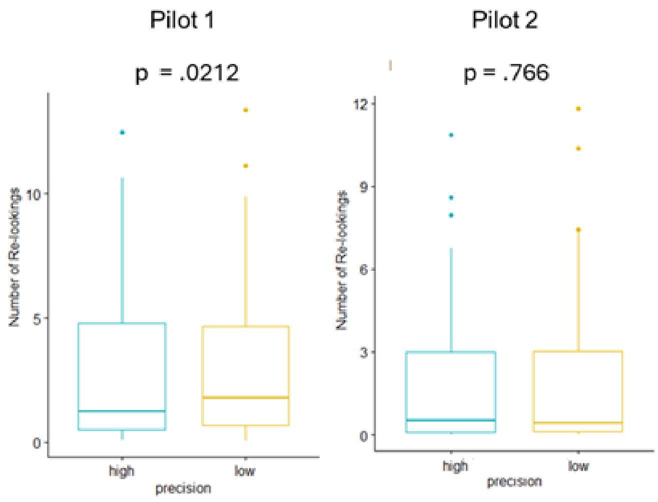
Figure 20.

Main effects of 3 key factors divided by pilot number.

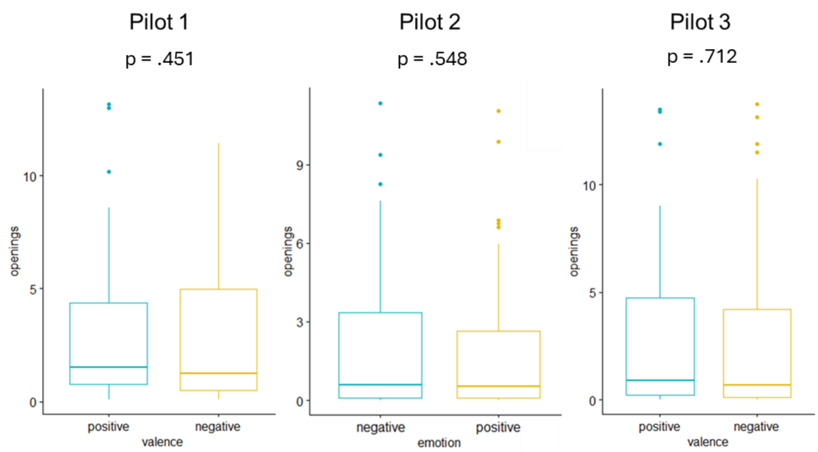
a) Information Ratio



b) Precision (note that Pilot 3 is not included as it did not have precision as a factor)



c) Valence of Stimuli



Note. A Wilcoxon signed rank test with continuity correction, selected due to non-normality of data distribution, was conducted to examine the main effect of each factor.

3.13. Discussion

Overall Discussion

A key issue present across all 3 pilots was that the re-lookings were clustered at 0. This was a concern as most of the data would be over a very small range and therefore lack discriminatory power. As this first occurred in Pilot 1 — without aversive stimuli — the aversive motivation was included to attempt to shift the graph rightwards, and much of the piloting process was spent on attempting to do so. However, this pattern continued to occur throughout the pilots and the final paradigm, leading to the conclusion that it was a pattern that would have to be analysed for understanding.

As the final paradigm has n = 306 participants and each pilot only has 30-40, the discussion will now focus on differences between pilots rather than the scientific implications of the results, which would have a greater validity with a greater number of participants; that will instead be discussed in Chapter 4.

Information Ratio

First, the main effect of information ratio was the clearest result in Pilots 1 and 2, but did not occur in Pilot 3. This was hypothesized to be due to the addition of a 6 second long 'worry period' after the presentation of the stimuli. This crucially could have allowed participants time to think, such that the sampling for more information happened inside their head instead of with the mechanism provided. As the aim of the experiment is to externalise sampling for information, this was removed, but provides some support for the hypothesis that what occurs without this 'worry period' is indeed what might happen in participants' minds. Another possible hypothesis is that the Gabor gratings changed the nature of the experiment, as they corresponded to the facial expressions, e.g., if the gratings were tilted more to the right, the facial expression was angrier. This meant that participants could simply use how far the gratings tilted left or right to calculate the overall emotion instead of looking at the facial expressions themselves, as intended. This provided another motivation to remove the gratings.

Precision

The difference between results in Pilot 1 and 2 was unexpected as the paradigm designs are broadly similar. As the main difference was that Pilot 2 incorporated aversive motivation, a possible reason is that an anxiety-inducing environment may affect the ability to accurately perceive precision or integrate it into their judgment. The threat of shock paradigm has been shown to affect working memory (Balderston et al., 2017; Vytal et al., 2013) and perceptual processes (O. J. Robinson et al., 2013), suggesting that placing people in situations where they may receive unexpected aversive stimuli may impair cognitive processes involved in processing stimuli. Another possibility is that there is imprecision in the link between re-lookings and resolving uncertainty. As each re-looking is not guaranteed to resolve uncertainty, there is no clear linear relationship between the number of re-lookings and the reduction of uncertainty. This might have limited the detectability of the effect of initial stimuli precision. Nevertheless, as the effect of precision was unclear rather than a clear lack of significance, and uncertainty is closely linked to worry, the precision factor was returned in the final paradigm.

Valence

Valence had no significant effect across the pilots but was retained as there may be an interaction in final analyses. Furthermore, variation in valence is necessary such that participants do not have the same correct answer for emotion reads in every trial, as this would cause a stronger learning effect if the participants realise this.

3.14. Conclusion

Multiple rounds of piloting were used to refine the final experimental paradigm, a process which is particularly important when validating a novel experimental paradigm. A summary of changes can be found in Table 8. The ensuing results may also provide provisional insights into how worry is elicited: e.g., the fact that the effect of information ratio is eliminated if there is a ‘worry period’ suggests that sampling within the experiment may in fact be what would otherwise naturally occur in one’s mind. Another example is that the failure to detect a main effect of precision challenges the assumption that people take it into account uncertainty when worrying, and may in fact not be able to assess uncertainty accurately. All in all, the piloting process has produced a paradigm which could, in principle, furnish novel insights, when deployed at scale.

4. Worry About Feelings Task (Part 1) – Key Factors and The Adaptiveness Question

4.1. Background

As established in the previous chapter, the experimental paradigm (see Figure 3 for a recap) was refined through multiple piloting cycles to be an ecologically valid way to capture the process of worry. However, while preliminary results demonstrated that some factors had significant main effects – most notably information ratio – sample sizes of 30-40 are insufficiently powered to investigate individual differences. To ensure sufficient statistical power to investigate between-subject effects accurately, a few hundred participants would be required.

Then, as discussed in Chapter 3, the power of the study to capture between-subject differences was increased by enriching the sample with participants screened with a worry questionnaire and invited if they score in the top and bottom 10% (i.e., increasing the experimental variance in terms of between subject effects). This affords increased sensitivity in detecting between-subject differences in how people's minds compute the process of worry, as well as individual differences which may make some more prone to worry. Furthermore, limiting the study to high and low worriers allows for a structure akin to a case-control study, as the processes of maladaptive compared to adaptive worry can be directly compared. Therefore, a large online study was conducted after 3 rounds of piloting.

This chapter discusses key results from the large online study. First, the analyses will focus on the main effects of the three experimental factors: information ratio, precision, and valence. Second, the relationship between self-reported trial-to-trial measures of worry and uncertainty and number of re-lookings in that trial will be examined. This exploration aims to determine whether re-lookings reflect a process of managing uncertainty through worry. Third, the adaptiveness of this worry-like re-looking behavior will be evaluated by analysing its relationship with task accuracy, measured by extent of errors made. Finally, the chapter provides a summary of the key findings and discusses their implications when considered collectively.

Importantly, this chapter will not explore psychological or social factors mediating vulnerability to worry or their effect on re-looking, or their potential interactions; this will be discussed in Chapter 5. This approach allows the core experimental effects and relationships to be established before delving into more complex mediating factors and their relationship with worry.

4.2. Participants

Testing was performed via the platform Prolific. To provide an efficient analysis of differences between high worriers and low worriers, 6950 participants were screened via the Penn State Worry Questionnaire (Meyer et al., 1990), and people whose scores were in the top and bottom decile were invited to participate in the main study. These are termed the ‘high worry’ and ‘low worry’ groups. In total, after excluding data — where checks were failed or behaviour was exactly the same in every trial, suggesting low effort – 306 participants (147 high worry, 159 low worry) were included for analysis. Inclusion criteria included fluency in English, residency in the UK, no psychological or neurological diagnoses, complete recovery from any COVID-19 episodes, and aged 18-65. It was determined as follows (recap from Chapter 3):

Box 4.

Inclusion and exclusion criteria as presented to participant.

Studies in how healthy people think to overcome problems

[Items appear in succession. Answers in blue result in exclusion and immediate directing to concluding thanking statement. Otherwise, the electronic Consent Form part of the document obtains permission for all Eligibility answers to be recorded]

Are you **between 18 and 65** years of age? [Yes] **[No]**
Do you **speak, read and write English fluently**? [Yes] **[No]**
Do you currently **live in the UK**? [Yes] **[No]**
Are you currently suffering from a **psychiatric condition** diagnosed by a professional? **[Yes]** [No]
Have you ever suffered from **a condition affecting the brain (neurological condition)**, such as serious head injury, epilepsy, or stroke? **[Yes]** [No]
Do you have a recognised learning difficulty [none] [mild] **[moderate]** **[severe]**

Most people that have had a COVID-19 illness will be eligible for our study, but in order to check we need to ask you a few questions. You do not have to be certain of the answers, please answer just to the best of your knowledge.

To the best of your knowledge, **have you been ill with COVID-19 at any time**? [Yes] [No]
(this is the stem question: If they answer 'yes', the following questions appear:]
.
Did COVID-19 make you **severely out of breath**?
[Yes] [No]
Did COVID-19 affect **your memory, concentration, or your ability to think clearly ('brain fog')** at any time?
[Yes] [No]
Are you **completely better from COVID-19** for 6 weeks (1 ½ months) or more?
[Yes] **[No]**

[This guidance then appears for everyone who reached the stem question above:]
Please note - our study is not designed to help you with COVID-19 related problems. If you are worried about COVID-19 related health problems, please use the NHS covid-19 App on your phone, or refer to the [COVID-19 NHS website https://www.nhs.uk/conditions/coronavirus-covid-19/]

Then, participants were invited to take part in the full study as part of the 'high worry' group if their PSWQ score was above 67 and the 'low worry' group if their PSWQ score was above 28. This was calculated by taking the cutoff points for the top and bottom deciles, taking into account the scores of all participants who responded to the 2-min screening questionnaire.

Below are tables summarising the demographics of the participants. Percentages are presented to one decimal place, apart from percentages less than 1%, which are presented to two decimal places, as per APA Guidelines.

Table 9.

Basic demographics – age.

	Overall	High worry	Low worry
Age (SD)	40.5 (12.4)	38.7 (11.2)	44.3 (12.0)

Note. The difference in age was 5.6 years, 95% CI [2.97, 8.19].

Table 10.

Basic demographics – sex

	Overall	High worry	Low worry
Female	46.4%	69.1%	29.2%
Male	53.6%	30.9%	70.8%
Non-binary / other	0.0%	0.0%	0.0%

Table 11.

Basic demographics – ethnicity (simplified).

Ethnicity	High Worry	Low Worry
White	90.1%	85.8%
Mixed	1.2%	1.8%
Asian	3.7%	7.1%
Black	3.7%	2.7%
Other	1.2%	0.89%

Overall ages were lower in the high worry compared to low worry group, while the high worry group has a greater percentage of women. This is in line with epidemiological patterns. Women express higher levels of common mental health symptoms such as worry; indeed, women have been shown to score significantly higher than men on the PSWQ itself, including in the original validation study (Dugas et al., 2001; Meyer et al., 1990; Topper et al., 2014). Similarly, younger adults show higher levels of anxiety and worry compared to older adults (Basevitz et al., 2008; Brenes, 2006; Granier & Segal, 2021), and lower subjective SES is associated with more anxiety symptoms, including worry (Moss et al., 2023; Nasirpour et al., 2024). These differences are also likely to be amplified due to the fact that the participants were drawn from the top and bottom decile. Nevertheless, further analyses will be conducted to examine the effect of these demographic variables on the findings.

Next, as each participant was also given questionnaires, below is a table summarising the questionnaire scores for each group. Detailed discussion of why each questionnaire was used will follow in Chapter 5; information provided here is for describing and characterising the study population.

Table 12.

Mean and SD (in brackets) of questionnaire scores in the two groups.

Measure	PSWQ	STAI	MFQ	BDI	RSES	Perfecti -onism	ICI	SES
Low Worry (SD)	25.7 (7.0)	52.6 (14.3)	1.37 (3.0)	3.7 (4.9)	16.7 (2.0)	93.9 (20.1)	111 (11.5)	5.6 (1.3)
High Worry (SD)	65.9 (10.7)	104 (25.2)	9.39 (6.7)	14.8 (9.8)	15.4 (2.1)	113 (20.4)	90.6 (13.9)	4.5 (1.6)
Difference [95% CI]	-40.2 [-47.2, -33.1]	51.4 [-62.2, -40.6]	8.02 [-11.9, -4.2]	11.1 [-17.3, -4.9]	1.3 [0.0, 2.6]	-19.1 [-26.7, -11.5]	20.4 [16.3, 24.5]	1.0 [0.1, 2.0]

Note. STAI is the State Trait Anxiety Inventory (higher indicates more anxiety), MFQ Mood and Feelings Questionnaire (higher indicates more depressive symptoms), BDI Beck Depression Inventory (higher indicates depressive symptoms), RSES Rosenberg Self - Esteem Score (higher indicates higher self-esteem), Perfectionism refers to the Multidimensional Perfectionism Scale (higher indicates more perfectionism), ICI the Duttweiler Internal Control Index (higher indicates a locus of control which is more internal), and lastly SES the McArthur subjective socioeconomic scale. Scores are reported to one decimal place as per APA Guidelines.

4.3. Methods

Statistical Modelling Approach

Statistical analyses were conducted using R (version 4.3.2; R Core Team, 2020).

<u>Basic Analyses</u>

For all basic analyses on numbers of re-lookings and self-reported trial-to-trial worry levels, the Wilcoxon signed rank test with continuity correction was used due to non-normality of data (see Figure 21 and Figure 22 below).

Figure 21.

Histogram of number of re-lookings across all trials.

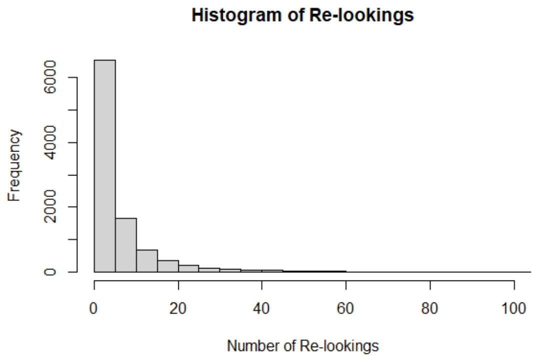
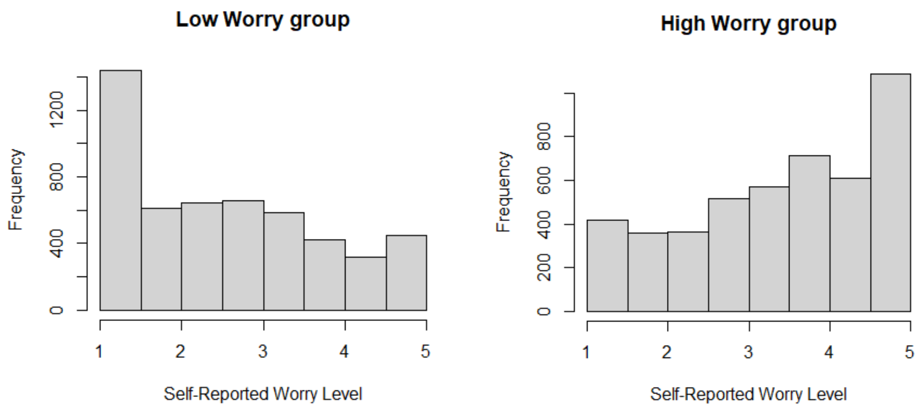


Figure 22.

Histogram of self-reported trial-to-trial worry levels.



For analyses involving errors (the unit difference between the participant's answer and the correct answer), one-sided t-tests were used due to approximate normality of data (see Figure 23 below) and plausible directionality of effects (high worry participants having lower errors).

Figure 23.

Histogram of errors in low worry and high worry groups.

All numerical results are reported to 3 s.f. unless they are p-values less than 0.001, in which case they are reported as p < .001, as per APA Guidelines.

<u>Mixed Effect Models</u>

For mixed-model analyses of re-lookings data, generalised linear mixed models (GLMMs) were implemented using the GLMMadaptive package (version 0.9.7; Rizopoulos, 2025), specifically using the negative binomial family. Models are specified in full mathematical equation form in Methods to demonstrate their full underlying structure, and then subsequently specified in Wilkinson notation (Wilkinson & Rogers, 1973) for brevity.

The used of a mixed effects model was because the data involved repeated measures, where re-lookings, uncertainty before re-lookings, and worry level before re-lookings were recorded over multiple trials per participant. This nesting required a model that could account for within-subject dependencies as well as individual variability via the inclusion of the random intercept for participant.

The negative binomial family was selected due to the following data characteristics.

1. Count data: The Poisson and Negative Binomial distributions are appropriate for modelling count data (as opposed to Gaussian models, for example, which are better suited for modelling continuous data).

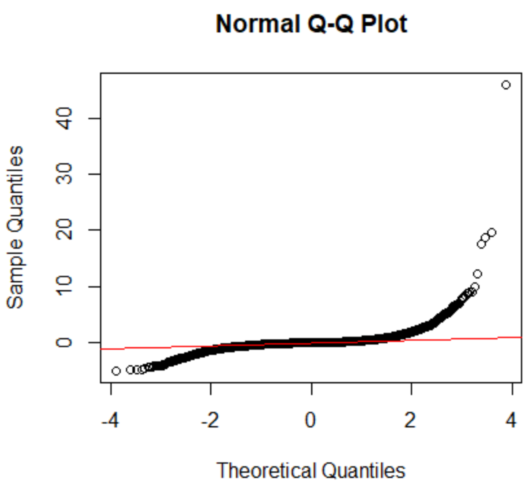
2. Leftward skew and long right-sided tail: Similarly, Poisson and Negative Binomial models can account for data which is skewed leftwards with a long ‘tail’ of values on the right, as this data demonstrates.
3. Overdispersion handling: Initial analyses to determine methods suitability showed that the variance (103) far exceeded the mean (5.71), indicating overdispersion. This makes the data less suitable for modelling with a Poisson distribution, which assumes that the mean and variance are the same. In contrast, the Negative Binomial model includes a dispersion parameter which can account for high dispersion in data (Hilbe, 2011; Ver Hoef & Boveng, 2007).

The dataset also failed the tests for suitability for modelling with a Gaussian model as it violated the assumptions of normally distributed residuals and constant variance when an attempt to model it with a Gaussian distribution was conducted (Figure 24 below). This was conducted with the lme function in the nlme package in R (version 3.1-167; (Pinheiro & Bates, 2000). Here, the fixed effect of trial-to-trial worry level and random effect of participant was used to predict number of re-lookings.

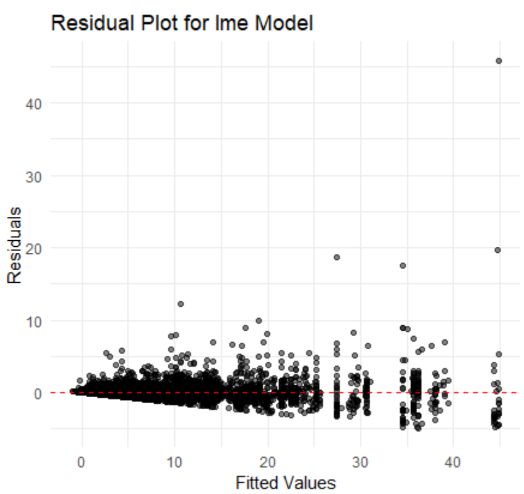
Figure 24.

Residual diagnostics.

a)



b)



Note. a) Q-Q plot showing that residuals deviate significantly from the red line, violating the normality assumption for residuals (Oppong & Agbedra, 2016; Tabachnick & Fidell, 2013) b) The funnel-shaped residual plot indicates that variance is not constant (J. Fox, 2015).

Due to the reasons above, and the unsuitability for modelling with a Gaussian model, the negative binomial model was deemed the most appropriate option. Specific equations used for each question will now be discussed below.

Accounting for Confounders

Following the primary analysis of each hypothesized effect, secondary analyses were conducted to examine the potential influence of demographic variables – specifically age, sex and SES. These were considered potential confounding factors and were particularly important to take into account given the observed imbalances in sex distribution, age and SES between the high and low worry groups.

For each primary analysis (e.g. the effect of information ratio on re-lookings), a subsequent analysis was performed incorporating age, sex and SES in the regression model. For re-lookings data, this model was specified as the following (given the use of the negative binomial distribution):

$$Y_{ij} \sim NB(\mu_{ij}, \theta)$$

$$log(\mu_{ij}) = \beta_0 + \beta_1 X_{ij} + \beta_2 Age_i + \beta_3 Sex_i + \beta_4 SES_i + u_i$$

Equation Set 1

Where:

- Y_{ij} is the number of re-lookings for participant i at trial j.
- NB is the negative Binomial distribution.
- μ_{ij} is the expected re-lookings count for participant i at trial j.
- θ is the dispersion parameter.
- β_0 is the intercept of model.

- X_{ij} is the value of the primary experimental factor (e.g., information ratio) for individual i in trial j.
- Age_i is the age of individual i.
- Sex_i is the sex of individual i.
- SES_i is the subjective socioeconomic status of individual i.
- u_i is the random intercept for individual i.
- β_1 is the coefficient for the primary experimental factor.
- β_2 is the coefficient for Age.
- β_3 is the coefficient for Sex.
- β_4 is the coefficient for SES.

For trial-to-trial worry data, a linear mixed effects model was used. While mathematical transformations were considered to improve the distribution of the data (see the Q-Q plot and residual plot in the Appendix for initial model fit), this were decided against for a few reasons. First, they cannot account for the non-independence of data, since data is grouped by participant. Second, linear mixed effects models can be robust to moderate departures from normality, especially in large data sets (Maas & Hox, 2004) such as the one here (305 participants with 32 trials means 9760 data points). The model was specified as follows:

$$W_{ij} = \beta_0 + \beta_1 X_{ij} + \beta_2 Age_i + \beta_3 Sex_i + \beta_4 SES_i + u_i$$

Equation 2

Where:

- W_{ij} is the self-reported worry level for participant i at trial j
- X_{ij} is the value of the primary experimental factor (e.g., information ratio) for individual i in trial j
- Age_i is the age of individual i

- Sex_i is the sex of individual i
- SES_i is the subjective socioeconomic status of individual i
- u_i is the random intercept for individual i
- β_0 is the intercept
- β_1 is the coefficient for the primary experimental factor
- β_2 is the coefficient for Age
- β_3 is the coefficient for Sex
- β_4 is the coefficient for SES.

This would allow checking of whether the inclusion of Age, Sex and SES altered the significance or magnitude of the primary effect and therefore if they are potential confounders.

4.4. Results

4.4.1. Information Ratio

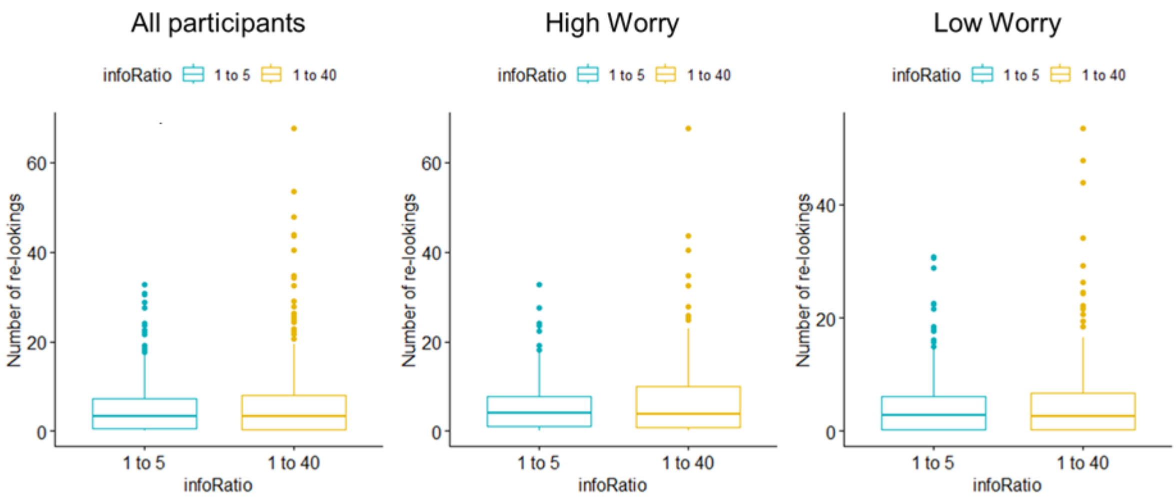
Pre-Experiment Hypotheses

1. Overall, in the combined group, re-lookings are significantly higher in the '1 to 40' compared to '1 to 5' condition.
2. This significant effect is present when the high worry group is analysed separately.
3. No significant effect is present when the low worry group is analysed separately.

Results

Figure 25.

Main effect of information ratio on re-lookings.



Note. Each data point represents a participant's mean number of re-lookings within that subset of trials (e.g. '1 to 5'). The number of re-lookings was significantly higher in the 1 to 40 condition across all participants (p < .001) as well as in the high worry group (p = .00116), but not in the low worry group (p = .0840). Information ratio is labelled as infoRatio.

Robustness Analysis

Table 13.

Results of Regression Model without Covariates – overall group

Fixed Effect	Value	Std. Error	z-value	p-value
infoRatio (1 to 5)	-0.177	0.0400	-4.42	< .001

Table 14.

Results of Regression Model with Covariates – overall group

Fixed Effect	Value	Std. Error	z-value	p-value
infoRatio (1 to 5)	-0.177	0.0400	-4.42	< .001
Age	-0.0239	0.0070	-3.41	< .001
Sex (Male)	0.210	0.1717	1.23	.220

SES	-0.0634	0.0546	-1.16	.246

Table 15.

Results of Regression Model without Covariates – high worry group

Fixed Effect	Value	Std. Error	z-value	p-value
infoRatio (1 to 5)	-0.119	0.0248	-4.80	< .001

Table 16.

Results of Regression Model with Covariates – high worry group

Fixed Effect	Value	Std. Error	z-value	p-value
infoRatio (1 to 5)	-0.119	0.0248	-4.79	< .001
Age	-0.0271	0.0115	-2.36	.0183
Sex (Male)	0.208	0.288	0.724	.470
SES	-0.0644	0.0852	-0.755	.450

Table 17.

Results of Regression Model without Covariates – low worry group

Fixed Effect	Value	Std. Error	z-value	p-value
infoRatio (1 to 5)	-0.0215	0.0308	-0.700	.484

Table 18.

Results of Regression Model with Covariates – low worry group

Fixed Effect	Value	Std. Error	z-value	p-value
infoRatio (1 to 5)	-0.0214	0.0308	-0.694	.488
Age	-0.0232	0.0139	-1.66	.0961
Sex (Male)	0.451	0.378	1.193	.233
SES	0.0681	0.130	0.525	.599

Further Exploratory Analysis

From previous qualitative feedback in the piloting stage of the experiment, some participants commented that they re-looked until they obtained a green-bordered image. In light of the result above that people re-look more in the ‘1 to 40’ than ‘1 to 5’ condition, to explain this finding, the following exploratory hypothesis was made:

Pre-Experiment Hypothesis: Participants have a higher probability of stopping the search process if they have just obtained new information.

Therefore, the following binomial regression model was run (presented in Wilkinson notation, using the GLMMadaptive package described in the Methods section):

stopping ~ newInfo + (1 | ptN)

Equation 3

where **stopping** refers to whether the participant stopped the search at during a specific search number within the trial (coded as a binary value where 1 = stopped and 0 = continued), **newInfo** refers to whether the information obtained was new during this search (coded as a binary value where 1 = new and 0 = old), and **ptN** refers to the participant.

Table 19.

Results of running regression model above – overall group

Fixed Effect	Value	Std. Error	t-value	p-value
newInfo	0.534	0.0403	13.2357	< .001

A robustness analysis was then conducted via testing the following model:

stopping ~ newInfo + Age + Sex + SES + (1 | ptN)

Equation 4

Table 20.

Results of running regression model above for a robustness analysis – overall group

Fixed Effect	Value	Std. Error	t-value	p-value
newInfo	0.534	0.0403	13.2	< .001
Age	0.0284	0.00910	3.13	.00174
Sex (Male)	-0.118	0.224	-0.529	.597
SES	0.0709	0.0710	1.00	.318

This was then repeated for the high worry and low worry participants separately.

Table 21.

Results of running regression model above – high worry group

Fixed Effect	Value	Std. Error	t-value	p-value
newInfo	0.606	0.0560	10.8	< .001

Table 22.

Results of running regression model above for a robustness analysis – high worry group

Fixed Effect	Value	Std. Error	t-value	p-value
newInfo	0.606	0.0560	10.8	< .001
Age	0.0273	0.0116	2.36	.0180
Sex (Male)	-0.215	0.291	-0.741	.459
SES	0.0652	0.0858	0.759	.448

Table 23.

Results of running regression model above – low worry group

Fixed Effect	Value	Std. Error	t-value	p-value
newInfo	0.457	0.0580	7.88	< .001

Table 24.

Results of running regression model above for a robustness analysis – low worry group

Fixed Effect	Value	Std. Error	t-value	p-value
newInfo	0.457	0.0580	7.87	< .001
Age	0.0271	0.0139	1.95	.0512
Sex (Male)	-0.391	0.377	-1.04	.300

SES	-0.0107	0.129	-0.0824	.930

4.4.2. Precision of Stimuli

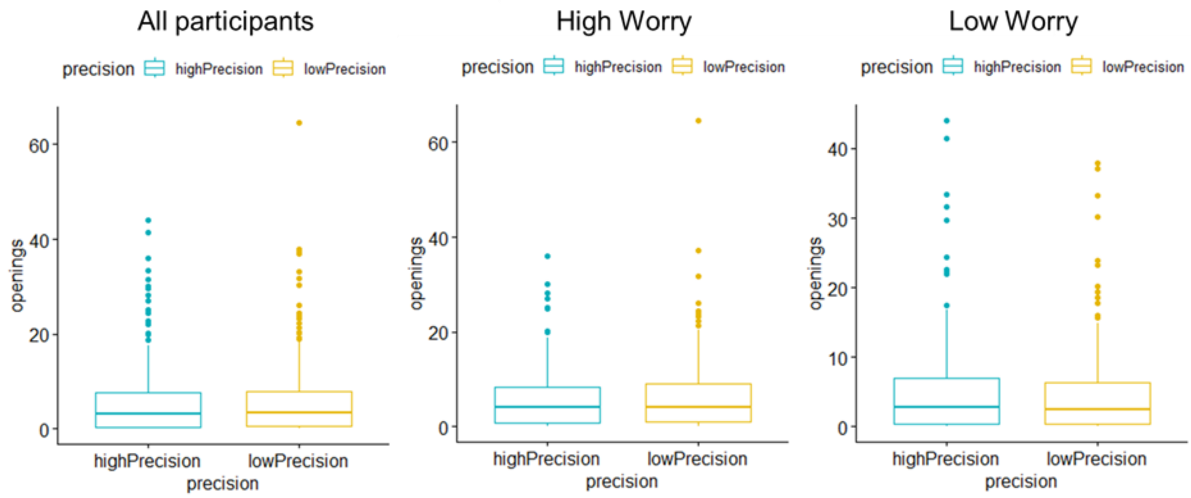
Pre-Experiment Hypothesis: Stimuli precision has no significant effect on re-lookings whether in the overall, high worry or low worry group.

Reasoning: In pilot studies, 2 out of 3 pilots demonstrated no effect of stimuli precision on number of re-lookings.

<u>Results</u>

Figure 26.

Main effect of precision.



Note. There was no significant difference in number of re-lookings between conditions where initial stimuli provided had a low or high precision whether in the overall (p = .160), high worry (p = .218) or low worry (p = .486) group.

<u>Robustness Analysis</u>

Table 25.

Results of Regression Model without Covariates

Fixed Effect	Value	Std. Error	t-value	p-value
Precision (low precision)	0.0102	0.0194	0.528	.597

Table 26.

Results of Regression Model with Covariates

Fixed Effect	Value	Std. Error	t-value	p-value
Precision (low precision)	0.0101	0.0194	0.520	.603
Age	-0.0245	0.00900	-2.72	.00661
Sex (Male)	0.457	0.224	2.04	.0412
SES	-0.0522	0.0705	-0.740	.459

4.4.3. Valence of Stimuli

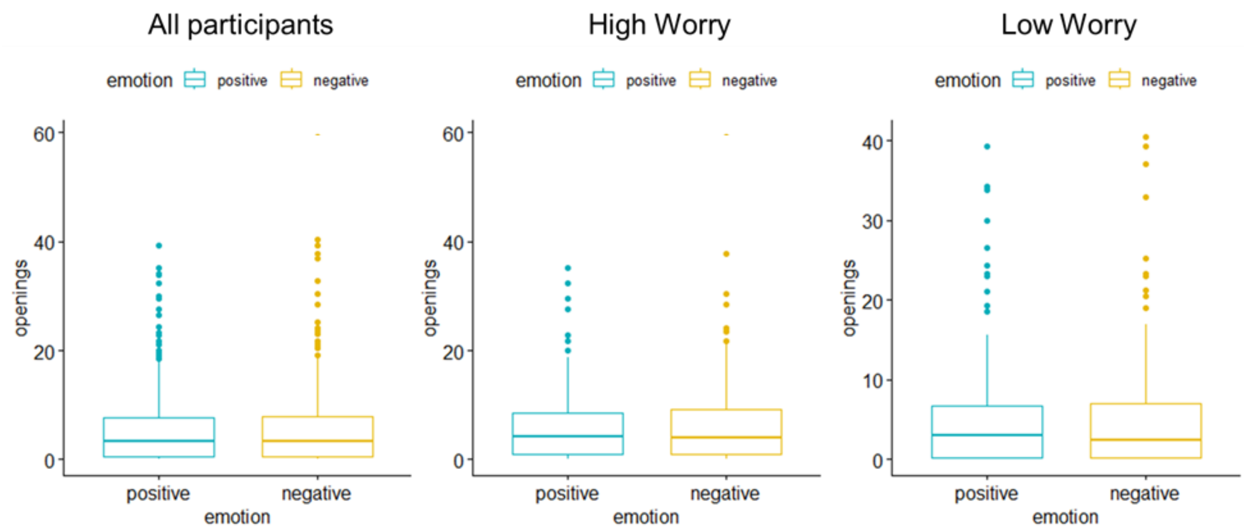
Pre-Experiment Hypothesis: Stimuli valence has no significant effect on re-lookings whether in the overall, high worry or low worry group.

Reasoning: All pilots found that stimuli valence has no significant effect on re-lookings.

<u>Results</u>

Figure 27.

Main effect of emotional valence.



Note. There was no significant difference in number of re-lookings between conditions where the facial expressions shown were overall positive or negative, whether in the overall (p = .160), high worry (p = .218) or low worry (p = .486) group.

Robustness Analysis

Table 27.

Results of Regression Model without Covariates

Fixed Effect	Value	Std. Error	t-value	p-value
Valence (positive)	-0.0289	0.0194	-1.49	.135

Table 28.

Results of Regression Model with Covariates

Fixed Effect	Value	Std. Error	t-value	p-value
Valence (positive)	-0.0290	0.0193	-1.50	.134
Age	-0.0176	0.00900	-1.95	.0509

Sex (Male)	0.306	0.222	1.38	.169
SES	-0.0739	0.0704	-1.05	.294

4.4.4. Interactions between Key Factors

Pre-Experiment Hypotheses:

1. There is no significant interaction between information ratio and valence.
2. There is no significant interaction between information ratio and precision.
3. There is no significant interaction between precision and valence.
4. There is no significant interaction between all 3 factors.

<u>Results</u>

The following mixed effects models were then run to check for interactions between the 3 key experimental factors (specified with Wilkinson notation):

a) relookings ~ infoRatio * valence + (1 | ptN)
b) relookings ~ infoRatio * precision + (1 | ptN)
c) relookings ~ valence * precision + (1 | ptN)
d) relookings ~ infoRatio * valence * precision + (1 | ptN)

Here, **relookings** refers to the number of times the participant re-looked in the trial, **infoRatio** refers to whether the information ratio in the trial was 1 to 40 or 1 to 5, **valence** refers to the whether the stimuli was overall positive or negative, **precision** refers to whether the stimuli had high or low precision, and **ptN** is the participant number. The fixed effects of interest are **infoRatio** ('1 to 5' coded as 1 and '1 to 40' coded as 0), **valence** (positive coded as 1 and negative as 0), and **precision** (low coded as 1 and high as 0); the random effect is **ptN**. Results are in Table 29 below.

Table 29.

Results of running infoRatio and valence model.

Fixed Effect	Value	Std. Error	t-value	p-value

infoRatio	-1.09	0.204	-5.32	< .001
valence	-0.145	0.204	-0.709	.478
infoRatio * valence	-0.190	0.280	-0.657	.511

Table 30.

Results of running infoRatio and precision model.

Fixed Effect	Value	Std. Error	t-value	p-value
infoRatio	-1.43	0.204	-7.01	< .001
precision	-0.207	0.204	-1.01	.311
infoRatio * precision	0.503	0.289	1.74	.082

Table 31.

Results of running precision and valence model.

Fixed Effect	Value	Std. Error	t-value	p-value
precision	0.189	0.205	0.920	.358
valence	-0.0956	0.205	-0.466	.641
precision * valence	-0.289	0.290	-0.996	.320

Table 32.

Results of running model for all 3 key factors.

Fixed Effect	Value	Std. Error	t-value	p-value

precision	-0.083	0.289	-0.288	.773
valence	-0.0212	0.289	-0.0735	.941
infoRatio	-1.36	0.289	-4.70	< .001
precision * valence	-0.248	0.409	-0.606	.545
precision * infoRatio	0.544	0.409	1.33	.183
valence * infoRatio	-0.149	0.409	-0.364	.716
precision * valence * infoRatio	-0.0825	0.578	-0.143	.887

4.4.5. Trait Worry and Self-Reported State Worry

Pre-Experiment Hypotheses:

1. Re-lookings are significantly higher in the high trait worry group.
2. Mean trial-to-trial worry is significantly higher in the high trait worry group.
3. Trial-to-trial self-reported state worry significantly predicts number of re-lookings in its corresponding trial in a regression model.

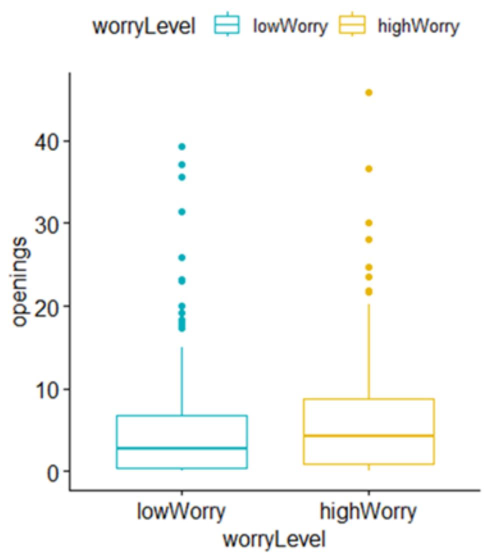
Results

Hypothesis 1

Using a Wilcoxon sign-ranked test to compare mean re-lookings between the high trait worry and low trait worry group, evidence was found supporting hypothesis 1. Mean re-lookings were significantly higher in people with high than low trait worry, as hypothesized ($p = .0178$). The means were 6.36 and 5.16 respectively; the medians were 4.22 and 2.84 respectively.

Figure 28.

Mean participant re-lookings by trait worry group.



Note. Trait worry group (high worry or low worry based on PSWQ score) was labelled as worryLevel.

<u>Robustness Analysis</u>

Table 34.

Results of Regression Model without Covariates

Fixed Effect	Value	Std. Error	z-value	p-value
worryLevel (low)	-0.20940	0.10334	-2.026	.0427

Table 35.

Results of Regression Model with Covariates

Fixed Effect	Value	Std. Error	t-value	p-value
worryLevel (low)	-0.281	0.116	-2.42	.0156

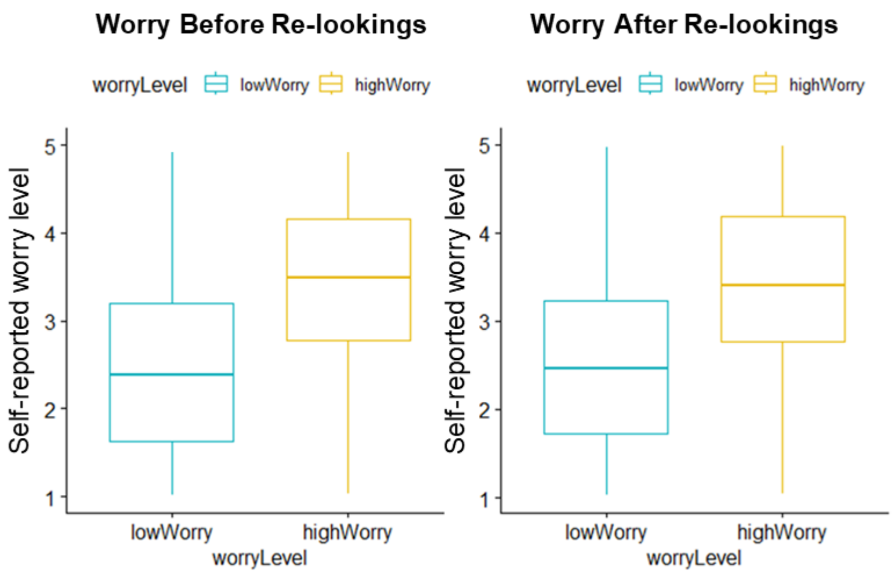
Age	-0.0153	0.00422	-3.63	< .001
Sex (Male)	0.456	0.110	4.15	< .001
SES	-0.0436	0.0343	-1.27	.203

Hypothesis 2

Using a Wilcoxon sign-ranked test to compare the high trait worry and low trait worry groups in terms of their self-reported worry levels, evidence was found supporting Hypothesis 2. As hypothesized, mean reported worry was significantly higher in the high trait worry than low trait worry group, and this applied for both worry before re-lookings ($p < .001$) and after re-lookings ($p < .001$).

Figure 29.

Main effects of trait worry on trial-to-trial reported worry both before and after re-lookings



Robustness Analysis

Table 36.

Results of Regression Model without Covariates – Worry before Re-lookings

Fixed Effect	Value	Std. Error	t-value	p-value
worryLevel (low)	-0.889	0.120	-7.42	< .001

Table 37.

Results of Regression Model with Covariates – Worry before Re-lookings

Fixed Effect	Value	Std. Error	t-value	p-value
worryLevel (low)	-0.676	0.132	-5.11	< .001
Age	-0.0173	0.00478	- 3.63	< .001
Sex (Male)	-0.447	0.124	-3.59	< .001
SES	0.0276	0.0391	0.706	0.481

Table 38.

Results of Regression Model without Covariates – Worry after Re-lookings

Fixed Effect	Value	Std. Error	t-value	p-value
worryLevel (low)	-0.853	0.121	-7.03	< .001

Table 39.

Results of Regression Model with Covariates – Worry after Re-lookings

Fixed Effect	Value	Std. Error	t-value	p-value
worryLevel (low)	-0.635	0.134	-4.74	< .001
Age	-0.0177	0.00484	-3.67	< .001

Sex (Male)	-0.445	0.126	-3.53	< .001
SES	0.0245	0.0396	0.618	0.537

Hypothesis 3

Using a mixed effects model (negative binomial regression as described in Methods), evidence was found supporting hypothesis 3. The fixed effect of self-reported worry on number of re-lookings immediately after was positive and significant (coefficient 0.481, $p < .001$)

This evidence was obtained from running the following mixed effects model, where **relookings** refers to the number of times the participant re-looked, **worry_before** refers to the self-reported worry rating immediately prior to the re-looking stage, and **ptN** is the participant number. The fixed effect of interest is **worry_before**, and the random effect is **ptN**.

relookings ~ worry_before + (1 | ptN)

Equation 5

Table 40.

Results of running regression analysis.

Fixed Effect	Value	Std. Error	z-value	p-value
worry_before	0.481	0.106	4.56	< .001

Robustness Analysis

Results of Regression Model with Covariates

Fixed Effect	Value	Std. Error	z-value	p-value
worry_before	0.111	0.0144	7.74	< .001

Age	-0.0200	0.00890	-2.24	.0249
Sex (Male)	0.385	0.221	1.74	.0810
SES	-0.0836	0.0699	-1.20	.231

4.4.6. Self-Reported Uncertainty

Pre-Experiment Hypothesis

Self-reported uncertainty level significantly predicts number of re-lookings immediately afterwards.

Results

When a mixed effects model (negative binomial regression as described in Methods) was run, no evidence was found for the above hypothesis, as the fixed effect of self-reported trial-specific uncertainty on re-lookings was not significant ($p = .420$).

This was based on the following mixed effect model, where **relookings** refers to the number of times the participant re-looked in the trial, **uncertainty_before** refers to the self-reported uncertainty rating immediately prior to the re-looking stage, and **ptN** is the participant number. The fixed effect of interest is **uncertainty_before**, and the random effect is **ptN**.

relookings ~ uncertainty_before + (1 | ptN)

Equation 6

Table 41.

Results of running linear mixed effects model above.

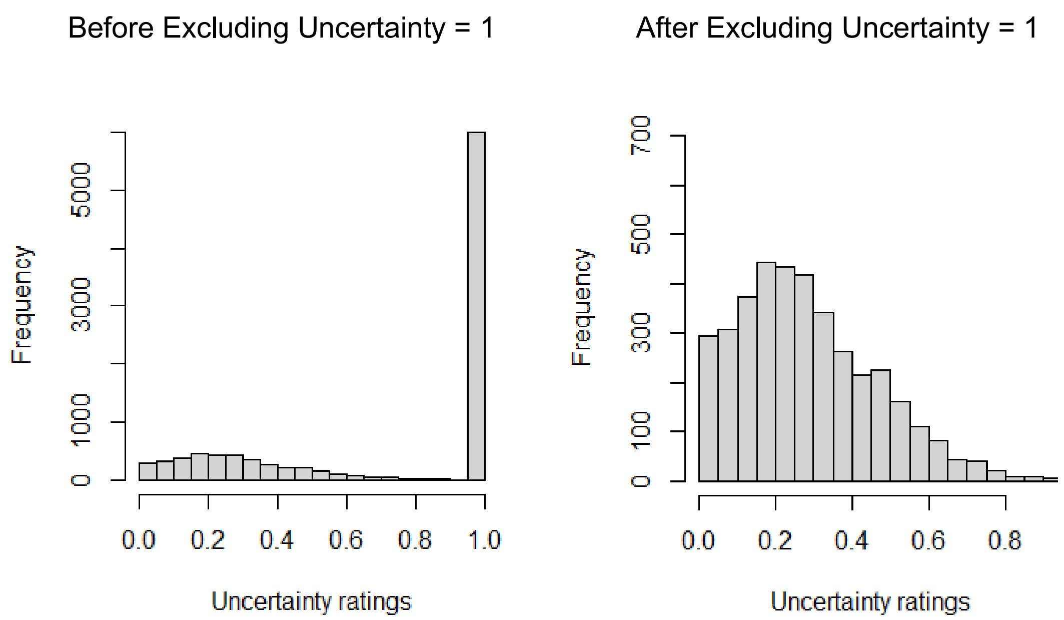
Fixed Effect	Value	Std. Error	z-value	p-value
uncertainty_before	0.425	0.527	0.806	.420

Quality Control Analysis

It was observed that the fixed effect's standard error (0.527) was much higher than the corresponding standard error for worry_before (0.106). As such, the distribution of uncertainty ratings in the dataset was plotted to check if the data showed any unexpected or unusual patterns (Figure 30, left hand side).

Figure 30.

Distribution of uncertainty ratings.



This showed that a large proportion of ratings were simply 1.0, which was the maximum, as well as default, rating. As this was likely due to participants not engaging with the uncertainty ratings question, ratings of 1 were excluded from the analysis, and the model was re-run. Note that after excluding these ceiling responses, the distribution had a more natural — e.g., lognormal — form (Figure 30, right hand side). The following results were obtained after the model was re-run with this modified dataset:

Table 42.

Results after re-running model with modified dataset.

Fixed Effect	Value	Std. Error	z-value	p-value
uncertainty_before	0.548	0.123	4.47	< .001

Table 43.

Corresponding robustness analysis.

Fixed Effect	Value	Std. Error	z-value	p-value
uncertainty_before	0.539	0.123	4.40	< .001
Age	-0.0519	0.0132	-3.93	< .001
Sex (Male)	0.1584	0.335	0.472	.637
SES	-0.0502	0.105	-0.480	.631

5993 trials out of 9792 trials were excluded (306 participants with 32 trials each), leaving 3799 trials where reported uncertainty before re-lookings was *not* 1. Since more than half of trials were excluded, further analyses were conducted to better understand this phenomenon. It was found that 174 people self-reported uncertainty levels of 1 in all trials, suggesting no engagement with the uncertainty rating question, 86 people had no values of 1, suggesting full engagement with the uncertainty rating question, and 46 people had a mix of 1s and non-1s, suggesting partial engagement.

The same mixed-effects model was then re-run again for the following groups: a) the 86 people with full engagement and b) the 46 people with partial engagement. The model could not be run on the 174 people with no engagement with the uncertainty question as all uncertainty_before values are 1. The results were as follows.

Table 44.

Results after re-running model with full engagement participants.

Fixed Effect	Value	Std. Error	t-value	p-value
uncertainty_before	0.650	0.152	4.29	< .001

Table 45.

Results after re-running model with partial engagement participants, ceiling values included

Fixed Effect	Value	Std. Error	t-value	p-value
uncertainty_before	-0.0156	0.0918	-0.169	0.866

Table 46.

Results after re-running model with partial engagement participants, ceiling values not included

Fixed Effect	Value	Std. Error	t-value	p-value
uncertainty_before	0.3267	0.2024	1.6140	0.107

Finally, to examine if these groups of participants are similar apart from their level of engagement, an Kruskal-Wallis analysis was conducted using the *kruskal.test* function in R (Kruskal & Wallis, 1952). It is suitable for comparing multiple groups but unlike an ANOVA does not require assumptions of normality of residuals and homogeneity of variance, which the dataset was found to not follow in the Methods section. The null hypothesis was that there is no significant difference in re-lookings between the three groups.

This hypothesis was rejected ($p = 0.0490$), providing evidence that there is a significant difference in re-lookings between the three groups. Therefore, the Dunn test was conducted for post-hoc analysis to identify specific group differences (Dinno & Dinno, 2017). It was selected due to using the same statistical approach – using the same rank sums from the Kruskal-Wallis test – and thus ensuring consistency, as well as having built in corrections for multiple comparisons (here, the Holm method was used).

The results showed that re-lookings were significantly higher in the full engagement compared to the no engagement group (p = 0.213), while there was no significant difference between the partial engagement group and either the full engagement group or no engagement group.

Table 47.

Results of Dunn test.

Column Mean - Row Mean	1	2
2	1.07 (p = .283)	
3	2.45 (p = .0213) *	0.773 (p = .220)

Note. Numbers 1, 2 and 3 refer to the full engagement, partial engagement, and no engagement group respectively. $\alpha = 0.05$. Reject H_0 if $p < \alpha/2$

4.4.7. Worry Before and After Re-lookings

Pre-Experiment Hypotheses

1. In low worriers, self-reported state worry would be significantly lower after the re-looking stage.
2. In high worriers, self-reported state worry would be significantly higher after the re-looking stage.

Reasoning

1. In low worriers, obtaining information may reduce uncertainty, therefore worry level would decrease after re-looking.
2. In high worriers, obtaining information via worry may cause a vicious cycle where worry causes more worry, increasing self-reported worry level.

Results

The t-tests showed that, contrary to Hypothesis 1, low worriers' self-reported state worry was significantly higher, not lower, after re-lookings (p = .00354). The results also did not provide evidence for Hypothesis 2, instead demonstrating no significant difference in self-reported worry before and after re-lookings in the high worry group (p =.478). P-values were obtained with paired two-sided t-tests due to normal distribution of differences (see Appendix) and lack of assumptions about directionality of effect.

Figure 31.

Self-reported worry levels before and after the re-lookings stage.

Table 48.

Self-reported state worry in all 3 groups before and after re-lookings.

	All participants	Low Worriers	High Worriers

Worry Before	2.95	2.52	3.41
Worry After	2.98	2.57	3.42
Absolute Effect Size	0.0291	0.0461	0.0100
Relative Effect Size	0.00986	0.00183	0.00293
p-value	.00354	.00110	.478

4.4.8. Accuracy and error

Hypothesis 1: High worriers have lower errors at the decision-making point than low worriers.

Reasoning 1: Worry can assist in problem-solving.

Hypothesis 2: Re-lookings significantly reduce the magnitude of errors.

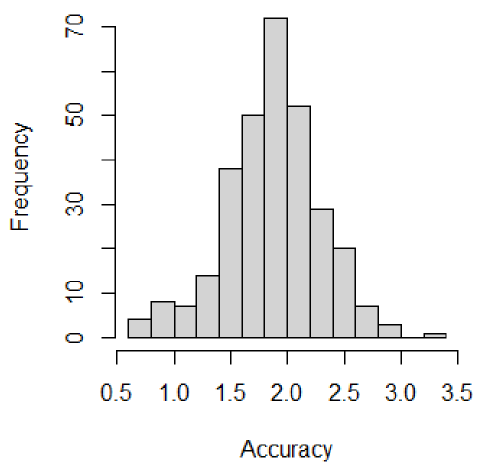
Reasoning 2: Re-lookings provide information, which in turn increases the precision of data obtained thus far, which then reduces error.

Results

Errors are calculated every trial by the absolute value of the difference between the true emotion rating and the rating provided by the participant when they made their decision (therefore a lower value is better). Error scores were approximately normal (Figure 32).

Figure 32.

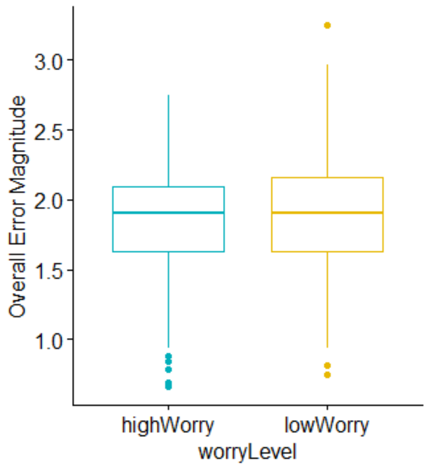
Histogram of errors (mean value across all trials per participant).



Then, the difference in error scores between the high and low worry group was calculated using a one-sided unpaired t-test. This was selected due to the plausible hypothesis that the high worry group would have lower errors, the two groups of participants not being paired, and normality of data.

Figure 33.

Overall Error Magnitude for High and Low Worriers.



Note. No significant difference in accuracy (p = .503). Each data point refers to the mean error value for one participant.

Robustness Analysis

Table 49.

Results of Regression Model without Covariates

Fixed Effect	Value	Std. Error	t-value	p-value
worryLevel (low)	0.0342	0.0484	0.706	.481

Table 50.

Results of Regression Model with Covariates

Fixed Effect	Value	Std. Error	t-value	p-value

worryLevel (low)	0.0875	0.0553	1.58	0.114
Age	-0.00337	0.00200	1.69	0.0923
Sex (Male)	-0.00337	0.0520	-1.81	0.0708
SES	-0.00423	0.0164	-0.258	0.790

Then, to test whether increased number of re-lookings reduces error, the following mixed effects model was run for the overall group as well as for the high and low worry groups (specified in Wilkinson notation):

error ~ relookings + (1 | ptN)

Equation 7

where **relookings** refers to the number of times the participant re-looked in each trial, **error** refers to the difference between the true emotion and the participant's rating in each trial, and **ptN** is the participant number. The fixed effect of interest is **relookings**, and the random effect is **ptN**.

Table 51.

Result obtained from running regression analysis on overall group

Fixed Effect	Value	Std. Error	t-value	p-value
relookings	-0.000473	0.00126	-0.375	.707

Table 52.

Result obtained from running regression analysis on overall group, with covariates

Fixed Effect	Value	Std. Error	t-value	p-value
relookings	-0.00189	0.00155	-1.219	.223

Age	-0.00314	0.00391	-1.575	.116
Sex (Male)	-0.0617	0.0491	-1.256	.210
SES	0.00391	0.0155	0.253	.801

Table 53.

Results obtained from running regression analysis on high worry group

Fixed Effect	Value	Std. Error	t-value	p-value
relookings	-0.00175	0.00169	-1.04	.300

Table 54.

Result obtained from running regression analysis on high worry group, with covariates

Fixed Effect	Value	Std. Error	t-value	p-value
relookings	-0.00177	0.00198	-0.895	.371
Age	-0.00563	0.00282	-2.00	.0478
Sex (Male)	-0.0618	0.0708	-0.874	.384
SES	0.00330	0.0208	0.159	.874

Table 55.

Results obtained from running regression analysis on low worry group

Fixed Effect	Value	Std. Error	t-value	p-value
relookings	0.00141	0.00191	0.741	.459

Table 56.

Result obtained from running regression analysis on low worry group, with covariates

Fixed Effect	Value	Std. Error	t-value	p-value
relookings	-0.00198	0.00249	-0.794	0.427
Age	-0.00168	0.00287	-0.585	0.560
Sex (Male)	-0.121	0.00287	-1.55	0.124
SES	-0.0179	0.0265	-0.676	0.500

4.5. Discussion

This chapter addressed key factors which affect re-lookings as well as the question of whether re-looking behaviour is adaptive. Key results will now be restated below.

It found that participants re-looked significantly more in the '1 to 40' than the '1 to 5' condition ($p < .001$), and that this effect was found in the high worry ($p < .001$) but not low worry group ($p = .484$). The probability of stopping search was found to be significantly higher if the last piece of information obtained was new ($p < .001$), which may explain why participant re-looked more in the '1 to 40' condition, as new information is harder to come by. Stimuli valence and precision, however, had no significant effect.

Next, it was found in regression analyses that trial-to-trial worry significantly predicts number of re-lookings within the same trial ($p < .001$). Trial-to-trial uncertainty did not significantly predict re-lookings in the full dataset ($p = .420$), but did after ceiling uncertainty ratings were removed ($p < .001$).

Lastly, there was no significant difference in error magnitudes between high and low worry groups ($p = .503$), and re-lookings did not decrease error magnitudes ($p = .707$).

4.5.1. Main Experimental Factors

Information Ratio

The number of re-lookings being significantly higher ($p < .001$) in the 1 to 40 condition indicates that participants perceive this search behaviour as worthwhile despite the known lower chance of success. To explain, each re-looking yields less information in the 1:40 than the 1:5 condition, meaning that re-looking in this condition yields less information gain. This suggests that there is a compensatory mechanism, where participants are driven to re-look more precisely because they have to compensate for the lower efficiency of each search. Some participants may also have the "search until success" strategy, where they keep searching up to the point where they successfully obtain information, a strategy which has been qualitatively reported.

Indeed, looking at the results of the regression model run for further exploratory analysis, participants do overall have a higher probability of stopping the search process if they have just obtained new information ($p < .001$). This suggests that the "search until success" strategy was evident, such that participants stop searching when they successfully see the green-bordered face. This captures the belief that searching – or worry – is worthwhile as it will eventually be fruitful, even if it does not initially produce useful information.

Importantly, as the overall significant effect of information ratio on re-lookings is driven by the high worry group ($p = .00116$) rather than the low worry group ($p = 0.0840$), this motivation is likely to be stronger in the high worry group. Indeed, while receiving a new piece of information significantly increases the chance of stopping the search in both groups ($p < .001$ for both), the coefficient of the fixed effect is higher in the high worry than low worry group (.606 compared to .457, non-overlapping standard errors). This is despite the fact that, given that high worriers re-look more, they are in fact less likely to stop searching overall. This suggests that high worriers are more likely to hinge their decision to stop on obtaining new information, providing a potential basis for the vicious cycle where one continues to worry when it has not been helpful, as they persist until useful information is obtained.

These results remained after a robustness analysis, where demographic factors, namely age, sex and socioeconomic status were controlled for by being included as covariates in a regression model ($p <.001$, no change in coefficient of fixed effect).

Precision

Precision having no significant effect on re-lookings ($p = .597$) was an unexpected result, as it was hypothesized that lower precision, i.e., higher uncertainty, would cause more re-lookings, aligning with theories that individuals seek information to resolve ambiguity and reduce anxiety (Carleton, 2016; Dugas et al., 2022; Vander Haegen & Etienne, 2016).

However, these results suggest that precision does not have an effect on worry-like sampling in this task. There are several possible reasons for this. First, as the faces are shown sequentially rather than simultaneously, participants reported that sets with similar facial expressions (i.e. high precision) can sometimes be more difficult to retain and process as a group (e.g. “Have I seen this face already or not?”, “The faces seem to blur together”), making them in fact harder, not easier, to process. Having to distinguish between similar faces may add an additional processing task, increasing perceptual load (Lavie et al., 2014) and hindering efficient processing.

Second, precision may simply not factor into the decision to re-look, as this decision may be influenced far more strongly by other heuristics e.g. “search until success” as mentioned in the information ratio section, or simply searching more if chance of success is lower. This aligns with dual-processing accounts which state that people may rely on automated rule-based processing rather than more effortful assessment of precision (J. S. B. Evans, 2008).

Valence

The valence of the facial expressions shown did not significantly affect the number of re-looking in either the high ($p = .218$) or low worry group ($p = .486$), contrasting with studies that show attentional bias to threat (Bradley et al., 1999; Cisler & Koster, 2010; McNally, 2019). This suggests that the facial expression information was perceived as data, not feedback, which was as intended. This was likely reinforced by the training, which matched specific numerical ratings to specific facial expressions (Section 3.6.,

Figure 10). This aligns with literature suggesting that explicit task goals can moderate or override the effect of emotion on decision-making (Etkin et al., 2006).

Interactions

While the main effects have now been discussed, the lack of interactions is also informative about the nature of re-looking. Specifically, while it has been shown that re-lookings differ in response to information ratio, there is no evidence that this response additionally differs based on stimuli valence or precision. This suggests that information ratio is indeed the sole factor among the three key factors which affects re-lookings.

4.5.2. Trait Worry and Self-Reported State Worry

Overall, the high worry group performed significantly more re-lookings than the low worry group ($p = .0178$), and this effect remained after robustness analyses. This provides support for the hypothesis that re-lookings reflect worry. Notably, there was not only a difference in means (6.36 and 5.16 for high worriers and low worriers respectively) but in medians (4.22 and 2.84), suggesting that this effect was not just driven by a subgroup which re-looked a lot more and skewed the mean upwards.

Next, and importantly, the results of the linear mixed effects model showed that within each trial, self-reported worry prior to re-lookings significantly predicts number of re-lookings ($p < .001$), and this effect remained after robustness analyses ($p < .001$). This suggests that re-lookings are in fact reflective of the process of worry, particularly since it is situated at a point in each trial where the participant may worry but is not given the time to do so internally, causing it to be externally manifested.

Lastly, as expected, trial-to-trial worry levels were higher in the high worry group, indicating that the screening and selection process was successful. This was the case for reported worry levels both before and after re-lookings (both timepoints were included to provide extra checks).

4.5.3. Self-Reported Uncertainty

Discussion

After excluding low-effort trials, trial-to-trial uncertainty significantly and meaningfully predicts trial-to-trial re-lookings ($p < .001$, coefficient: 0.548). This suggests that re-lookings are attempts to resolve uncertainty. Interestingly, this finding coupled with the earlier finding that precision of stimuli does not affect number of re-lookings (Section 4.3.1.) suggests that it is not *objective* uncertainty that affects worry, but *subjective*, perceived uncertainty. This suggests a role for metacognition, which was identified as a key element in worry models in the systematic scoping review. Specifically, this suggests that high worries may have a metacognitive bias where stimuli are perceived to be more uncertain than it actually is. This contributes to the literature of what metacognitive processes are implicated in worry (Wells, 2010; Yıldırım & Bahtiyar, 2022), as well suggesting a mechanistic basis for how intolerance of uncertainty may occur in worry (Bomyea et al., 2015; Vander Haegen & Etienne, 2016).

4.5.4. Worry Before and After Re-lookings

Within each trial, worry level after re-lookings was significantly higher than worry level before re-lookings in both the overall ($p = .00354$) and low worry group ($p = .00110$), while there was no significant difference in the high worry group ($p = .478$).

However, it must be noted that the relative effect sizes are very small, at 0.00986 and 0.0183 respectively. A possible reason for the small effect size could be that another trend could have cancelled out a statistical increase in worry, e.g., perhaps there is, in fact, some reduction in worry from resolving uncertainty, Nevertheless, this suggests that the effect hypothesised to occur in high worriers – that worry in the form of re-lookings places people in a state which induces further worry – has in fact occurred in low worriers only.

This counterintuitive result may have been obtained for several reasons. First, there may be a ceiling effect, such that high worriers are already maximally worried for the given conditions. Although the mean value is far from 5 (the maximum value on the scale), they may have reported worry levels close to 5 on individual trials. Second, high worriers may be unable to modulate their moment-to-moment worry level, resulting in a constant, high level of worry. In other words, they cannot increase their level of worry only when it is needed. In general, a possible explanation for worrying increasing after re-lookings is that the results of re-lookings can produce a prediction error about the usefulness of re-lookings, as people would assume that re-lookings would reduce their uncertainty. Therefore, when re-lookings do not yield useful information, worry may rise in response to this aversive prediction error. This dovetails with the fact that people re-look more with a lower chance of success, as they are unable to understand that re-looking would be generally ineffectual, leading to disappointment and increased worry.

Another possible reason for why worry ratings did not decrease with reducing uncertainty was due to the structure of the experimental paradigm. In each trial, the possible aversive stimuli always occurred after re-lookings. If the experiment had 2 points of possible aversive feedback — both before and after re-lookings — worry level before re-lookings would be based on the uncertainty in the initial 5 faces, which would then be reducible before the second point of aversive feedback within the same trial.

4.5.5. Re-lookings and Reducing Errors

The finding that re-lookings did not significantly reduce errors, whether in the overall, high worry or low worry group, presents an intriguing distinction between groups that was not originally predicted. This result subverts the typical paradigm in computational psychiatry, which often links differences between healthy and non-healthy individuals to the results of near-optimum decision-making. Instead, this study reveals a task that is insensitive to performance differences between individuals but remains sensitive to worry levels and worry-like behaviour. This distinction is valuable as it moves beyond the use of improved performance as the only marker of behaviour being more optimal.

There are several potential explanations for this unexpected outcome. First, given the low probability of obtaining useful information, most re-lookings were likely ineffective, especially considering that many participants had a low number of re-lookings and may not have reached the point where re-lookings became useful. Second, when useful information did get obtained, due to it being drawn randomly from the underlying distribution, there is a chance that it may have pointed participants in an inaccurate direction. Modelling, which will be discussed in a subsequent chapter, could provide insights into how the beliefs of participants shift when they are given certain stimuli. An experiment where the green bordered image simply provided the correct answer, rather than being a sample from the underlying distribution, could have yielded different results. Therefore, while in theory accuracy would improve if one continued to re-look to obtain useful information, given the low median number of re-lookings in the experiment, the above reasons may explain why re-looking did not improve accuracy.

4.5.6. Adaptiveness

Contrary to the initial hypothesis, the high-worry group did not perform better error-wise compared to than the low-worry group ($p = .503$), despite engaging in significantly more re-lookings. This suggests that the effortful and time-consuming worry-like behaviours observed throughout the experiment – namely, increased re-lookings and self-reported feelings of worry – were maladaptive, if we assess maladaptiveness by non-reduction of the probability of hearing a scream.

This is in the context of the adaptiveness discussion in Chapter 1, where it was concluded that for the purposes of an experimental paradigm, the most appropriate definition of adaptiveness is that the benefits are worth the costs. In this case, the cost was greater and there was no difference in benefit. The cost was the higher extent of self-reported worry which is by nature distressing, as well as the time and effort of re-lookings. The lack of benefit was that they had similar error rates and therefore similar chances of experiencing a scream.

While some may argue that the design of the experiment disadvantaged high worriers – given the limitations of re-looking as discussed in Section 4.3.3.1 – this mirrors real-world situations. In both everyday worry and problem-solving, there is no certainty that increased cognitive effort will lead to valuable insights.

4.6. Limitations

Key limitations of the findings thus far will now be discussed. Broader study constraints, such as sample size limitations, which are relevant to both this chapter and the subsequent results chapter, will be addressed comprehensively in the final discussion section. This allows for overarching methodological considerations to be examined in relation to the study's findings as a whole after all of them have been discussed.

First, a lack of significant results being found for the valence and precision factors, as well as in interactions involving them, does not conclusively show that they are irrelevant; they could still have interactions with factors which have not been discussed thus far, e.g. between-subject factors. Furthermore, this could be due to the characteristics of the paradigm; for example, as discussed, the strong focus on task-specific goals in this paradigm may have limited the effect of valence.

Second, as discussed, a large number of trials had to be excluded from the uncertainty analysis due to ceiling values. This could have occurred due to several reasons. First, there was no incentive to provide an accurate uncertainty rating, unlike the motivation to provide an accurate read of emotion. Second, the experiment did not prevent the participant from progressing even if they did not interact with the uncertainty rating bar. Either of these could be ideally implemented to provide a fuller picture of uncertainty.

The hypothesis that these ceiling ratings were caused by lack of engagement is supported by the higher re-lookings in the full-engagement group: if one were to take the maximal uncertainty of the no-engagement group at face value, based on the finding above, one would expect that the no-engagement group would have higher re-lookings as their uncertainty is greater. However, given that they in fact had significantly fewer re-lookings instead, this suggests that their maximal uncertainty rating was indeed due to lack of engagement rather than genuine uncertainty. The lower number of re-lookings in this group — but no significant difference in worry — also aligns with the hypothesis that this is due to low engagement rather than a difference in worry levels.

Therefore, while the uncertainty result must be caveated with the fact that these trials may not be representative of all trials, given that there is a significant difference in mean re-lookings in the full engagement compared to the no engagement group, evidence does point towards this being caused by lack of engagement rather than other reasons. An improved method of capturing uncertainty – to be discussed in more detail in the further work section – would shed light on whether this finding is more generally applicable.

Lastly, while these results provide evidence for high worriers' behaviour being maladaptive if it is defined by comparing cost and benefit, this may be an overlyrestrictive way of capturing whether behaviour is optimal. For instance, behaviour which is suboptimal in terms of an object cost-benefit analysis can still improve one's well-being by providing a sense of control or reassurance. This has been discussed in Chapter 1 and will be further discussed in the Discussion chapter (Chapter 7) due to overarching implications, but is included here for completeness.

4.7. Conclusion

These are the key results obtained thus far:

1. High worriers reported higher trial to trial worry (Section 4.4.5.)
2. Trial-specific worry level predicts trial-specific re-lookings (Section 4.4.5.)
3. High worriers re-look more than low worriers (Section 4.4.5.)
4. High worriers re-looked significantly more in the low success than high success condition; low worriers did not (Section 4.4.1.)
5. Accuracy levels were not significantly different between high and low worry groups (Section 4.4.8.)

Points 1-3 support the hypothesis that re-lookings are indeed a proxy for worry. Point 4 suggests that high worriers are more inclined to re-look, or worry, even when chances of success are explicitly known to be low, while low worriers are less likely to do so. Point 5 suggests that the behaviour of high worriers is maladaptive, as their actions did not lead to better accuracy.

Together, these suggest that the experimental paradigm was successful in making the internal process of worry external and measurable, and that it has captured key differences between adaptive and maladaptive worry. Interestingly, responsiveness to chance of success, i.e., the information ratio factor, emerged as a possible marker for differentiating between people who worry adaptively or maladaptively, as it distinctly occurs significantly only in high worriers, who have been shown to expend unnecessary time and effort with no effect on accuracy.

5. Worry About Feelings Task (Part 2) – Questionnaires and Additional Manipulations

5.1. Background

A myriad of factors can cause worry, and understanding these factors allows for a holistic understanding of worry. First, low social status provides a functional motivator for anxiety and worry to emerge (Jonason & Perilloux, 2012), as discussed in Chapter 3. Second, links can be drawn between re-lookings and traits such as perfectionism (Xie et al., 2019) between re-lookings and vulnerability factors such as high trait anxiety or depressive symptoms (Spinhoven et al., 2017). Each factor and their reason for inclusion will be discussed further on in this chapter. Drawing links between re-lookings and known risk factors for worry such as perfectionism (Flett et al., 2016) allows this novel measure of re-lookings to be understood in terms of its relationships with already known constructs. This includes risk factors which can be important for management or intervention, useful for considering potential clinical applications.

To this end, this chapter examines the effects of manipulating perceived social status, as well as individual differences such as perfectionism and trait anxiety, on re-lookings, which we have previously established as a useful measure of worry in Chapter 4.

5.2. Methods

5.2.1. Status Manipulation

This subsection below is copied from content in Chapter 3 (Section 3.5.)

A brief experimental manipulation, the Power Manipulation Writing Task (Gruenfeld et al., 2008; Schaerer et al., 2018), was included before the main experiment. This was included as social status has links to worry. Specifically, low social status provides a functional motivator for anxiety and worry to emerge (Jonason & Perilloux, 2012), providing a further incentive to adapt strategically. It also increases deliberation and decreases tendency to act (Galinsky et al., 2003) as well as impairs executive function (Smith et al., 2008).

The manipulation involves placing participants in a frame of mind of feeling either relatively powerful, powerless or neutral by reminding them of a life experience that evinced these feelings. This allows a better exploration of the mechanisms of worry, as participants are expected to more readily experience worry when in a subjectively less powerful state of mind. A sense of low or high power can be induced via cues (Dubois et al., 2012; Galinsky et al., 2003) and has been shown to influence behaviour predictably and meaningfully.

As a between-participant intervention, participants were randomised to either ‘high power’ or ‘low power’ manipulations prior to the main experiment.

High Power:

Please think of a professional relationship you have, or have had in the past, that is hierarchical. The relationship should be one in which your work partner either reports directly to you or in which you have disproportionate power or control (or both) over him/her. Briefly describe your partner, and the nature of your relationship in the space below.

Low Power:

Please think of a professional relationship you have, or have had in the past, that is hierarchical. The relationship should be one in which you report either directly to your work partner or in which your work partner has disproportionate power or control (or both) over you. Briefly describe your partner, and the nature of your relationship, in the space below.

The participants were also given the Trait Sense of Power questionnaire (Figure 5) (Anderson & Galinsky, 2006) prior to the power manipulation writing exercise. Following Schaerer et al. (2018) — as a manipulation check — the ‘State Sense of Power’ questionnaire was then completed after the power manipulation writing exercise. This was completed after asking participants to reflect on the relationship they described in the writing exercise. They completed similar items from the ‘Trait Sense of Power’ scale, adapted to measure ‘State Sense of Power’. E.g. “In my relationship with this person, I can get him/her to do what I want.”

Figure 5.

The Trait Sense of Power questionnaire.

In rating each of the items below, please use the following scale:

1	2	3	4	5	6	7
Disagree strongly	Disagree	Disagree a little	Neither agree nor disagree	Agree a little	Agree	Agree strongly

In my relationships with others . . .

______I can get people to listen to what I say.
______My wishes do not carry much weight.
______I can get others to do what I want.
______Even if I voice them, my views have little sway.
______I think I have a great deal of power.
______My ideas and opinions are often ignored.
______Even when I try, I am not able to get my way.
______If I want to, I get to make the decisions.

Note. For state sense of power, the sentences were edited to refer specifically to the person they wrote about. Note that this means it would have limited value as a between-participant measure, as it does not measure a trait but a specific relationship (the relationship between the participant and the colleague they wrote about.)

To check if this writing task was effective as a status manipulation, SOP scores before and after this manipulation were compared via statistical testing. T-tests were used due to approximate normality of data (see Figure 34 below). For re-lookings and trial-to-trial worry levels, the Wilcoxon sign rank test was used to obtain p-values due to non-normality of data (both previously discussed in Chapter 4).

Figure 34.

Histogram of State Sense of Power (SOP) Scores.

Lastly, before the main experiment, they were asked to imagine the facial expressions they would be seeing later are of either a person they report to, or a person who reports to them, depending on the power manipulation they received.

5.2.2. Questionnaires

Apart from the manipulation of social status, questionnaires were also administered to obtain measures unaffected by manipulation, as these reflect inherent traits and dispositions, such as trait worry and perfectionism.

The following questions or questionnaires were given to each participant after the main experiment (Table 57).

Table 57.

Questionnaires included with justifications and hypotheses.

Questionnaire / question	Abbreviation	Reason for including	Hypothesis
'How preoccupied were you by the chance of a scream?' (rate from 1-5)	PS	Capturing individual sensitivity to the specific aversive stimuli used in the experiment	A higher value predicts more re-lookings.
State-Trait Anxiety Inventory (Spielberger et al., 1971)	STAI	Allows the effects of state, trait and overall anxiety to be analysed separately	Higher STAI scores, including both trait and state subscales, predict higher re-lookings.
Adult Mood and Feelings Questionnaire (MFQ) (Costello & Angold, 1988)	MFQ	Mood and anxiety disorders are frequently comorbid (Saha et al., 2021). Exploring the effects of not just anxiety but depression on worry	Higher MFQ and BDI scores predict higher re-lookings.
Beck Depression Inventory (BDI)	BDI		

(Jackson-Koku, 2016; Richter et al., 1998)		would aid in having a broader understanding of factors that predispose one to worry.	
Multidimensional Perfectionism Scale (MPS) (Frost et al., 1990) 4 subscales: concern over mistakes and doubts about actions, excessive concern with parents' expectations and evaluation, excessively high personal standards, and concern with precision, order and organisation.	MPS	It is more self-oriented than Hewitt and Flett's alternative (Frost et al., 1993), fitting with the internalising aspect of worry. Perfectionism may lead to certain behaviours which manifest to a strong extent in this experiment e.g. the desire to fully obtain information (i.e. "reach perfection" about amount of information obtained) about each trial by performing re-lookings until one has obtained all available information may be increased in people with perfectionist traits. Hence, the interaction between perfectionist traits and experimental	High MPS scores, as well as its subscales, predict higher numbers of re-lookings.

		outcomes should be examined.	
McArthur subjective socioeconomic scale (Galvan et al., 2023)	SES	This was included to check for subjective socioeconomic scale as a potential confound.	NA
Duttweiler Internal Control Index (Duttweiler, 1984)	ICI	Questionnaires capturing beliefs about the capability and confidence of the self in solving problems. ICI: Addresses issues with the older Rotter Locus of Control Scale, and has good internal consistency and reliability. People with an internal locus of control believe that they are able to affect the environment around them and therefore may be more inclined to problem-solving rather than passive acceptance. RSES: Similar to above but with a component of self-	Given that here is evidence that locus of control is inversely correlated with anxiety (Hoehn-Saric & McLeod, 1985), and high self-esteem is protective against mood and anxiety disorders (Sowislo & Orth, 2013), it is hypothesized that higher scores in either measure are associated with lower numbers of re-lookings.
Rosenberg Self-Esteem Scale (Rosenberg, 1965).	RSES		

		worth, it may also incline people to problem-solve by boosting their self-belief in their problem-solving abilities. These are relevant due to the hypothesis that worry is a form of problem-solving. If true, it follows that people who are inclined to problem-solve might worry more, although this might be tempered by an ability to stop when it is no longer useful. These questionnaires therefore might allow for analyses of the effects of the opposing forces of a desire to problem-solve and stopping when no longer useful or when distress is unbearable.	

5.2.3. Statistical Tests

Statistical analyses were conducted using R (version 4.3.2; R Core Team, 2020). Negative binomial regression via the *glm.nb* function from the MASS package (Venables & Ripley, 2013) was used to analyse data. Note that unlike in Chapter 4 where the dependant variable of re-lookings was on the trial-to-trial level, here it is the mean number of re-lookings the participant averaged over the entire experiment, averaged across all 32 trials. In other words, the dependent variable in question is $\bar{Y}_i$ (mean number of re-lookings for participant i) not Y_{ij} (number of re-lookings for participant i at timestep j).

Justification for the use of the negative binomial model (similar to in Chapter 4):

1. Underlying count structure: While the data is continuous, it is derived from count data aggregated over multiple trials, therefore retaining count-based interpretation suitable for modelling by Negative Binomial and Poisson models.
2. Skewed data: Negative Binomial and Poisson models can account for a leftward skew with a long tail, which is the structure of the data.
3. Overdispersion handling: Initial analyses to determine methods suitability showed that the variance (103) far exceeded the mean (53.9), indicating overdispersion. This makes it more suitable for modelling with a Negative Binomial than Poisson model as the Poisson model assumes that the mean and variance are the same.

It was also shown in Chapter 4 that the dataset failed the tests for suitability for modelling with a Gaussian model.

For each questionnaire or measure, a separate negative binomial model was fitted using the following formulation:

Probability Distribution Function:

$$\overline{Y_i} \sim \mathcal{NB}(\mu_i, \theta)$$

Log-linear model:

$$\log(\mu_i) = \beta_0 + \beta_1 X_i$$

Equation Set 8

Where:

- $\bar{Y}_i$ = Number of re-lookings for participant i

- μ_i = Expected count for participant i
- θ = Dispersion parameter
- β_0= Intercept of model
- β_1 = Effect of the questionnaire score
- X_i = Questionnaire score for participant i

The symbol *NB* is commonly used in scientific literature to denote the Negative Binomial distribution (e.g Stoklosa et al., 2022; Yirga et al., 2020).

If a significant effect of questionnaire score was found in this initial model (i.e. $p < .05$), the model was refitted with Age, Sex, and Socioeconomic Status (SES) as covariates:

Probability Distribution Function:

$$\overline{Y_i} \sim \mathcal{NB}(\mu_i, \theta)$$

Log-linear model:

$$\log(\mu_i) = \beta_0 + \beta_1 X_i + \beta_2 \mathrm{Age}_i + \beta_3 \mathrm{Sex}_i + \beta_4 \mathrm{SES}_i$$

Equation Set 9

Where:

- $\bar{Y}_i$ = Number of re-lookings for participant i
- μ_i = Expected count for participant i
- θ = Dispersion parameter
- β_0= Intercept of model
- β_1 = Effect of the questionnaire score
- X_i = Questionnaire score for participant i
- Age_i = Age of participant i
- B_2 = Effect of age
- Sex_i = Sex of participant i
- B_3 = Effect of sex

- SES_i = Subjective SES of participant i
- B_4 = Effect of subjective SES
- μ_i = Random intercept for participant i

This additional step was included to assess the robustness of the initial findings. Age, sex and SES were included to control or potential confounding findings given their established associations with various psychological outcomes including worry (Topper et al., 2014; van der Heiden et al., 2009). This is especially since there were found to be demographic differences between the high and low worry group in this particular study. Including these covariates is crucial to ensure that any observed questionnaire effects were not better explained by demographic patterns.

All numerical results are reported to 3 s.f. unless they are p-values less than 0.001, in which case they are reported as $p < .001$, as per APA Guidelines.

5.2.4. Correcting for Multiple Comparisons

The following decisions about correcting for multiple corrections were made to balance the risk of Type I and Type II errors:

1. No correction for Pre-Experiment Hypotheses (except for in extensive comparisons)

Multiple comparison corrections were not applied for most cases where there were clear pre-experiment hypotheses – e.g. in this chapter, the effect of power manipulation was hypothesized about prior to data collection. This aligns with the argument that a priori hypotheses grounded in prior evidence or theory have a lower risk of producing spurious findings. In fact, routine correcting carries the risk of increasing Type II errors, i.e. missing a true effect, and is therefore advised against (Perneger, 1998; Rothman, 1990).

In this case, the Power Manipulation Writing Task and Trait State of Power Questionnaire had been previously validated for more than a decade (Anderson & Galinsky, 2006; Gruenfeld et al., 2008; Schaerer et al., 2018), therefore well-grounded hypotheses could be crafted about the results prior to data collection. (What these specific hypotheses are will be discussed later on in this methods section when question-specific methods are addressed.) Therefore, correcting for multiple corrections was not done for these results.

However, when a large number of comparisons were made – such as when involving all questionnaires – corrections for multiple comparisons were still applied. Specifically, they were applied when the effect of each questionnaire on number of re-lookings was analysed, as the effects of more than 10 questionnaires were analysed. Furthermore, although pre-experiment hypotheses were made, the novelty of the paradigm makes hypotheses less well-grounded. Therefore, to mitigate the risk of Type I errors (false positives), correcting for multiple comparisons was conducted here.

2. Correction for Exploratory Analyses

Multiple comparison corrections were applied for all exploratory analyses. This includes cases where the selection of which fixed effects to include in a multifactorial model was based on their observed significance in prior analyses rather than theoretical pre-specification. This is because exploratory analyses inherently involve more risk of spurious findings and Type I errors (Westfall & Young, 1993). This was done with the Holm-Bonferroni procedure (Holm, 1979) (the procedure will be described in detail below).

3. No Correction Necessary for Robustness Analyses

To assess the robustness of the findings above additional models were estimated with age, sex and SES. As this does not introduce new hypotheses but simply tests the stability and reliability of an already evaluated effect, no new corrections are needed; the Holm-Bonferroni procedure has also already accounted for family-wise error rate. In fact, robustness analyses have been specified as a case where multiple comparisons corrections are unnecessary (X. Cui et al., 2021). Instead, robustness analyses are evaluated not just by maintained significance (at $p < .05$), but also consistent effect direction and effect size compared to the original finding. These values (p-value, effect size and effect direction before and after robustness analysis) will therefore be reported.

<u>Procedure</u>

The Holm-Bonferroni procedure (Holm, 1979) was used to correct for multiple comparisons. It is the most widely recommended method of reducing Type I error rates, being as effective as the classical Bonferroni procedure in correcting error rates while being more flexible and powerful (Giacalone et al., 2018; Rubin, 2016). It has been noted to be particularly suitable for analysing neuropsychological data as they often include interrelated outcome measures (e.g. BDI and STAI in this dataset), such that the universal null hypothesis assumption is much less valid (Eichstaedt et al., 2013). The procedure is as follows:

Box 5.

The Holm-Bonferroni procedure.

1. All *p*-values are sorted from smallest to largest. Let's indicate with K the number of the *p*-values;
2. If the first *p*-value is greater than or equal to α/K, the procedure is stopped and no p-values are significant. Otherwise, we go on.
3. The first *p*-value is declared significant and afterwards the second p-value is compared to α/(K-1). If the second *p*-value is greater than or equal to α/(K-1), the procedure is stopped and no further p-values are significant. Otherwise, we go on until the *i*-th ordered *p*-value is such that:

$$p_{(i)} \geq \alpha /(K-i + 1)$$

(Copied from Rubin 2016)

Pre-Experiment Hypotheses:

1. High power manipulation increases SOP score and low power manipulation decreases SOP score.
2. High power manipulation decreases number of re-lookings and low power manipulation increases number of re-lookings.
3. High power manipulation decreases mean trial-to-trial worry levels and low power manipulation increases mean trial-to-trial worry levels.

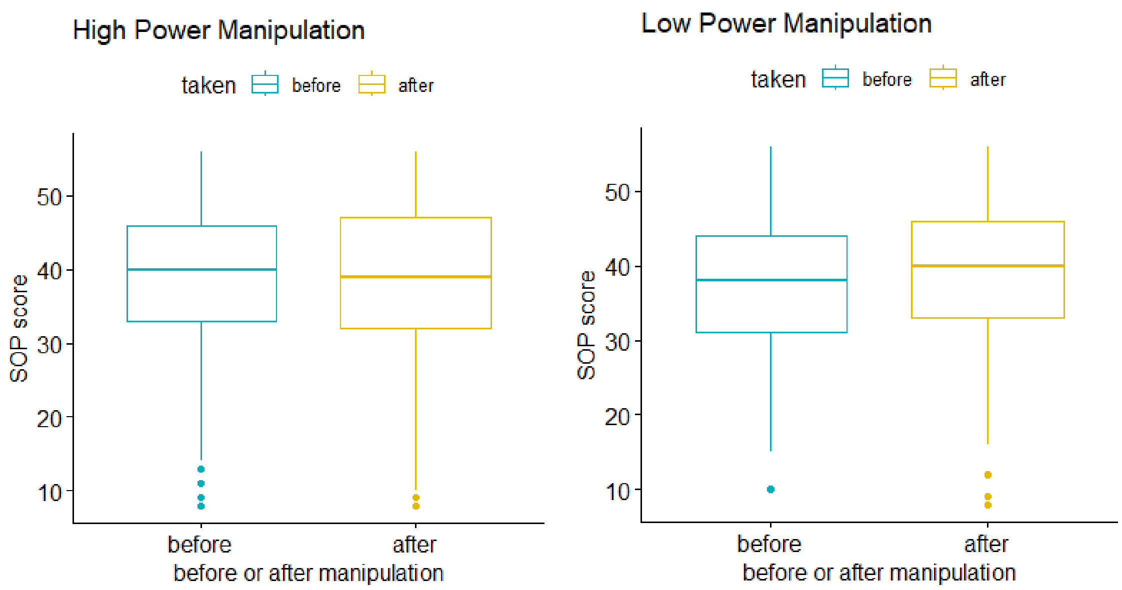
All hypotheses refer to the overall group (with both high and low worry participants).

Contrary to Hypothesis 1, high power manipulation had no significant effect on SOP scores (p = .302); this was the case in both high and low worriers (p = .910 and p = .197). Similarly, low power manipulation in fact significantly increased, rather than decreased, SOP scores (p = .0254). This was also seen in the high worry group (p = .0350), while low power manipulation had no significant effect on the low worry group (p = .705).

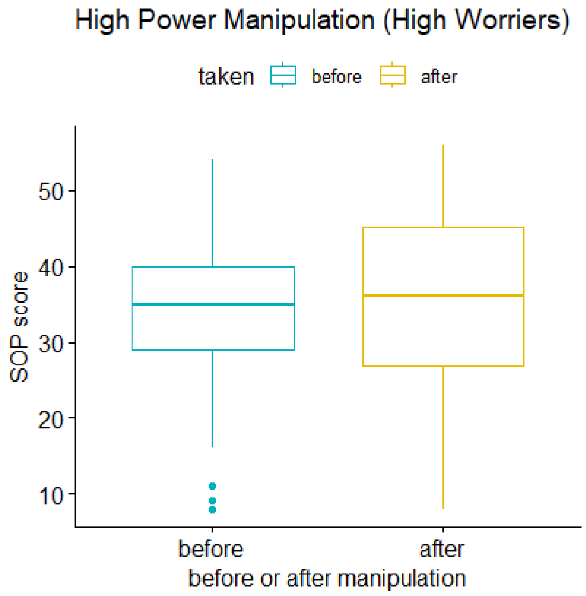
Figure 35.

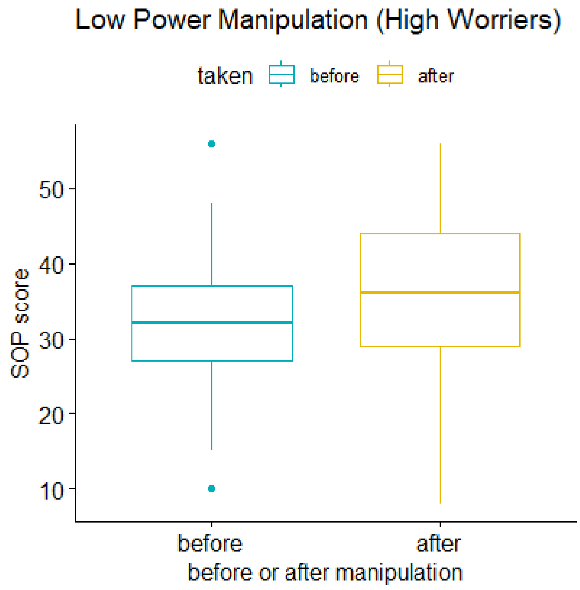
Main effect of power manipulation on Sense of Power (SOP) scores.

a) All participants

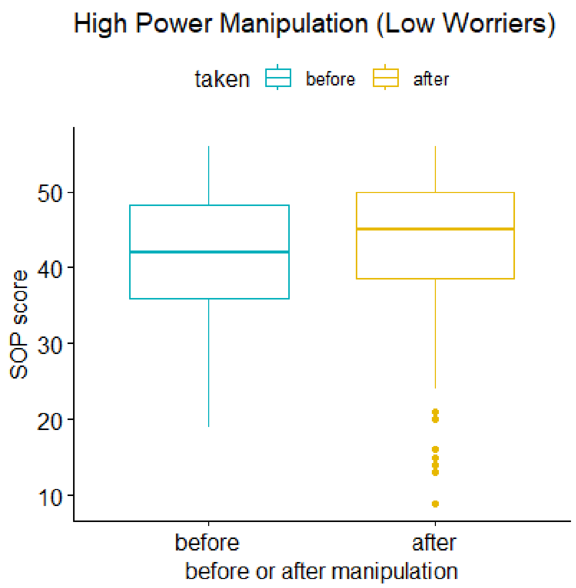


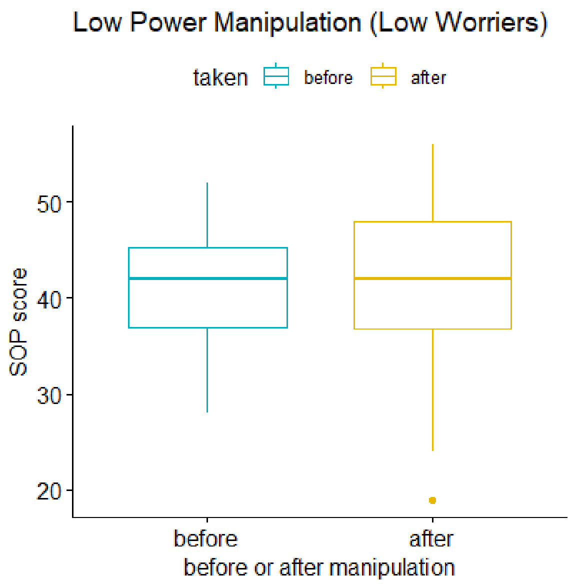
b) High worriers





c) Low worriers

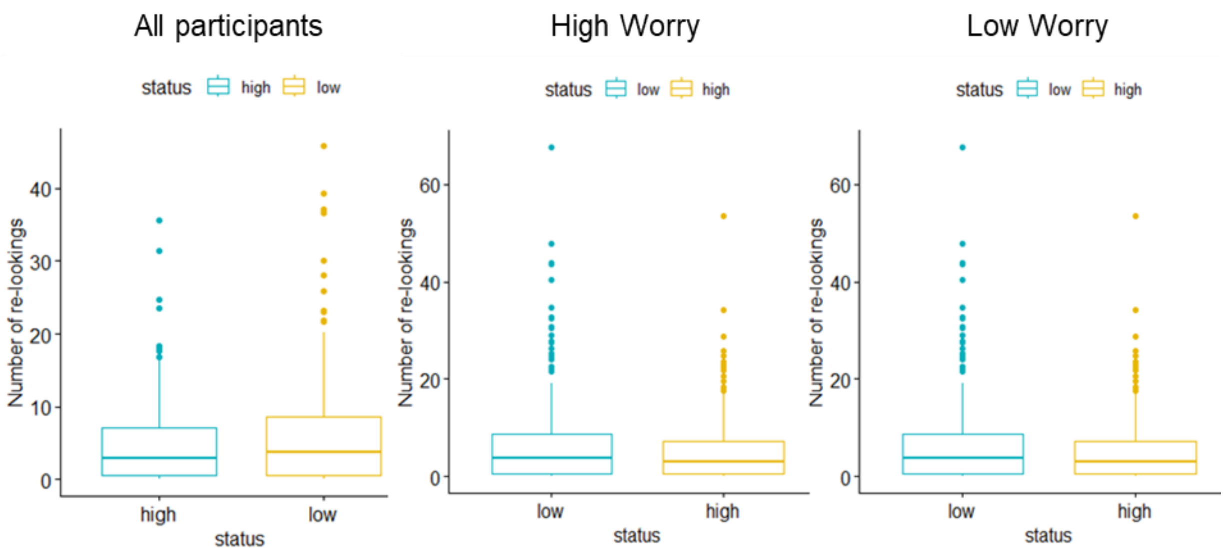




Next, no evidence was found for Hypothesis 2, as power manipulation did not have a significant effect on re-lookings in either the overall (p = .301), high worry (p = .425) or low worry (p = .394) group.

Figure 36.

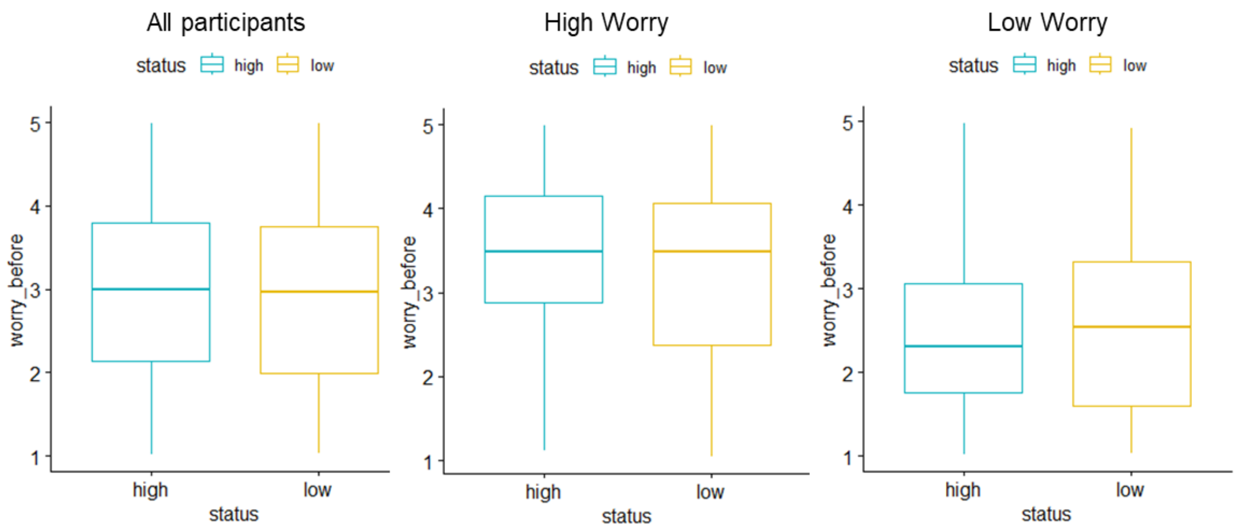
Main effect of power manipulation on re-lookings.



Lastly, no evidence was found for Hypothesis 3, as status manipulation had no significant effect on mean number of re-lookings per participant in the overall (p = .617), high worry (p = .444) or low worry (p = .801) group.

Figure 37.

Main effect of power manipulation on trial-to-trial worry.



5.3.2. Univariate Regressions

Table 58.

Results of univariate regression models.

Question/questionnaire	p-value	z-value	scaled coefficient	original coefficient
a) How preoccupied were you by the chance of a scream?	.00104	3.23	0.226	0.165
b) BDI	.0343	2.12	0.147	0.0156
c) STAI	.0247	2.25	0.157	0.00480
d) STAI – State	.0274	2.21	0.154	0.00940
e) STAI – Trait	.0258	2.23	0.156	0.00935
f) Adult MFQ	.00541	2.78	0.191	0.0295
g) Multidimensional Perfectionism Scale (MPS) – overall	< .001	4.25	0.294	0.0132
h) MPS – concern over mistakes and doubts about actions	< .001	3.69	0.256	0.0275
i) MPS – excessive concern with parents' expectations and evaluation	< .001	3.99	0.278	0.04225
j) MPS – excessively high personal standards	< .001	3.92	0.272	0.0523
k) MPS – concern with precision, order and organisation	.00562	2.77	0.264	0.0419
l) Duttweiler Internal Control Index	.212	-1.25	-0.088	- 0.00539
m) Rosenberg Self-Esteem Scale	.379	-0.879	-0.0621	-0.0291
n) McArthur subjective socioeconomic scale	.180	-1.34	-0.0948	-0.0604

Note. For each regression model, the coefficient of the fixed effect of the questionnaire being analysed (β1 in Equation Set 8) is reported in both original and normalised form, along with the p-value and z-value of the effect. Regression coefficients were normalised by multiplying the original coefficient by the standard deviation of the question or questionnaire's responses.

Table 59.

Assessing significance of questionnaire effect using the Holm-Bonferroni procedure.

Corrected Significance Threshold	p-value	Questionnaire
.00357	< .001 *	Multidimensional Perfectionism Scale (MPS) – overall
.00385	< .001 *	MPS – concern over mistakes and doubts about actions
.00417	< .001 *	MPS – excessive concern with parents' expectations and evaluation
.004545	< .001 *	MPS – excessively high personal standards
.00500	.00104 *	How preoccupied were you by the chance of a scream?
.00556	.00541 *	Adult MFQ
.00625	.00562 *	MPS – concern with precision, order and organisation
.00714	.0247	STAI
.00833	.0258	STAI - Trait
.0100	.0274	STAI - State
.0125	.0343	BDI
.0167	.180	McArthur subjective socioeconomic scale
.0250	.212	Duttweiler Internal Control Index
.0500	.379	Rosenberg Self-Esteem Scale

Note. Significant effects are indicated with an asterisk (*).

<u>Robustness checks for effects found to be significant</u>

Table 60.

Results of regression model for the effect of MPS scores on re-lookings with age, sex and SES as covariates.

Fixed Effect	Coefficient	Std. Error	z value	p-value
MPS	0.0113	0.00315	3.60	< .001
Age	-0.0117	0.00579	-2.02	.0433

Sex	0.0433	0.139	2.57	.0102
SES	-0.0722	0.0436	-1.66	.0979

Table 61.

Results of regression model for the effect of the scores on the 'concern over mistakes and doubts about actions' subscale of the MPS (MPS_m) on re-lookings with age, sex and SES as covariates.

Fixed Effect	Coefficient	Std. Error	z value	p-value
MPS_m	0.0232	0.00753	3.08	.00207
Age	-0.0130	0.00581	-2.25	.0247
Sex	0.341	0.139	2.45	.0141
SES	-0.0736	0.0437	-1.68	.0921

Table 62.

Results of regression model for the effect of the scores on the 'excessively high personal standards' subscale of the MPS (MPS_s) on re-lookings with age, sex and SES as covariates.

Fixed Effect	Value	Std. Error	z value	p-value
MPS_s	0.0365	0.0106	3.45	< .001
Age	-0.0134	0.00575	-2.34	.0194
Sex	0.360	0.139	2.59	.00969

SES	-0.0688	0.0438	-1.57	.116

Table 63.

Results of regression model for the effect of the scores on the 'excessive concern with parents' expectations and evaluation' subscale of the MPS (MPS_e) on re-lookings with age, sex and SES as covariates.

Fixed Effect	Value	Std. Error	z value	p-value
MPS_p	0.0436	0.0135	3.23	.00126
Age	-0.0116	0.00580	-2.00	.0452
Sex	0.370	0.139	2.66	.00773
SES	-0.0658	0.0438	-1.50	.133

Table 64.

Results of regression model for the effect of the answer to 'how preoccupied were you by the chance of a scream?' (PS) on re-lookings, with age, sex and SES as covariates.

Fixed Effect	Value	Std. Error	z value	p-value
PS	0.155	0.0522	2.98	.00293
Age	-0.0115	0.00576	-2.00	.0460
Sex	0.444	0.141	3.14	.00168
SES	-0.0634	0.0439	-1.45	.148

Table 65.

Results of regression model for the effect of the Mood and Feelings Questionnaire (MFQ) score on re-lookings, with age, sex and SES as covariates.

Fixed Effect	Value	Std. Error	z value	p-value
MFQ	0.0304	0.0118	2.58	.00995
Age	-0.0141	0.00577	-2.44	.0148
Sex	0.446	0.143	3.11	.00187
SES	-0.0372	0.0473	-0.787	.432

Table 66.

Results of regression model for the effect of the scores on the 'concern with precision, order and organisation' subscale of the MPS (MPS_o) on re-lookings with age, sex and SES as covariates.

Fixed Effect	Value	Std. Error	z value	p-value
MPS_o	0.0358	0.0151	2.37	.0180
Age	-0.0139	0.00575	-2.41	.0158
Sex	0.374	0.140	2.668	.00763
SES	-0.0770	0.0441	-1.75	.0806

When robustness analyses were conducted (Table 67 below), results remained significant and in the same direction. Most coefficients show small-to-moderate changes (<30%) apart from the extent of preoccupation with the chance of a scream (PS), which showed a 68% decrease.

Table 67.

Summary of results of robustness analyses.

Fixed Effect	p-value		Corrected Coefficient		% Change in Coefficient
	original	robustness analysis	original	robustness analysis	
MPS	< .001	< .001	0.0132	0.0113	-14%
MPS_s	< .001	< .001	0.0523	0.0365	-30%
MPS_m	< .001	.00207	0.0275	0.0232	-16%
MPS_p	< .001	.00126	0.0423	0.0436	+3%
MPS_o	.00562	.0180	0.0419	0.0358	-15%
PS	.00104	.00293	0.165	0.0522	-68%
MFQ	.00541	.00995	0.0295	0.0304	+3%

5.3.3. Results of Multiple Regression (Additional Analysis)

Multivariate models offer a comprehensive framework for exploring multiple variables at once, providing a more nuanced understanding of their relationship with the data. This is particularly pertinent in this study where re-lookings are influenced by a multitude of factors, including both trial-level and participant-level factors, as well as psychological and environmental factors.

However, not all variables and questionnaires can be included, as doing so can risk overfitting, especially when the number of parameters exceeds the amount and nature of data available to constrain it. As such, the following limited number of factors were selected for inclusion in a multivariate analysis based on both theoretical relevance and prior analyses, including the univariate analysis above. Participant was included as a random effect. ‘Sex = Male’ and ‘f = 1 to 40’ were coded as 0; ‘Sex = Female’ and ‘f = 1 to 5’ were coded as 1.

Table 68.

Factors included in multiple regression, with reasoning.

<table>
<tr><td>Factor</td><td colspan="2">Reasoning</td></tr>
<tr><td>W</td><td colspan="2">Trial-to-trial worry before re-lookings predicting number of re-lookings is one of the central hypotheses of this thesis, and it was demonstrated in Chapter 4 that it does indeed significantly predict re-lookings.</td></tr>
<tr><td>f</td><td colspan="2">Trial-to-trial Information Ratio was the only main effect which had a significant effect on number of re-lookings, and it did so with a large effect size. Information ratio is also central to hypotheses made (see Chapter 4) and could interact with psychopathology. As such, it is an important variable and its relationship with the data should be examined.</td></tr>
<tr><td>MFQ</td><td rowspan="3">One questionnaire each from the categories of depression symptoms, anxiety symptoms, and perfectionism was included, to cover all symptom categories.</td><td>The effect of MFQ score was significant after correcting for multiple comparisons, unlike the BDI score.</td></tr>
<tr><td>STAI</td><td>STAI was the only anxiety questionnaire included.</td></tr>
<tr><td>MPS</td><td>While 3 subscales of the MPS also had significance effects after correction at $p < .001$, the overall MPS score had the highest scaled coefficient magnitude.</td></tr>
<tr><td>Age</td><td colspan="2" rowspan="3">Included as demographic covariates</td></tr>
<tr><td>Sex</td></tr>
<tr><td>SES</td></tr>
</table>

Note. This discussion above, as well as the multivariate model below, is here instead of in the main methods section due to needing to follow from the results of the univariate regressions (as presented above) to justify variable selection. In other words, 'what model should be used' is part of the results of this study.

Therefore, the following multivariate model was fitted to the data.

Probability Distribution Function:

$$Y_{ij} \sim \mathrm{NB}(\mu_{ij}, \theta)$$

Log-linear model:

$$\log(\mu_{ij}) = \beta_0 + \beta_1 W_{ij} + \beta_2 f_{ij} + \beta_3 \mathrm{MFQ}_i + \beta_4 \mathrm{STAI}_i + \beta_5 \mathrm{MPS}_i + \beta_6 \mathrm{Age}_i + \beta_7 \mathrm{Sex}_i + \beta_8 \mathrm{SES}_i + u_i$$

Equation Set 10

Where:

- Y_{ij} = Number of re-lookings for participant i at timestep j
- μ_{ij} = Expected count for participant i at timestep j
- θ = Dispersion parameter
- β_0= Intercept of model
- W_{ij} = Self-reported worry level for participant i at timestep j
- β_1 = Effect of self-reported worry level for participant i at timestep j
- f_{ij} = Information ratio presented to participant i at timestep j ('1 to 5' coded as 0 and '1 to 40' coded as 1)
- β_2 = Effect of information ratio presented to participant i at timestep j
- MFQ_i = Score of participant i on the MFQ
- β_3 = Effect of MFQ score
- $STAI_i$ = Score of participant i on the STAI
- β_4 = Effect of STAI score
- MPS_i = Score of participant i on the MPS
- β_5 = Effect of MPS score
- Age_i = Age of participant i
- B_6 = Effect of age

- Sex_i = Sex of participant i
- B_7 = Effect of sex
- SES_i = Subjective SES of participant i
- B_8 = Effect of subjective SES
- μ_i = Random intercept for participant i

Table 69.

Multiple Regression results (no interaction terms).

Fixed Effect	Coefficient	Std. Error	z value	p-value
W	0.108	0.0143	7.51	< .001
f (1 to 40)	0.0696	0.0194	3.58	< .001
MFQ	0.0142	0.0333	0.425	.671
STAI	0.0031	0.00700	0.446	.656
MPS	0.00980	0.00560	1.74	.0818
Age	-0.0205	0.00910	-2.25	.0247
Sex (Male)	0.316	0.230	1.38	.169
SES	-0.0115	0.0766	-0.150	.881

Following this, another model was run, similar to the previous one except including an interaction term of the two experimental factors which were significant, f_{it} and W_{it}:

Probability Distribution Function:

$$Y_{ij} \sim \mathrm{NB}(\mu_{ij}, \theta)$$

Log-linear model:

$$\log(\mu_{ij}) = \beta_0 + \beta_{1ij} + \beta_2 f_{ij} + \beta_3 \mathbf{MFQ}_i + \beta_4 \mathbf{STAI}_i + \beta_5 \mathbf{MPS}_i + \beta_6 \mathbf{Age}_i + \beta_7 \mathbf{Sex}_i + \beta_8 \mathbf{SES}_i + \beta_9 (W_{ij} \cdot f_{ij}) + u_i$$

Equation Set 11

Where:

- Y_{ij} = Number of re-lookings for participant i at timestep j
- μ_{ij} = Expected count for participant i at timestep j
- θ = Dispersion parameter
- β_0= Intercept of model
- W_{ij} = Self-reported worry level for participant i at timestep j
- β_1 = Effect of self-reported worry level for participant i at timestep j
- f_{ij} = Information ratio presented to participant i at timestep j
- β_2 = Effect of information ratio presented to participant i at timestep j
- MFQ_i = Score of participant i on the MFQ
- β_3 = Effect of MFQ score
- $STAI_i$ = Score of participant i on the STAI
- β_4 = Effect of STAI score
- MPS_i = Score of participant i on the MPS
- β_5 = Effect of MPS score
- Age_i = Age of participant i
- β_6 = Effect of age
- Sex_i = Sex of participant i
- β_7 = Effect of sex
- SES_i = Subjective SES of participant i
- β_8 = Effect of subjective SES
- β_9 = Effect of interaction term of W_{ij} and f_{ij}
- μ_i = Random intercept for participant i

Table 70.

Multiple Regression results with interaction term.

Fixed Effect	Coefficient	Std. Error	z value	p-value
W	0.144	0.0162	8.88	< .001
f (1 to 40)	-0.148	0.0496	-2.97	.00294
W × f	0.0705	0.0148	4.76	< .001
MFQ	0.0275	0.0334	0.826	.409
STAI	0.00160	0.00700	0.226	.822
MPS	0.0108	0.00560	1.92	.0554
Age	-0.0176	0.00910	-1.93	.0540
Sex (Male)	0.203	0.230	0.882	.378
SES	-0.00590	0.0767	-0.0766	.939

5.4. Discussion

To recap, the aim of this chapter is to understand how re-lookings are linked to between-subject factors such as perception of social status and individual dispositions such as perfectionism. To this end, the key findings will now be restated.

First, status manipulation did not yield the expected effects, having no significant effect on sense of power (SOP) scores, worry levels, or re-lookings, except for low status manipulation unexpectedly increasing sense of power in the high worry group.

Second, in univariate analyses, the following questionnaires were found to significantly and positively predict re-lookings: the Multidimensional Perfectionism Scale (MPS), all four of its subscales, the Mood and Feelings Questionnaire (MFQ), and the paradigm-specific question 'how preoccupied were you by the chance of a scream' (PS). All effects remained significant after robustness analyses, with most coefficients showing small-to-moderate changes apart from PS which showed a 68% decrease.

Lastly, in a multiple regression involving key within- and between- participant factors, what emerged as significant predictors of re-lookings were trial-to-trial self-reported worry (W), information ratio (f) and their interaction term (W × f). Notably, MPS and MFQ were significant in univariate analyses, but were no longer significant in this multiple regression.

Status Manipulation

There was no significant effect of status manipulation on number of re-lookings or state worry in any group (Figure 36 and 37). To check that the power manipulation worked, SOP scores before and after manipulation were compared. High power manipulation had no significant effect in all groups. However, unexpectedly, the low power manipulation had a significant *positive* effect in the overall ($p = .0254$) and high worry ($p = .0350$) group, meaning that the manipulation intended to induce feelings of low power in fact induced feelings of high power — and this was especially so in the high worry group.

First, the unclear effect of the power manipulation explains the lack of effect on re-lookings and state worry. Second, the finding that a power manipulation which asks one to recall and describe being in a subordinate role causes high worriers to feel *more* powerful bears further exploration.

A possibility is that being the subordinate can be surprisingly positive for high worriers. Given that the SOP Questionnaire is specific to each person, they may have had positive professional relationships with their superior, such that statements such as "I can get this person to listen to what they say" are true. High worriers may be more likely to voice concerns in the first place, such that they have positive experiences of being supported, reassured or advocated for to draw from. It also challenges the assumption that having power in the workplace leads one to *feel* empowered; high worriers may counterintuitively feel more empowered in subordinate roles which may have fewer challenges or responsibilities. Perhaps, like self-esteem (Low et al., 2022), it is not the objective level of power that matters, but a relative one, that determines *feelings* of power; high worriers be more comfortable in a role with a smaller range or frequency of possible challenges, or an environment where they have more control even if they are objectively less powerful.

This is supported by the observation that in the high-power manipulation, there is no overall increase in sense of power in either group. Furthermore, the variance of the SOP scores is higher in the high worry group: a Kolmogorov-Smirnov test, which tests if two distributions are equal, yielded a p-value of .0351. Even in the low worry group, there is a group of people whose SOP scores were very low after the high-power manipulation. This suggests that the experiences people wrote about are diverse, and that in some people, being asked to describe an experience when they were the superior counterintuitively causes them to feel less powerful. This may be because of negative leadership experiences; one may have difficulty getting their subordinate to heed their instructions, and the contrast expecting to be listened to but not receiving this treatment may produce feelings of powerlessness. The fact that the effect of the high power and low power manipulations did not work as expected suggests that the experiences written about were more egalitarian than expected; this may have occurred in the context of broader trends over the years such as abuse of power being more frowned upon and more people believing that good leadership does not make someone feel degraded or powerless.

Overall, this suggests that power manipulation had a complex relationship on sense of power and consequently worry, and someone with low power cannot be simply assumed to have more need for worry.

Regression Models – Univariate Analyses

After correcting for multiple comparisons, the effects of the MPS, all 4 of its subscales, ‘how preoccupied were you by the chance of a scream?’ and the MFQ were significant. The individual results will now be discussed below.

How preoccupied were you by the chance of a scream?

The significant positive effect of scream preoccupation on number of re-lookings (p = .00104) suggests that the aversive stimuli was effective in motivating people. Notably, as this question has a different function from the standardised questionnaires, it could be argued to be in a different family of tests, and that the significance threshold is overly conservative; however, it was included for more rigour.

MFQ, STAI and BDI

MFQ score had a significant positive effect on re-lookings (p = .00541). STAI (both state and trait) and BDI positively predicted re-lookings but not significantly after correcting for multiple comparisons. The direction of effect is as expected. Firstly, worry is a key component of anxiety. Secondly, worry predicts both anxiety and depressive symptoms (Spinhoven et al., 2017; Taylor & Snyder, 2021; Yilmaz, 2015; Young & Dietrich, 2015); although some studies show an association only with anxiety but not depression symptoms, this may be only so in children and adolescents (Calmes & Roberts, 2007; Verstraeten et al., 2011). Furthermore, for both anxiety and depression symptoms, worry can be both caused by and cause these symptoms, suggesting a vicious cycle rather than a simple cause and effect. While conclusions may not be as conclusively drawn compared to if the effects of all depression and anxiety questionnaires were significant, the direction of effects does suggest that re-lookings do reflect a psychological process which is increased in anxiety and depression.

MPS and its subscales

MPS scores and scores on all 4 of its subscales had a significant positive effect on re-lookings (p = .00562 for the ‘concern with precision, order and organisation’ subscale, and $p < .001$ for the overall questionnaire and all other subscales). Perfectionism as a vulnerability factor for worry has been discussed in literature; for instance, Flett et al (2016) describes “perseverating perfectionists” as people who worry obsessively due to chronic self-doubt and self-uncertainty (Flett et al., 2016). Indeed, a recent meta-analysis showed that worry, alongside rumination, is what mediates the relationship between perfectionism and distress (Xie et al., 2019). These findings contribute to literature about which dimensions of perfectionism contribute to worry, as past studies differ in which dimensions were found to be associated with worry (Handley et al., 2014; Stöber & Joormann, 2001).

Duttweiler Internal Control Index and Rosenberg Self-Esteem Scale

The fixed effects of both questionnaires were not significant. This may be due to several reasons. As mentioned previously, there is evidence that locus of control is inversely correlated with anxiety (Hoehn-Saric & McLeod, 1985), and low self-esteem predicts vulnerability to mood and anxiety disorders (Sowislo & Orth, 2013). Therefore, the expected direction of effects is that there would be an inverse relationship between these questionnaires and re-lookings. However, while the coefficients were indeed negative, the lack of significance of effects suggests that there might be another factor at play, perhaps that of self-efficacy promoting that of some level of problem-solving i.e. adaptive worry.

McArthur subjective socioeconomic scale

There was no significant effect of subjective socioeconomic status on level of worry. This is despite lower socioeconomic status being associated with higher anxiety and depression (Galvan et al., 2023; Yu & Williams, 1999). However, SES should still be included in analyses as a factor to control for.

Results of Multiple Regression

1. Further support for prior findings

The additive model, which was presented first, assumed that worry (W) and information ratio (f) are independent variables with additive effects. In this model, the positive and significant effect of W (coefficient: 0.108, $p < .001$) indicates that overall, after all other factors in the model have been controlled for, worry increases re-lookings. Similarly, the positive and significant effect of f (coefficient: 0.0696, $p < .001$) indicates that the ‘1 to 40’ information ratio (low success chance) causes more re-lookings overall in the experiment. Both of these results have been discussed in Chapter 4, though this provides further certainty that the effects are not due to other factors such as demographics.

2. Findings about nature of trial-to-trial worry

The interaction term $W \times f$ being significant ($p < .001$) indicates that an interaction term is required to best explain data, and therefore that the interaction model is the better model for data interpretation compared to the purely additive model. Nevertheless, a compare and contrast of both models can reveal insights, and this will be done now.

First, W's significance across models ($p < .001$ for both) suggests that its effect is resilient, underscoring the theoretical importance of worry to re-lookings and providing further support that re-lookings are an external proxy for momentary worry. Second, the interaction between W and information ratio being significant and positive ($p < .001$, coefficient: 0.0705) suggests that the effect of worry is amplified when the chance of success is lower. This suggests that high worriers worry more in response to low chances of success, possibly creating a vicious cycle where lack of success causes continued worry-like behaviour instead of termination of a non-helpful process.

Third, the main effect of f being negative in the interaction model (-0.148, $p = .00294$) despite being positive in the additive model is intriguing, as it suggests that behaviour differs at low and high levels of worry. As main effects in interaction models represent the effect when the interacting variable is at baseline, this indicates that when W is 0 – i.e. no state worry – low success chance decreases re-lookings. However, as W increases, low success chance becomes increasingly associated with re-looking behaviour. This suggests that the effect of information ratio is moderated by worry.

Together, this suggests that re-lookings are consistently driven by state worry. Then, on top of this, low perceived chance of success increases or decreases re-lookings depending on state worry; if state worry is low, it decreases re-lookings, and if state worry is high, it increases re-lookings. This provides a possible explanation for the mechanism behind high worry causing maladaptive behaviour, in that high worry increases the inclination to worry particularly when it will be ineffectual.

3. In-task variables fully mediate between-participant variables

Looking at the results of the interaction model, a key finding emerges: the in-task variables of trial-to-trial self-reported worry (W), information ratio (f) and their interaction term ($W \times f$) fully mediate the effect of the self-report questionnaires.

Specifically, the between-participant fixed effects that were previously significant in univariate analyses, namely MPS and MFQ ($p < .001$ and $p = .00541$ in univariate analyses respectively), became non-significant in this model ($p = .0554$ and $p = .409$ respectively). Conversely, the in-task variables demonstrated significant effects: worry

($p < .001$), information ratio ($p = .00294$), and their interaction ($p < .001$). This aligns with perfectionism and depressive symptoms having strong links with worry (Handley et al., 2014; Stöber & Joormann, 2001; Yilmaz, 2015; Young & Dietrich, 2015), such that it is plausible that trial-specific worry ratings capture their effect entirely.

The fact that trial-specific factors completely mediate between-subject measures in capturing re-lookings has two key implications. First, this also suggests that between-subject factors such as perfectionism might act on worry via the mechanisms captured in this paradigm. In other words, perfectionism and depressive symptoms may cause worry by increasing sampling. Second, this suggests re-lookings successfully capture moment-to-moment fluctuations of worry, especially in response to the environment. This is crucial to capturing worry, as while the *tendency* to worry is a trait, the actual *phenomenon* of worry is by nature changeable, not constant. This means that moment-to-moment re-lookings successfully capture worry in a measurable way, enabling insight into the factors that increase it.

5.5. Conclusion

The key finding from this chapter is that while perfectionism (MPS) and depressive symptoms (MFQ) initially predicted re-lookings in univariate analyses, these effects were fully mediated by dynamic in-task variables: trial-to-trial worry (W), information ratio (f), and their interaction ($W \times f$). This highlights the paradigm's capacity to capture moment-to-moment fluctuations in worry as participants respond to environmental changes (e.g., shifting success probabilities). It also suggests that person-specific factors such as perfectionism may cause worry by increasing the tendency to sample. Other between-subject factors or manipulations did not have a significant effect on re-lookings, and possible reasons were discussed in this chapter. The importance of worry was also reinforced by its robustness in predicting re-lookings, solidifying the function of re-lookings as an external proxy for worry. In sum, this chapter has demonstrated that this experimental paradigm can provide a measure that sensitively and successfully captures the phenomenon of worry, eventually allowing for an understanding of the factors that underwrite worry and cause it to persist.

6. Modelling Worry

This chapter is about the construction and validation of a computational model aimed at capturing the processes behind worry. First, the model's key components will be detailed, alongside their mathematical formalisation. This includes modelling alternatives; these will be explained and discussed. Second, analyses of how model behaviour varies with parameter variation will be presented. Third, and last, examples of data generated by the model will be provided, illustrating its similarity to real data and therefore potential utility.

6.1. Background

Given that an experimental paradigm — which can capture worry — has been established, and data has been collected, models can be crafted to explain the mechanisms that mediate worry-like behaviour. As explained in the introduction, mathematical modelling is uniquely suitable for precise (i.e., formal) capturing and testing of hypotheses: in this case, testing hypotheses about the mechanisms of worry. To this end, a mechanistic (i.e., generative) model can be built which captures the following key hypothesis about worry, discussed in the introduction:

Worry is characterised by:

1. A disposition to problem solve
2. Information seeking, or searching, in one's head
3. Choosing to keep searching, i.e., decision making
4. In order to avoid an aversive outcome.

The systematic scoping review (Chapter 2) highlighted the suitability of evidence accumulation models to explain worry and identified key elements which could be included in a model: metacognitions, uncertainty, and optimum stopping. What kind of evidence accumulation model should be used, then? First, it must model discrete timesteps, as the paradigm consists of discrete timepoints and decisions, while also being able to output continuous worry ratings. Second, it should accumulate evidence, i.e. the facial expression stimuli presented, in order for the participant to decide how far to search, their final decision, and their feelings and beliefs along the way.

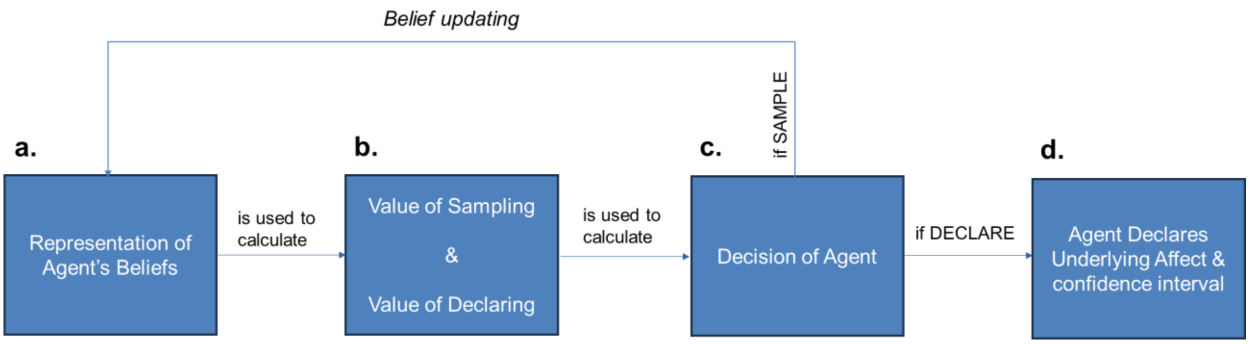
Ideally, 4 different kinds of data need to be explained by a model of the task we have established: the number of re-lookings, their reported uncertainty level, the emotion read they provide, as well as the reported worry level. This chapter will focus on the first 3 to first build a strong basis for capturing behaviour itself, such that in the future this foundational model can be built upon to generate reported worry, which is less directly reflective of the experimental stimuli.

To this end, an evidence accumulation model, in the reinforcement learning framework was considered. It captures worry as accumulating evidence about a situation — in the context of this experimental paradigm, another person's mood — in order to infer the underlying true state accurately. Hypotheses based on the model will be discussed at the end of the detailed model overview.

6.2. Overview of Model

Figure 38.

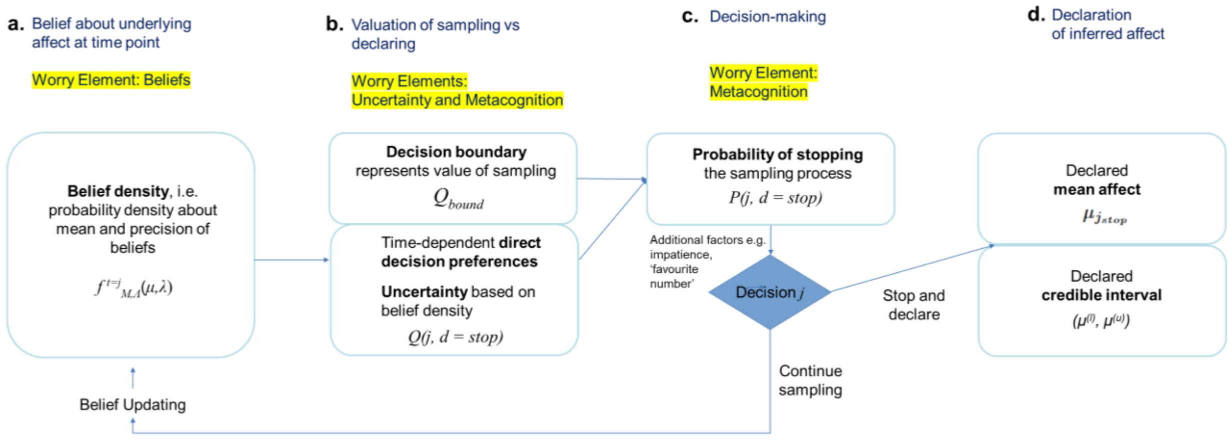
Descriptive, non-mathematical overview of model.



Note. When each corresponding part of the model is being discussed in this chapter, it will be indicated with a red rectangle.

Figure 39.

Mathematical overview of model.



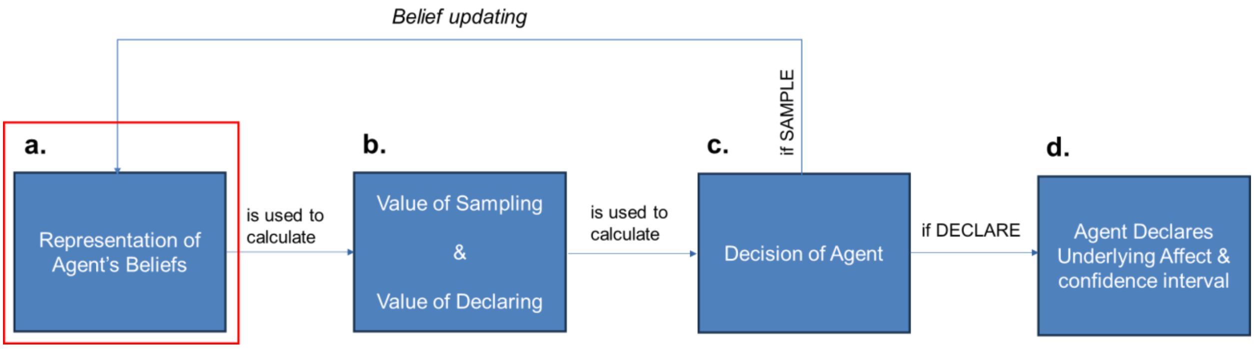
Note. The labels of a-d here correspond to the boxes in the non-mathematical overview above. This will be explained in detail later; the figure is not meant to be completely self-explanatory at this point in time. A brief overview is now provided. a) The agent starts with a set of prior beliefs about the underlying mean effect of the other person; these get updated which each sample they take. b) At each timestep (either the initial state or every time a sample is taken), the value of stopping is calculated, and there is a decision bounary. The value of stopping includes time-dependent direct decision preferences such as impatience. c) These values are then used to compute the probability of stopping the sampling process (or not starting sampling at all, if one is at the initial state). d) If sampling has stopped, the inferred underlying mean affect and its credible interval are calculated.

In addition to these visual overviews, a tabular overview will be included at the end of this section (Table 74) which includes symbols, definitions and ranges for the free parameters for the model. Note also that in this chapter, all instances of P refer to probability e.g. P(j, o = safe) refers to the probability of the outcome *o* being 'safe' at timestep *j*.

6.2.1. Prior Beliefs

Figure 40.

Indication of part of model being discussed – representation of agent's beliefs



In this section, we introduce the concept of prior beliefs in the worry model. Before information is accumulated, people have pre-existing or prior beliefs. This prior is represented in the form of a Bayesian belief (i.e. a probability distribution). This is a distribution over the parameters μ and λ (Equation 12 below), which represent the mean and precision of the belief distribution respectively. This distribution will be discussed in further detail below.

This prior is updated which each new observation i.e. observed facial expression image. Therefore, for easy, analytic updates, a conjugate-prior formulation (where the prior and posterior are in the same parametric family, so new information can be added naturally) is used. $f_{X,Y}(x, y)$ is notation for a joint probability density function (Casella & Berger, 2002; Ross, 2014); here, it denotes the joint probability density of μ and λ. Hence, the distribution takes the following form: at timestep j,

$$f_{M,\Lambda}(\mu, \lambda) = \mathcal{N}(\mu\,;\, \mu_j, \sqrt{\frac{\lambda^{-1}}{k_j}})\ \mathcal{G}(\lambda\,;\, \frac{n_j}{2}, \frac{\psi_j^2}{2})$$

Equation 12

The Gamma distribution G represents the prior over precision (λ). Here, the shape parameter (the first parameter) is proportional to the effective amount of data about precision (n_j), such that the peak of the distribution shifts further to the right with more data, meaning that precision increases with amount of data. The rate parameter (the second parameter) is proportional to the effective sum-squared deviation (ESSD) ψ^2_j with respect to the mean of the belief, such that with a higher ESSD, the distribution broadens, meaning that the estimate of the precision itself has greater variance. The leads to an expected precision of $\alpha/\beta = n_j/\psi^2_j$.

Then, the normal distribution N represents the Gaussian for beliefs about the mean, parameterised by μ_j and a standard deviation which is calculated using λ and the effective amount of data about the mean at timestep j, k_j.

To sum up, here we specified the form of the prior, i.e. the generative distribution before a new item of evidence is taken into account. This prior is defined by 4 parameters: the expected mean μ_j, the effective sum-square deviation (ESSD) $\psi^2{}_j$, the effective number of data items for the mean k_j, and the effective number of data items for the ESSD, n_j. Note that these equations (for the mean, and for the precision) are not written as separate and independent as the mean depends on the variance.

6.2.2. Beliefs about the Mean

Based on the above formula, because the mean is dependent on the variance, one needs to integrate over all the different values of λ (precision) to determine beliefs about the mean. Hence, the above 4 parameters are used to form a t distribution, where $f_M(\mu)$ denotes the probability density function over the mean μ:

$$\begin{aligned} f_M(\mu) &= \frac{1}{s_\mu} t((\mu - \mu_j)/s_\mu, n_j) \text{ with} \\ s_\mu &= \sqrt{\frac{\psi_j^2}{n_j k_j}} \end{aligned}$$

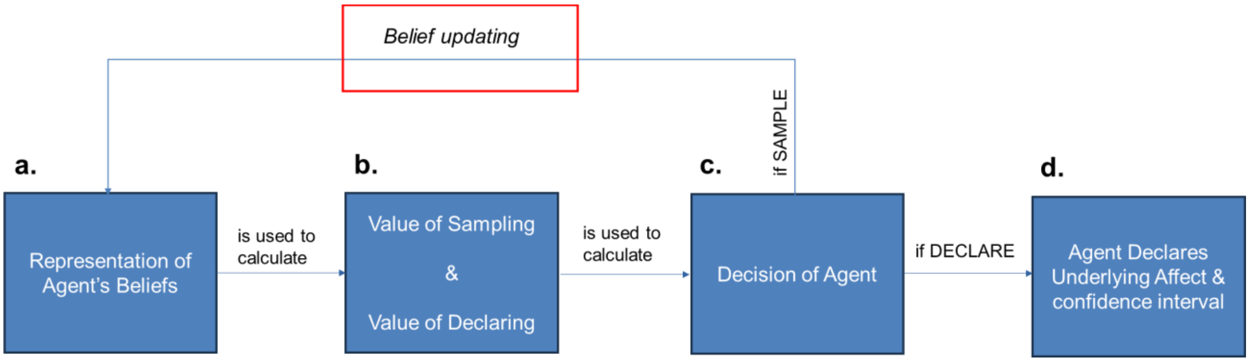
Equation 13

s_μ is the spread parameter, which is defined in the second equation above, based on ESSD, n, and k. This then affects the spread of the beliefs about the mean – the larger the ESSD, the larger the spread parameter, the flatter the graph, and the greater the variance of the estimate of the mean. μ_j shifts the graph to the right by μ_j units and determines the mean of the distribution. Initially (at j = 0), this equation describes the prior beliefs the participant holds before the entire experiment. Subsequently, as it is updated with items of information over the course of the experiment, it becomes the equation which describes beliefs about the underlying mean.

6.2.3. Accumulating Evidence into Beliefs about State

Figure 41.

Indication of part of model being discussed – belief updating



This section now introduces belief updating via evidence accumulation, referring to the process of accumulating evidence about another's emotional state in the agent's mind.

Recall that facial expression information is represented by numbers which represent the position of the facial expression on a 1-9 scale (Section 3.5., Figure 5). Each of the initial 5 faces shown, and each subsequent search, will produce such a number. For example, the first 5 faces may be represented by '4 1 3 2 1'. Then, '5 1 3' would mean that the agent searched 3 times afterwards, and obtained the following information: 'neutral, extremely happy, somewhat happy'. The full set would therefore be '4 1 3 2 1 5 1 3', where the last 3 are images the participant obtained via searching.

This information is then incorporated into the <u>beliefs about the underlying state</u> described above (Equation 2), using the same 4 parameters at timestep j: mean (μ_j), ESSD ($\psi^2{}_j$), effective number of samples for mean (n_j), and effective number of samples for ESSD (k_j). For simplicity of modelling, the last two are considered equal ($n_j = k_j$). The assumption here is that people bring in initial beliefs about mean and variance in equal numbers; subsequently, each face in this paradigm then also provides equal amounts of mean and variance information.

These beliefs are updated with each facial expression using the following equations:

$$\begin{aligned} n_{j+1} &= n_j + 1 \\ k_{j+1} &= k_j + 1 \\ \mu_{j+1} &= \mu_j + \frac{1}{k_j + 1}(x - \mu_j) \\ \psi^2_{j+1} &= \psi^2_j + \frac{k_j}{k_j + 1}(x - \mu_j)^2 \end{aligned}$$

Equation Set 14

This assumes that there are *j* timesteps so far (and *j* may be 0), and that there are no errors or forgetting (loss-less evidence accumulation). The new observation is *x*. These are standard textbook methods of updating mean and variance (Finch, 2009; West, 1979).

However, in real life people are not ideal Bayesian observers, and imperfectly retain and incorporate information into their beliefs. This may explain why learning rates do not tend to zero after many timesteps, even in a static environment, as if volatility is expected. Furthermore, there is evidence that people rely on their prior beliefs when information about current stimuli or context is forgotten (Hopkins, 2021). In other words, there is some degree of reversion to priors (sometimes referred to as Bayes optimal forgetting in the face of volatility). The conjugate-prior formulation lends itself well to accommodating this aspect of evidence accumulation: we can model this partial reversion to prior beliefs via a decay of beliefs (Equation Set 15 below). The conjugate-prior updating is illustrated by how the parameters change when updated but continue to describe the same distribution (the distribution in Equation 13 above).

$$\begin{aligned} \text{step 1:} \quad & n_{j+1} = n_{bsl} + \omega(n_j - n_{bsl}) + 1 \\ & k_{j+1} = k_{bsl} + \omega(k_j - k_{bsl}) + 1 \\ \text{step 2:} \quad & \mu_{j+1} = \mu_{bsl} + \omega(\mu_j - \mu_{bsl}) + \frac{1}{k_{j+1}}(x - (\mu_{bsl} + \omega(\mu_j - \mu_{bsl}))) \\ \text{step 3:} \quad & \psi^2_{j+1} = \psi^2_{bsl} + \omega(\psi^2_j - \psi^2_{bsl}) + \frac{k_{j+1} - 1}{k_{j+1}}(x - \mu_{j+1})^2 \end{aligned}$$

Equation Set 15

This is the equation set used in the model. Here, the baseline beliefs of the agent are denoted with a subscript *bsl*, e.g. in n_{bsl} and k_{bsl}. Then, the memory parameter ω captures the extent of the decay the information gathered so far. Mathematically, it represents people forgetting information more than $N_{max} = 1/(1 - \omega)$ observations ago.

We then update these equations every time new information is obtained, i.e., every draw of a new facial expression, as above.

6.3. Modelling Alternatives

From this point onwards, some aspects of the model have alternatives which each represent a different hypothesis about the cognitive process underlying worry. The following alternatives will be discussed (Table 71 below); more details will be provided subsequently. Please note that the points were modelling alternatives are available are not consecutive; the first two points (Sections 6.3.1. and 6.3.2.) occur *before* the overall probability of stopping is calculated (Sections 6.3.3. and 6.3.4.), but the last two points occur *after* this computation occurs (Sections 6.3.5. and 6.3.6.). These will all be discussed in greater detail subsequently.

Table 71.

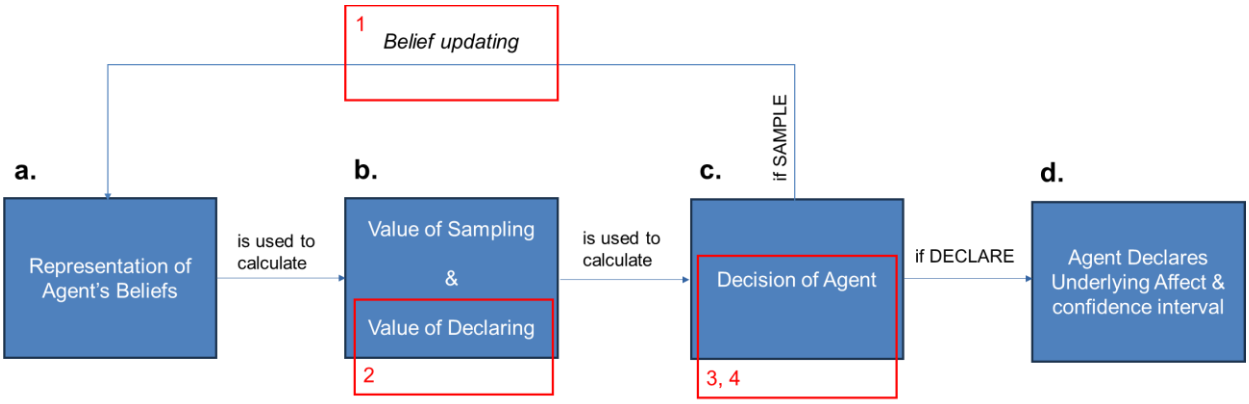
Overview of model alternatives with descriptions of models.

Aspect of Model	**Purpose**	**Modelling Alternatives**
1) Belief Updating (Section 6.3.1.)	How does the mind handle the storage and processing of non-novel information during worry?	a) 'Decay only' – when old information is encountered, no belief updating occurs, the belief simply decays. b) 'Lower learning rate' – when old information is encountered, belief updating still occurs, but with a much smaller learning rate.
2) Value (of stopping sampling and declaring an emotion read) (Section 6.3.2.)	How does the mind decide to stop worry? → Examines possible mechanisms behind prolonged worry	a) Inversely proportional to SEM of belief distribution – the smaller the SEM, the higher the precision of the agent's beliefs, and therefore the more confident they are of their answer

		b) Chance of avoiding a scream – the higher the perceived chance of avoiding a scream based on the agent's held beliefs, the higher the value of stopping and declaring.
3) Decision-Making – impatience factor	How does the agent's impatience affect their decision-making? → Examines non-uncertainty factors which affect length of worry episodes e.g. heuristics	a) Impatience increases at a decreasing rate b) Impatience increases at an increasing rate c) Impatience increases linearly and plateaus at a specific value
4) Decision-Making – 'favourite number'	Does the agent have a preferred number of searches, and if so, how does this affect their decision-making? → Examines non-uncertainty factors which affect length of worry episodes – e.g. beliefs about needing to worry for a set amount to be safe	a) No preferred number of searches b) The 'favourite number' bonus (added to the value of stopping) increases as agent approaches the 'favourite number' of searches and remains at the maximum value afterwards. c) The 'favourite number' bonus (added to the value of stopping) increases as agent the approaches 'favourite number', peaks at that number, and decreases afterwards.

Figure 42.

Model overview with points of multiple model alternatives indicated.

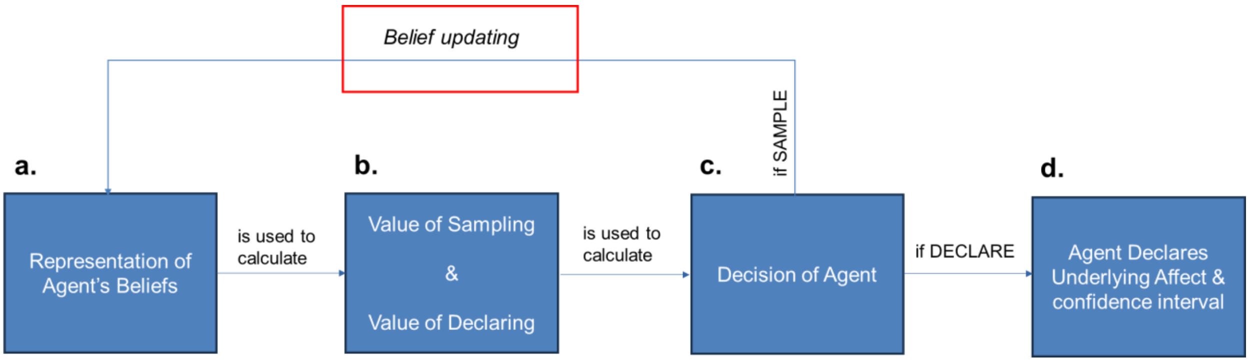


Note. Numbers refer to numbering in the table above.

6.3.1. Updating old and new information (Model Alternatives Point 1)

Figure 43.

Indication of part of model being discussed – belief updating



Key to the experimental paradigm is that the agent may receive either information they have already obtained or completely new information. Therefore, while the above update equations apply for a case where every piece of information obtained is new and should be integrated, they need to be modified for the cases where the participant obtains information they are already aware of. Here, there are two hypotheses for how the equations can be modified, which will be listed below and then discussed in turn:

1. The belief distribution decays and there is no update (decay only model).
2. The learning rate for already known information is much smaller than the learning rate for new information (lower learning rate model).

Either of these models can be fitted to data and the evidence for each model can be compared with Bayesian model comparison to test the implicit hypotheses or mechanisms that underwrite information foraging.

Information model 1 – decay only model

If the information obtained was old information i.e. a facial expression they have already seen, the following equation replaces Equation Set 15:

$$\begin{array}{ll} \text{step 1:} & n_{j+1} = n_{bsl} + \omega(n_j - n_{bsl}) \\ & k_{j+1} = k_{bsl} + \omega(k_j - k_{bsl}) \\ \text{step 2:} & \mu_{j+1} = \mu_{bsl} + \omega(\mu_j - \mu_{bsl}) \\ \text{step 3:} & \psi^2_{j+1} = \psi^2_{bsl} + \omega(\psi^2_j - \psi^2_{bsl}) \end{array}$$

Equation Set 16

As can be seen, there is only the decay term, and there are no update terms.

Information model 2 – lower learning rate model (Reminder model)

It is intuitive to have a lower learning rate for information which has already been seen. However, what exactly should this lower learning rate be?

The first 5 faces are integrated into the agent's beliefs via equation set 15 (as all of them are considered new information). At the end of integrating these 5 faces, the value of n given a value of n_{bsl} can be calculated; this is termed n_5. Given that this value decays at every time step, the value that can be added to 'cancel out' the decayed amount each time can be calculated. This value, termed the update rate, is denoted by u_r in Equation Set 17 below (derivation in Appendix).

As decay is based on forgetting, this represents the agent getting a *reminder* of the information they have already obtained. The term u_r is then incorporated into the update equations as follows. As the update u_r is <1 and generally close to 0, it functions as a learning rate which is smaller that would be for new information.

$$\begin{array}{ll} \text{step 1:} & n_{j+1} = n_{bsl} + \omega(n_j - n_{bsl}) + u_r \\ & k_{j+1} = k_{bsl} + \omega(k_j - k_{bsl}) + u_r \\ \text{step 2:} & \mu_{j+1} = \mu_{bsl} + \omega(\mu_j - \mu_{bsl}) + u_r(x - (\mu_{bsl} + \omega(\mu_j - \mu_{bsl}))) \\ \text{step 3:} & \psi^2_{j+1} = \psi^2_{bsl} + \omega(\psi^2_j - \psi^2_{bsl}) + u_r(x - \mu_{j+1})^2 \end{array}$$

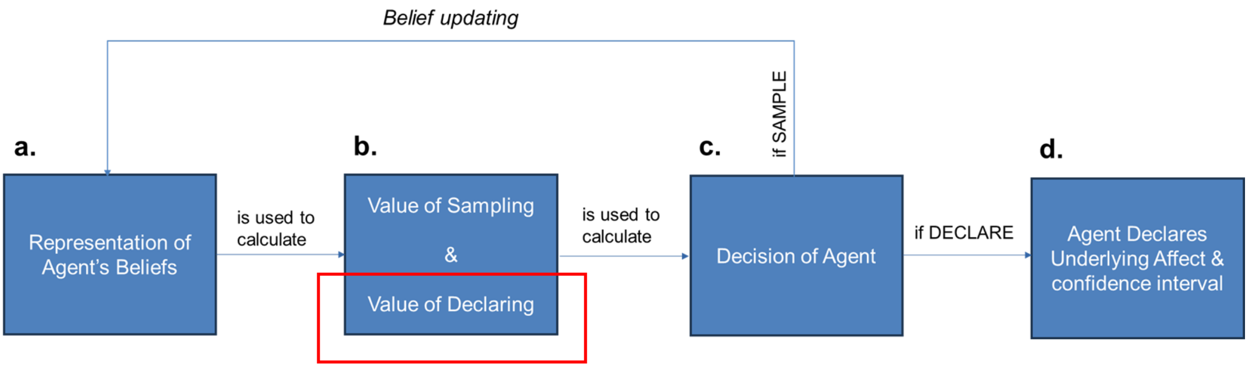
$$where \qquad u_r = (1-w)(n5 - n_{bsl})$$

Equation Set 17

6.3.2. Value of Declaring (Model Alternatives Point 2)

Figure 44.

Indication of part of model being discussed – value of declaring



At any given timestep, the agent computes the values of their two choices: declaring or sampling. In this model, the value of declaring, i.e. stopping the sampling process, and declaring a choice (of underlying emotion read) can be calculated with two alternative hypotheses:

1. Inversely proportional to the Standard Error of the Mean (SEM)
2. Chance of avoiding a scream

Inversely proportional to SEM

The basis of this mechanism is that the higher the certainty of the agent, the more likely it is that the emotion they declare would be accurate. Therefore, in this case, where *Q(j, d = stop)* is the value of deciding to stop sampling to declare an answer at timestep *j*:

$$Q(j, d = stop) = \frac{10}{SEM_j}$$

$$where \qquad SEM_j = \frac{SD_j}{\sqrt{n_j}}$$

$$and \qquad SD_j = \sqrt{\psi_j^2 / n_j}$$

Equation Set 18

The ESSD (Ψ^2) and *n* at timestep *j* are obtained from the update equations above (Equation Sets 15, 16 or 17 depending on whether the most recently obtained piece of information is new or old, and depending on which model is used). The value of 10 is an arbitrary scaling value which was selected to reproduce empirical data. The equation for SEM here is based on the standard equation for SEM, which is the standard deviation divided by the square root of the sample size (presented this way for clarity).

Chance of avoiding a scream

This model was built to be a more direct representation of the chance of the agent avoiding an aversive outcome. This is based off the fact that in the experimental paradigm, the agent hears a scream if they are more than one unit inaccurate from the actual reading.

First, the SD of the participant's beliefs about the underlying emotion is calculated (note that this is the same SD as in Equation Set 18):

$$SD_j = \sqrt{\psi_j^2 / n_j}$$

Equation 19

Then, this is used to calculate the probability of the outcome being safe, i.e. no scream, at timestep j, *P(j, o = safe)*:

$$P(j, o = safe) = \Phi + (1 - \Phi)/2$$

$$where \qquad \Phi = \int_{\mu-1.5}^{\mu+1.5} N(x; \mu_j, SD_j)dx$$

Equation Set 20

In this equation, *P(o = safe)* is calculated by adding two values, both based on current beliefs: the probability of being in the correct range ϕ, and probability of not being in the correct range (1- ϕ), multiplied by 50% as there is only a 50% chance of hearing a scream even if one is wrong.

Next, to get ϕ, +/-1.5 is used in the integrand because firstly, there is only punishment if they are more than one step wrong, and secondly, due to rounding, a difference of

0-0.5 from the boundary would still round down to them selecting the boundary integer and therefore still be safe. Although the agent's beliefs in the model are in the form of a t-distribution, a Gaussian is used here due to its parameters being more intuitively understood in a mental approximation.

Lastly, a scaling factor multiplies *P(j, o = safe)* to make *q(j, d = stop)*.

$$q(j, d = stop) = 30P(j, o = safe)$$

Equation 21

6.3.3. Additional Decision-Making Factor – Impatience (Modelling Alternatives Point 3)

The impatience parameter captures the natural impatience that occurs after sampling for a period of time, increasing the desire to stop and declare a decision. There are a few hypotheses for the formalisation of impatience in this model, which were chosen to provide different patterns of impatience (Table 72). The impatience parameter *I*, which is a function of timestep *j*, is added from *q(j,d = stop)* from Equation 21, modifying it as follows (Equation 22 below); the modified value *Q(j,d = stop)* will be used to compute a decision (in Equation 28, to be discussed later). The parameter is added at every time-step, regardless of whether new or old information is seen.

$$Q(j, d = stop) = q(j, d = stop) + I(j)$$

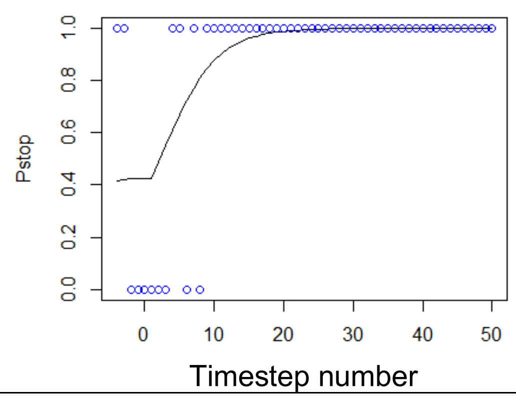
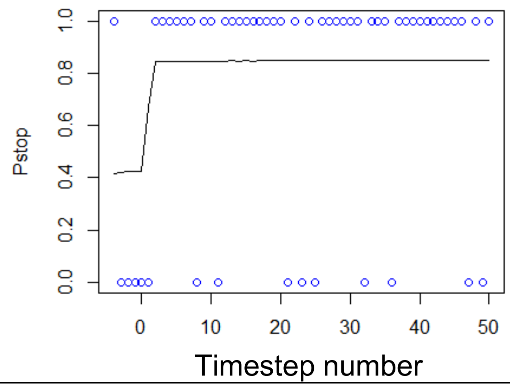
Equation 22

Where:

- *q* is the action value based on SEM or probability of shock alone
- *Q* is the action value after accounting for time-dependent preferences e.g. impatience, favourite number
- *I* is the function that calculates the time-dependant bonus added to the value of stopping and declaring due to the agent's impatience

Table 72. A schematic overview of the 2 hypotheses i.e. model comparison options, for the impatience parameter (*I*).

Equation	Graph

1. $I(j) = max(0, s_I(j - I_t))$ Equation 23. Parameters are s_I and I_t	
2. $I(j) = cs/(1 + e^{-10(j-st)})$ Equation 24. Parameters are *cs* and *st* (Adapted from Hauser et al., 2017)	

Note. The timestep number is *j*; each timestep refers to each discrete point where information is shown to the participant. The probability of stopping, and declaring, is *P(j, d = stop)* and labelled as Pstop in graphical visualisations such as in the above. Blue dots indicate generated synthetic data (generated independently of each other and assuming the agent has continued sampling to that point); 1 indicates stopping and declaring, and 0 indicates continuing to sample. Synthetic data is generated probabilistically using the value of *P(j, d = stop)*, such that, for example, a value of 0.8 is more likely to return a 1 than 0. Negative timesteps are included to illustrate what the decision would have been if participants could choose to stop or continue during the initial 5 images. They are included because belief updating starts *from* the first face of the initial 5 being shown, not only when the participant can start making decisions. Similarly, the baseline prior refers to the agent's prior before any information is provided, including these 5 faces. These are therefore included for a more complete visualisation of the belief-updating process.

6.3.4. Additional Decision-Making Factor – 'Favourite Number' (Modelling Alternatives Point 4)

A behavioural phenomenon seen in the data which may need to be taken into account is that some participants, regardless of trial-specific factors such as information ratio, seem to have a specific number of samples below which they do not fall, although they may search more than this number. In other cases, their number of samples tends to cluster around a specific number regardless of trial characteristics.

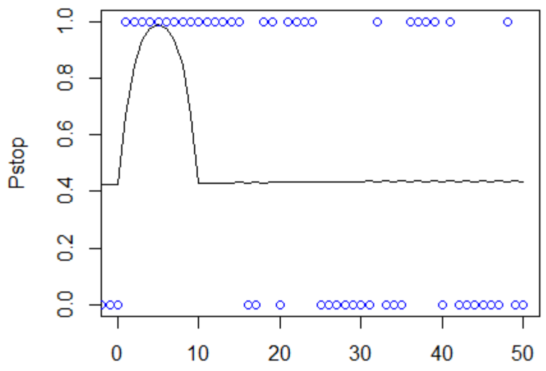
Therefore, an additional timestep-dependant ‘favourite number’ function *F(j)* can be added, similarly to the impatience function, as follows:

$$Q(j, d = stop) = q(j, d = stop) + I(j) + F(j)$$

Equation 25

Table 73.

A visual overview of the ‘favourite number’ hypothesis.

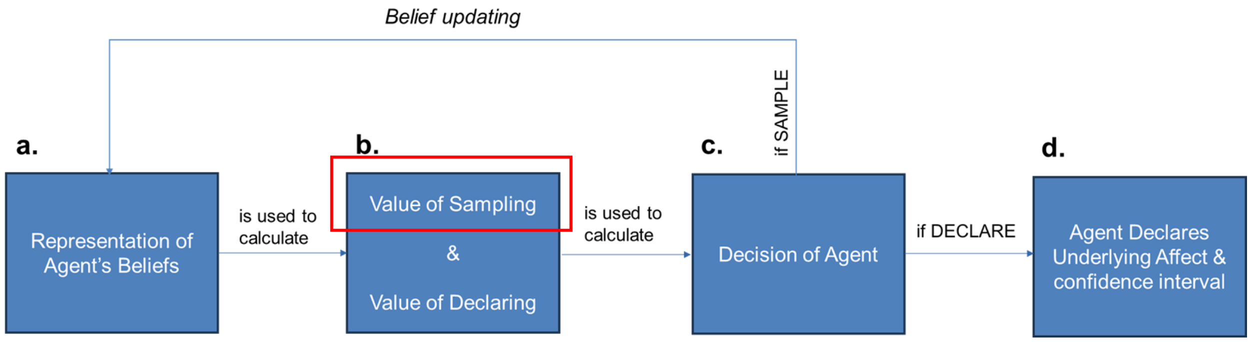
Equation	Graph
$F(j) = max(0, t_F - \|t_F - j\|)s_F$ Equation 26. Parameters are t_F and s_F	 Timestep number

Note. The alternative hypothesis is that of no favourite number preference. Here, similar to the impatience models, the timestep number is *j* and *P(j, d = stop)* is labelled as *Pstop*. Blue dots indicate generated synthetic data; 1 indicates stopping and declaring, and 0 indicates continuing to sample.

6.3.5. Value of Sampling

Figure 45.

Indication of part of model being discussed.



Next, at any given search number, the agent has a belief about the value of sampling. Here, the value of sampling is given by a single value Qb_{max}, creating a linear decision boundary. This value, Q_{bound}, is hypothesized to be greater in high worriers.

$$Q_{bound} = Qb(Qb_{max})$$

$$where \qquad Qb(x) = x$$

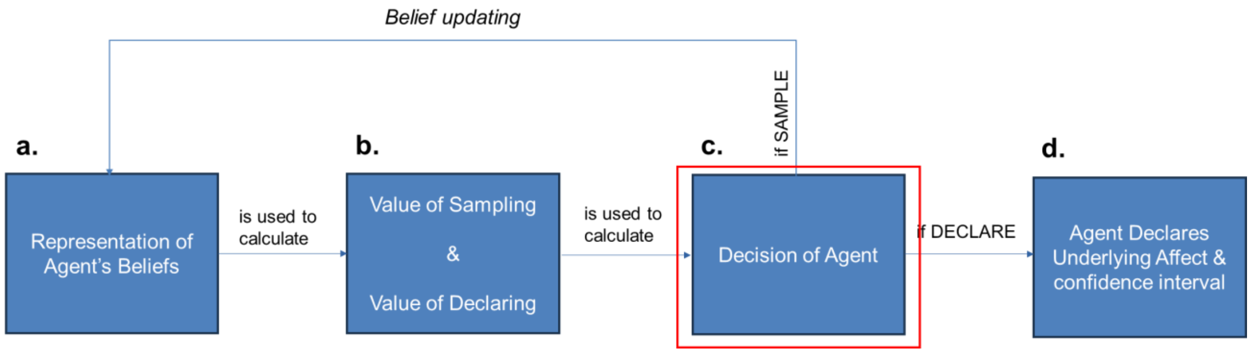
Equation 11

Qb_{max} is implemented as a parameter in the function, rather than directly using Q_{bound} as a parameter, to allow for flexibility in future versions of the model. This ensures compatibility with potential versions where the decision boundary might become more complex, such as timestep-dependant $Qb(Qbmax, j)$.

6.3.6. Decision Making

Figure 45.

Indication of part of model being discussed – decision of agent.



Given that the agent has calculated the values of declaring and sampling, integrating these values into the same decision equation allows a decision to be made. Hence, the probability of the decision (*d*) being to *stop* at timestep *j* is the following:

$$P(j, d = stop) = \frac{1}{1 + e^{\beta(Q_{bound} - Q(j,d=stop))}}$$

Equation 28

The β parameter is the precision (a.k.a., inverse of the temperature parameter) commonly used in decision-making functions. The greater the value of β, the more deterministic the choice is; the lower the value of β, the more random, or exploratory, the choice is. In the context of this experimental paradigm, people with a greater β value are more sensitive to changes in the value of $Q_{bound} - Q(j, d = stop)$.

This also explains why Q_{bound} is considered a decision boundary – it is when $Q(j, d=stop)$ exceeds Q_{bound} that the decision-making probability tilts in favour of stopping.

6.3.7. Lapse

A lapse parameter L is included to account for the fact that sometimes choices are made at random due to external factors e.g. accidental keyboard presses.

$$P_{lapse}(j, d = stop) = 0.5L + (1 - L)P(j, d = stop)$$

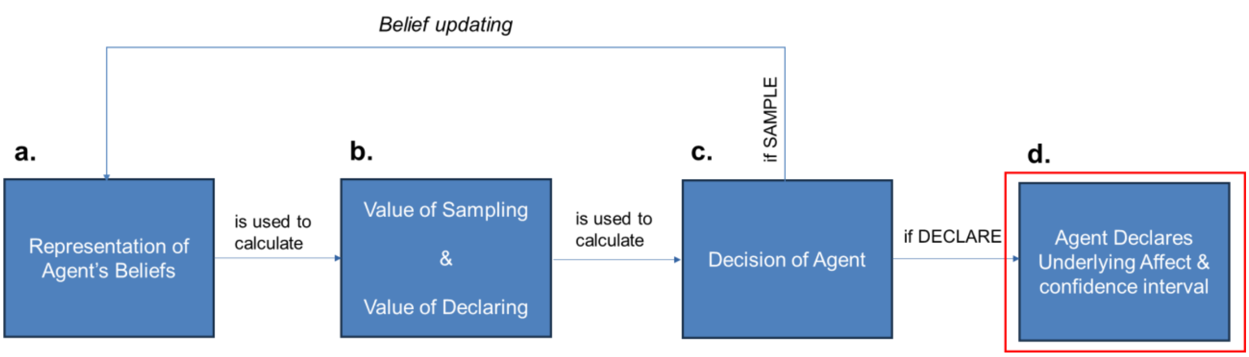
Equation 29

where P_{lapse} is the probability of stopping at a given timestep if lapses are accounted for.

6.3.8. Simulating Data

Figure 46.

Indication of part of model being discussed – agent declares underlying affect and confidence interval



Emotion report and 80% Credible Interval

Recall that participants, upon choosing to stop sampling and declare an answer, are asked to indicate their emotion report as well as the values in which they are 80% certain the true value is within. Therefore, to generate synthetic data, the reported emotion read is given by Equation 30, then rounded to the nearest integer. μ_{jstop} in the equation is the mean of the distribution representing the agent's beliefs (Equation 2) at j_{stop}, the timepoint where the agent stops sampling. The temperature parameter (*Tr*) is a parameter which is unique to each agent, determining the amount of noise around their reported data. A normal distribution is used for approximation for intuitiveness, as discussed in Section 6.3.2. Calculations are done the 1-9 space (which represents each facial expression with an integer from 1-9). To obtain the value, a single sample is drawn from the following distribution:

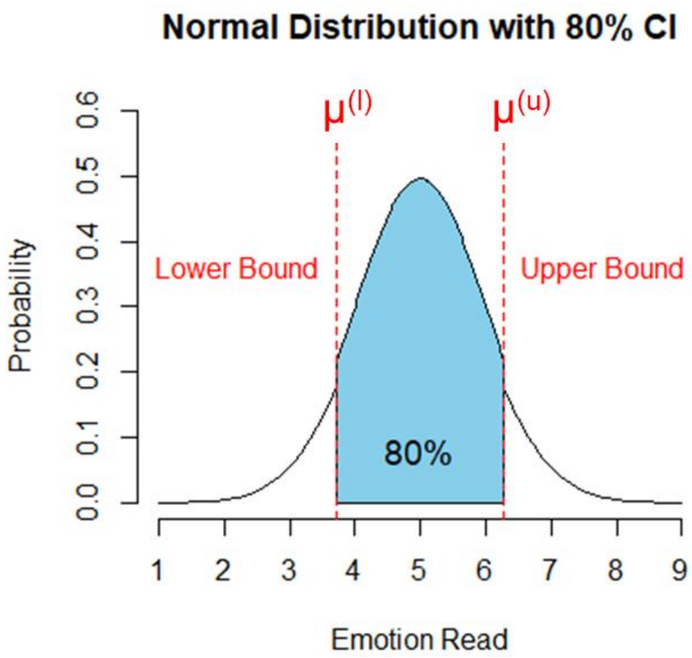
$$\mu_{gen} \sim N(\mu_{j_{stop}}, Tr)$$

Equation 30

Next, recall that the participant is asked for the interval in which they are 80% confident the true value lies. This means calculating the lower and upper bound of this interval around μ_{jstop}, which would be ($\mu^{(l)}$, $\mu^{(u)}$). A graphical illustration of this is below:

Figure 47.

Illustration of upper and lower bounds of confidence interval.



Note. The distribution represents the beliefs of the participant. Note here that this means the top and bottom 10% of the distribution are excluded.

To do this, first the critical value (*z*) needs to be calculated using a standard formula (Snedecor & Cochran, 1968) and the credible interval of 0.8. The margin of error is then calculated using μ_j, n_j and the standard deviation σ_j estimated from the belief distribution when $j = tstop$ (Equation 13). Then, the upper and lower bounds are produced by adding or subtracting the margin of error from the mean respectively (Equation Set 31).

$$\mu^{(l)} = \mu_j - z\frac{\sigma_j}{\sqrt{n_j}}$$
$$\mu^{(u)} = \mu_j + z\frac{\sigma_j}{\sqrt{n_j}}$$

$$where \quad z = \Phi^{-1}((1 + CI)/2)$$

Equation Set 31

In this paradigm, CI = 0.8, as the participant was asked for the interval in which they are 80% confident the true value lies (see above).

Then, upper and lower limits in synthetic data are generated ($\mu^{(l)}_{gen}$ and $\mu^{(u)}_{gen}$). Similarly to Equation 30, a single sample is drawn from each of the distributions below.

$$\mu^{(l)}_{gen} \sim N(\mu^{(l)}, Tr)$$
$$\mu^{(u)}_{gen} \sim N(\mu^{(u)}, Tr)$$

Equation Set 32

As it should be that lower limit ≤ mean declared ≤ upper limit, and there are non-trivial cases where the values in Equations 30 and 32 are not generated satisfying this inequality, the code was re-run if this happened and the values re-generated. Furthermore, values exceeding 9 were returned as 9, and values lower than 1 were returned as 1. Thus, a set of 3 generated values were produced via approximation, taking into account noise, which is represented by the temperature parameter.

6.3.9. Overall Hypotheses

1. Within participant: Qb_{max} values are higher in trials where more worry is reported.

2. Between participants: Qb_{max} values are higher in high worriers.

This is because a larger Q_{bound} value corresponds to the agent placing a greater value on sampling i.e. worrying in this model, and $Q_{bound} = Qb_{max}$. Therefore, these hypotheses correspond to the policy of worrying, or sampling, being overvalued in people who worry more and during moments of higher worry.

Alternative hypothesis:

1. Worry (both state and trait) is inversely correlated with slope parameters in impatience e.g. if impatience model 1 is used, higher worry corresponds to a smaller value of s_I.

In the model, the impatience parameter is added after the values of choices are computed. Therefore, this hypothesis corresponds to a higher-level bias towards a policy of sampling which is applied on top of the computations of value for either stopping or sampling, rather than changing the value of sampling itself. This was considered to be a secondary hypothesis as this may simply be an indicator of higher patience rather than anxiety-driven search e.g. 'I am patient because I am not in a rush today'.

While the main hypothesis and alternative hypothesis are not necessarily contradictory, further analyses may reveal which one contributes more, and therefore on which level the overvaluation of worry occurs.

6.4. Model Testing

6.4.1. Background and Overview of Parameters

There are several stages to model testing. The first step is to check that varying the parameters shifts dependent variables in the correct direction (i.e., establish face validity). Graphs which are produced from 3 different values of each parameter were used to establish residency. Then, the values produced by the model were hand-calculated mathematically to check that there have been no mathematical errors and the equations are faithfully represented in R. This was done for every parameter in the model, and is reviewed below.

The list of possible parameters are as follows. Note that because of the different model options, i.e. different hypotheses, some parameters are only applicable to some versions of this model.

Figure 48.

Mathematical overview of model with parameters for the corresponding part of the model included.

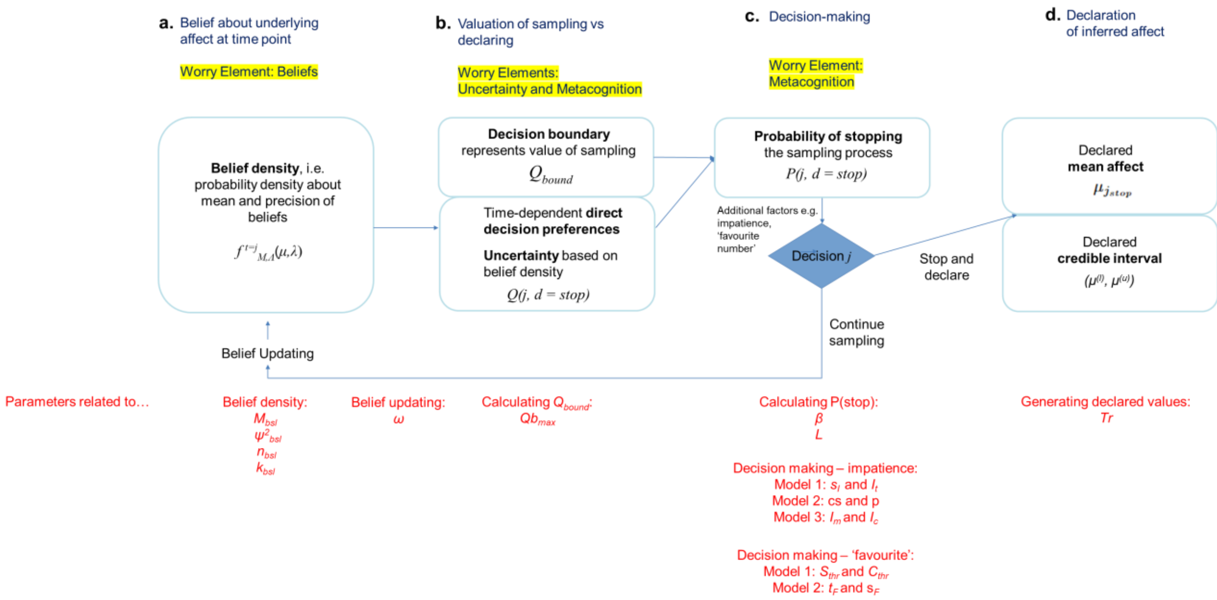


Table 74.

Symbols, definitions and ranges for the free parameters for the model.

a)

Parameter	Range	Definition	Psychological Construct (if relevant)
μ_{bsl}	≥0	Baseline value for belief mean	Initial **expectation** of the mood of other person
ψ^2_{bsl}	≥0	Baseline value for belief effective sum squared deviation	Initial **uncertainty** about mood of other person
n_{bsl}	≥0	Baseline value for the effective number of observations about belief mean	Amount of **prior experience** or information the agent perceives they have about the mean.

k_{bsl}	≥0	Baseline value for the effective number of observations about belief precision. In this model, for simplicity, $n_{bsl} = k_{bsl}$, so they may be considered to be one parameter.	Amount of **prior experience** or information one perceives they have about the precision. A lower n_{bsl} or k_{bsl} implies less prior information and greater openness to new evidence.
ω	0-1	Memory parameter; captures extent of information decay	Reflects how quickly information or thoughts are **forgotten** or discounted, potentially related to the persistence of worry.
Qb_{max}	≥0	Value of Q_{bound} function	**Perceived value** of seeking information via worry
β	≥0	Captures how deterministic an agent's choices are; a greater value indicates more deterministic decision-making, and a lower value more random decision-making.	Not psychological constructs – parameters for mapping psychological constructs to measured behaviour
L	0-1	Lapse parameter	
Tr	0-9	For generating synthetic data only; indicates decision noise in reporting confidence bounds.	

b)

Impatience model	Parameter	Range	Definition	Psychological Construct (if relevant)

1	s_I	≥0	Slope of impatience function	Reflects how quickly impatience builds
	I_t	$\mathbb{Z}^+$	Timestep where impatience function starts to be applied	Reflects the timepoint at which impatience starts increasing at a decreasing rate.
2	*cs*	≥0	Slope of impatience function	Reflects how quickly impatience builds (cs represents cost of search).
	st	$\mathbb{Z}^+$	Timestep where impatience function starts to be applied	Reflects the timepoint at which impatience starts increasing at a constant rate.

c)

'Favourite number' model	Parameter	Range	Definition	Psychological Construct (if relevant)
	t_F	≥0	Timestep which 'favourite number' function is centered around, i.e. the agent's most preferred number of samples	Reflect the agent's preferred amount of worry, regardless of other factors; may be related to a heuristic where one feels that there is an optimum amount to worry.
	s_F	≥0	Slope of 'favourite number' function; here, the sharpness of the peak	Reflects how strongly one's preference for

			around the 'favourite number'	this optimum amount of worry is

Note. a) Table of parameters present in every version of the model. b) Table of parameters which depend on which impatience model is chosen. c) Table of parameters for 'favourite number' model.

Note that the psychological construct mappings here are simplifications; the psychological processes behind worry are complex and likely involve interactions between multiple parameters. However, these provide a starting point for understanding the model's links to psychological constructs.

6.4.2. Model Behaviour by Parameter Values

The effects of different parameter values on model behaviour will now be shown in order of Table 74 above. The process of generating graphs with different parameters is important as it allows for the mathematical basis of the model to be checked for errors as well as demonstrating how varying parameters can vary behaviour.

To generate these graphs, a set of observations and a set of parameters are fed into the model. The observations used are:

1. Initial 5 faces, represented by the values 5 3 6 2 3, then
2. 50 potential searches, all with the value 9, and information is alternately labelled as new, old, new, old, etc.

Negative timesteps are included to illustrate because, as discussed previously, belief updating starts *from* the initial 5 faces, not only when the participant can start making decisions. It is useful in this section to pinpoint the point where the parameters cause the graphs to deviate, as omitting these timesteps would lead to it being unclear when exactly the graphs diverge.

In the following checks, all model parameters behaved as expected, and therefore no further actions to correct any issues were needed, and the next appropriate action was simply to produce synthetic data (Section 6.5.). However, the analyses are presented here for transparency and completeness.

$\underline{n_{bsl}}$ and $\underline{k_{bsl}}$

Table 75.

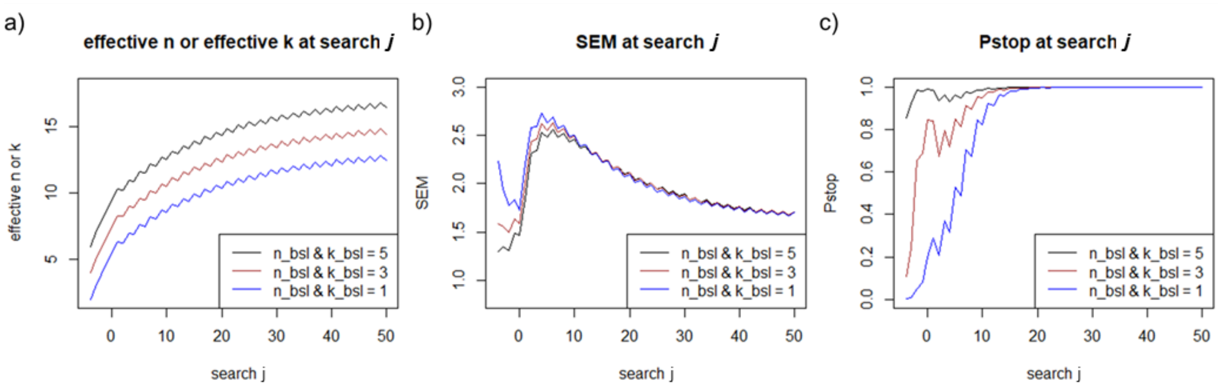
Parameters used to generate model behaviour.

n_{bsl} / k_{bsl}	μ_{bsl}	ψ^2_{bsl}	ω	Qb_{max}	β	L
5	5	10	0.95	10	1	0.05
3	5	10	0.95	10	1	0.05
1	5	10	0.95	10	1	0.05

Note. The parameter being varied is highlighted. Here, value model 1 was used (selection is arbitrary), and no impatience or 'favourite number' models were included for ease of visualization and calculation.

Figure 49.

Model behaviour at different values of n_{bsl} or k_{bsl}



Note. a) shows the effective n or k at each timestep t, b) shows the SEM at each time step, and c) shows the probability of stopping and declaring at each time step. The time steps start at -5 for clarity as the first 5 timesteps are the 5 initial facial expressions; therefore, if the agent samples, the first sample is given the timestep j = 1.

Model behaviour was as expected. For a), effective n or k increases with baseline n or k, for b) the SEM is lower when baseline n or k are higher as SEM is inversely proportional to total number of samples, and for c) *P(j, d= stop)* increases with higher baseline n, as it is inversely proportional to SEM.

Calculations were also done to check the mathematical integrity of the model. To illustrate the process, the model produces the following values for effective n at t = 0 and t = 1: 9.52 and 10.3. To check if this is correct, given the update equation (Equation Set 15) $n_{j+1} = n_{bsl} + \omega(n_j - n_{bsl}) + 1$, the second value can be manually calculated: 5 +

0.95(9.52-5) + 1 = 10.3. Therefore, the model updates the values of n as intended. This process was conducted for all subsequent parameters tested as well.

μ_{bsl}

Table 76.

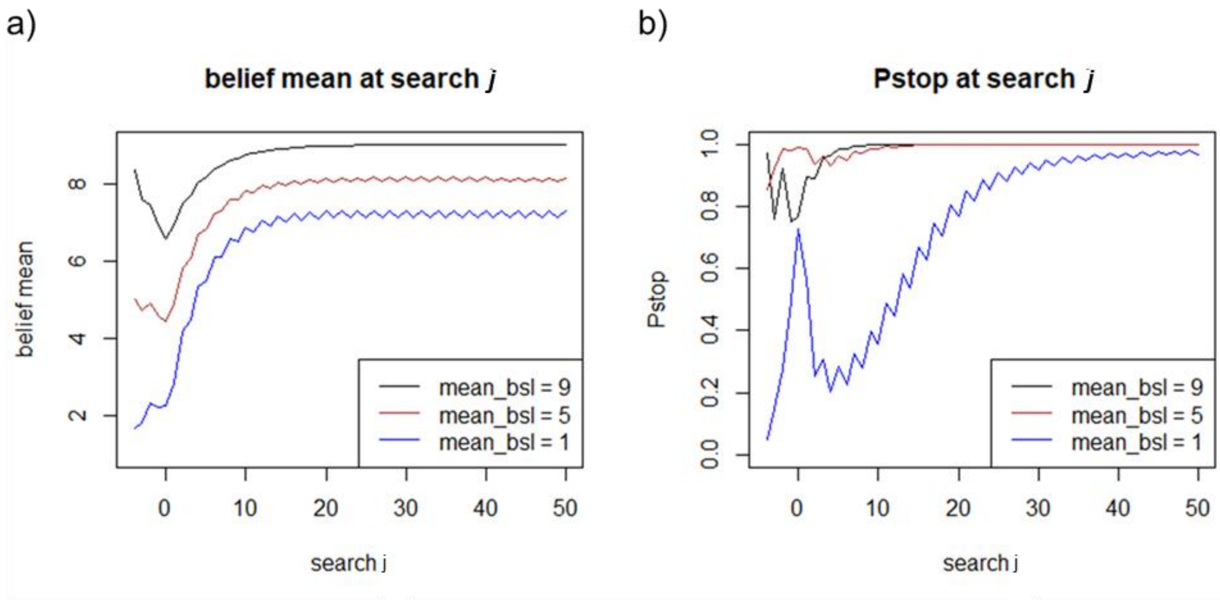
Parameters used to generate model behaviour.

n_{bsl} / k_{bsl}	μ_{bsl}	ψ^2_{bsl}	ω	Qb_{max}	β	L
5	9	10	0.95	10	1	0.05
5	5	10	0.95	10	1	0.05
5	1	10	0.95	10	1	0.05

The parameter being varied is highlighted. Here, value model 1 was used (selection is arbitrary), and no impatience or 'favourite number' models were included for ease of visualization and calculation.

Figure 50.

Model behaviour at different values of μ_{bsl}.



Note. a) shows the belief mean at each timestep and b) shows *P(j, d = stop)* at each timestep.

Model behaviour was as expected. For a) a higher baseline mean results in higher belief means. For b) for the first 5 timesteps (-5 to 5), the values fluctuated depending on how close the baseline mean was to the first 5 facial expressions. Then, when all data points provided were 9, the graph produced by a baseline mean (mean_bsl) of 9 reached *P(j, d = stop)* = 1 the fastest, as it was closest to the data provided and therefore would have a lower SEM, followed by mean_bsl = 5 and mean_bsl = 1.

ψ^2_{bsl}

Table 77.

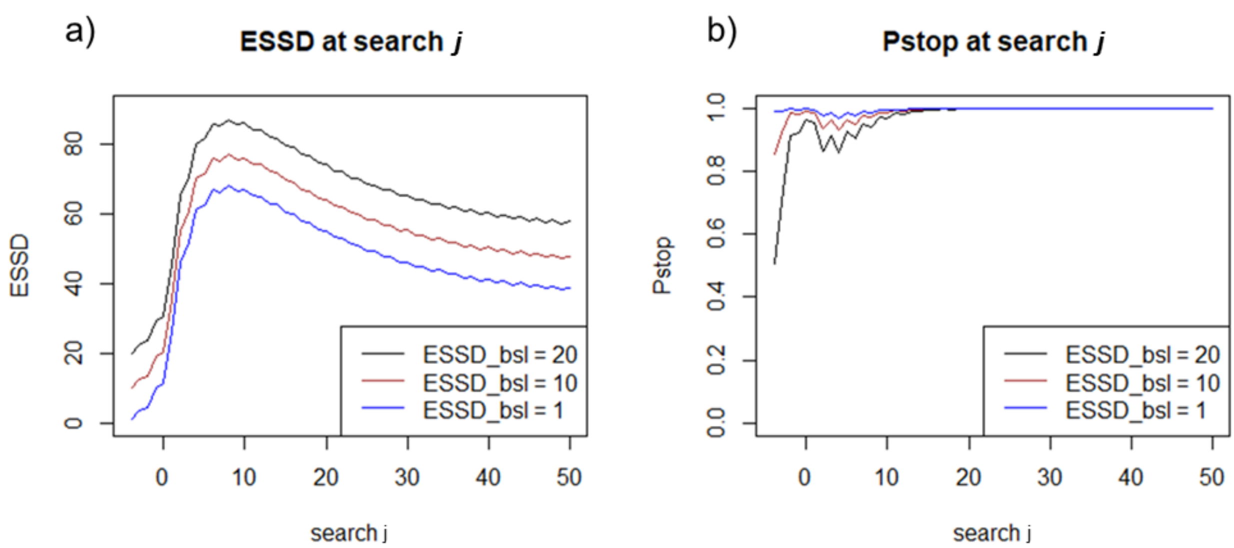
Parameters used to generate model behaviour.

n_{bsl} / k_{bsl}	μ_{bsl}	ψ^2_{bsl}	ω	Qb_{max}	β	L
5	5	20	0.95	10	1	0.05
5	5	10	0.95	10	1	0.05
5	5	1	0.95	10	1	0.05

The parameter being varied is highlighted. Here, value model 1 was used (selection is arbitrary), and no impatience or 'favourite number' models were included for ease of visualization and calculation.

Figure 51.

Model behaviour at different values of ψ^2_{bsl}.



Note. a) shows the ESSD at each timestep and b) shows the *P(j, d = stop)* at each timestep.

Model behaviour was as expected. a) ESSD increased with higher baseline ESSD and b) lower ESSD_bsl causes a lower SEM to be computed, which is in turn inversely proportional to *P(j, d = stop).*

ω

Table 78.

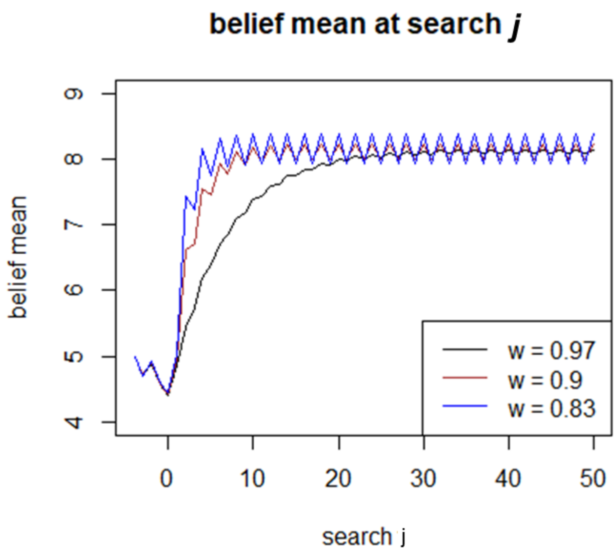
Parameters used to generate model behaviour.

n_{bsl} / k_{bsl}	μ_{bsl}	ψ^2_{bsl}	ω	Qb_{max}	β	L
5	5	10	0.97	10	1	0.05
5	5	10	0.9	10	1	0.05
5	5	10	0.83	10	1	0.05

The parameter being varied is highlighted. Here, value model 1 was used (selection is arbitrary), and no impatience or 'favourite number' models were included for ease of visualization and calculation.

Figure 52.

Belief mean at different values of ω.



Model behaviour was as expected, as a greater decay term would cause evidence to decay slower, resulting in a slower shift of the mean towards 9.

Qb_{max}

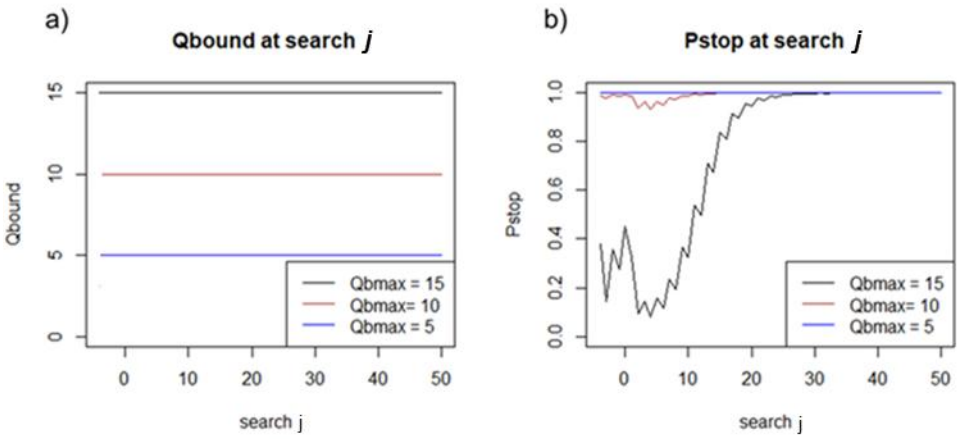
Table 79.

Parameters used to generate model behaviour.

n_{bsl} / k_{bsl}	μ_{bsl}	ψ^2_{bsl}	ω	Qb_{max}	β	L
5	5	10	0.95	15	1	0.05
5	5	10	0.95	10	1	0.05
5	5	10	0.95	5	1	0.05

The parameter being varied is highlighted. Here, value model 1 was used (selection is arbitrary), and no impatience or 'favourite number' models were included for ease of visualization and calculation.

Figure 53. Model behaviour at different values of *Qb_{max}*.



Note. a) shows the value of Q_{bound} and b) $P(j, d = stop)$.

Model behaviour was as expected. For a) greater Qb_{max} indeed increases the value of the Q_{bound} function and for b) a greater Qb_{max} increases the threshold that $Q(j, d = stop)$ needs to cross in order for the decision-making equation (Equation 28) to be in favour of stopping, therefore decreasing $P(j, d = stop)$.

B

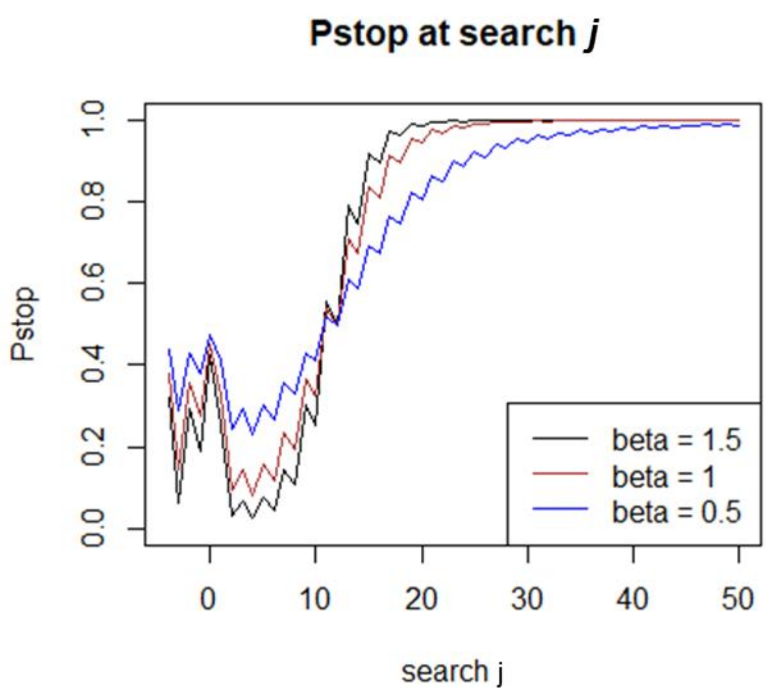
Table 80.

Parameters used to generate model behaviour.

n_{bsl} / k_{bsl}	μ_{bsl}	ψ^2_{bsl}	ω	Qb_{max}	β	L
5	5	10	0.95	15	1.5	0.05
5	5	10	0.95	15	1	0.05
5	5	10	0.95	15	0.5	0.05

The parameter being varied is highlighted. Here, value model 1, impatience model 1, and 'favourite number' model 1 are used (selection is arbitrary).

Figure 54. ***P(j, d = stop)*** **at different values of β.**



Model behaviour is as expected as β increases the sensitivity of decision-making to changes in the values of Q_{bound} – *Q(j, d = stop)*. Hence, the higher the β, the more *P(j, d = stop)* shifts towards either end of the probability range for the same values of Q_{bound} and *Q(j, d = stop)*, which is the case here.

<u>L</u>

Table 81.

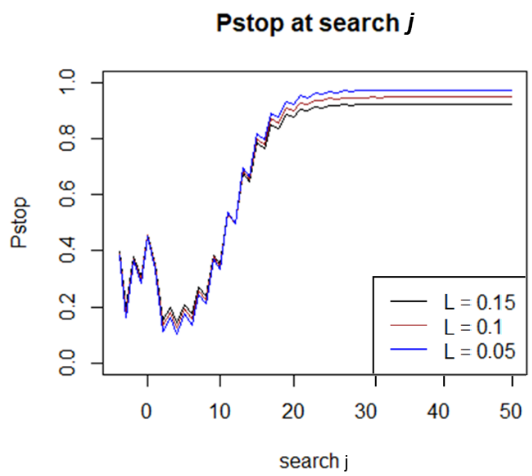
Parameters used to generate model behaviour.

n_{bsl} / k_{bsl}	μ_{bsl}	ψ^2_{bsl}	ω	Qb_{max}	β	L
5	5	10	0.95	15	1	0.15

5	5	10	0.95	15	1	0.1
5	5	10	0.95	15	1	0.05

The parameter being varied is highlighted. Here, value model 1, impatience model 1, and ‘favourite number’ model 1 are used (selection is arbitrary).

Figure 55. ***P(j, d = stop)*** **at different values of L.**



Model behaviour is as expected as a higher lapse rate would cause the value of *P(j, d = stop)* to be closer to 0.5; indeed, as L increases, values are closer to 0.5.

This process of analysing model behaviour based on parameter variation will now be applied to the aspects of the model with alternatives. Specifically, it will be applied to the two value models (recall the two different ways of computing the value of stopping sampling), the two belief updating models (different ways of handling how belief decay occurs), the two impatience models, and the optional ‘favourite number’ model (Table 71 for overview of all modelling alternatives).

Value models

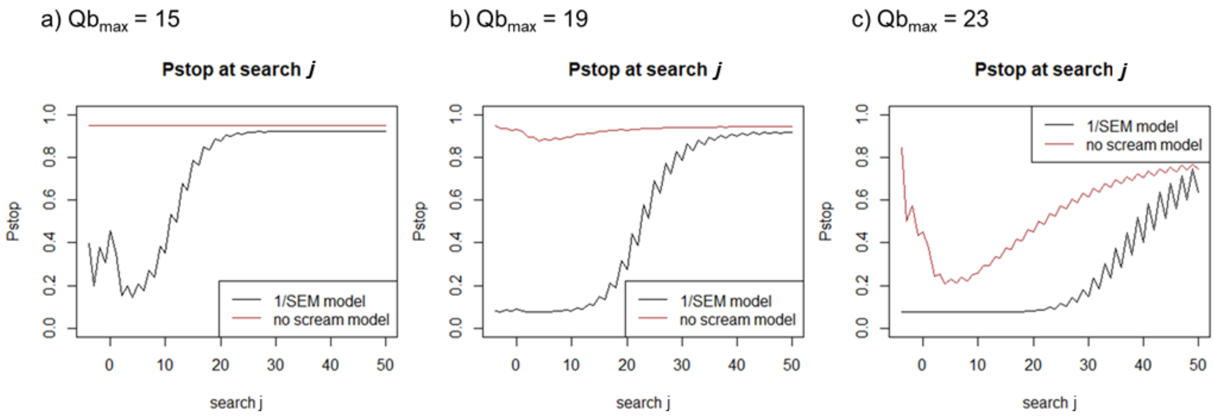
Since all the testing above involved value model 1, which is based on 1/SEM, there is also a need to test value model 2, which is based on the chance of avoiding a scream. Therefore, the following parameters were used to generate model behaviour (Table 24). Qb_{max} was varied as it directly changes the value of $Q_{bound} - Q(j, d = stop)$, and this value is what provides input into either value function.

Table 82.

Parameters used to generate model behaviour for value models 1 and 2.

n_{bsl} / k_{bsl}	μ_{bsl}	$\psi^2{}_{bsl}$	ω	Qb_{max}	β	L
5	5	10	0.95	15	1	0.05
5	5	10	0.95	19	1	0.05
5	5	10	0.95	23	1	0.05

Figure 56. *P(j, d = stop)* for different value models at different values of Qb_{max}.



The two models generate different *P(j, d = stop)* values from the same set of parameters, with the 1/SEM model generally generating higher *P(j, d = stop)* values. Both are able to capture how *P(j, d = stop)* changes with evidence accumulation, able to cover close to the full range of probability given appropriate parameters.

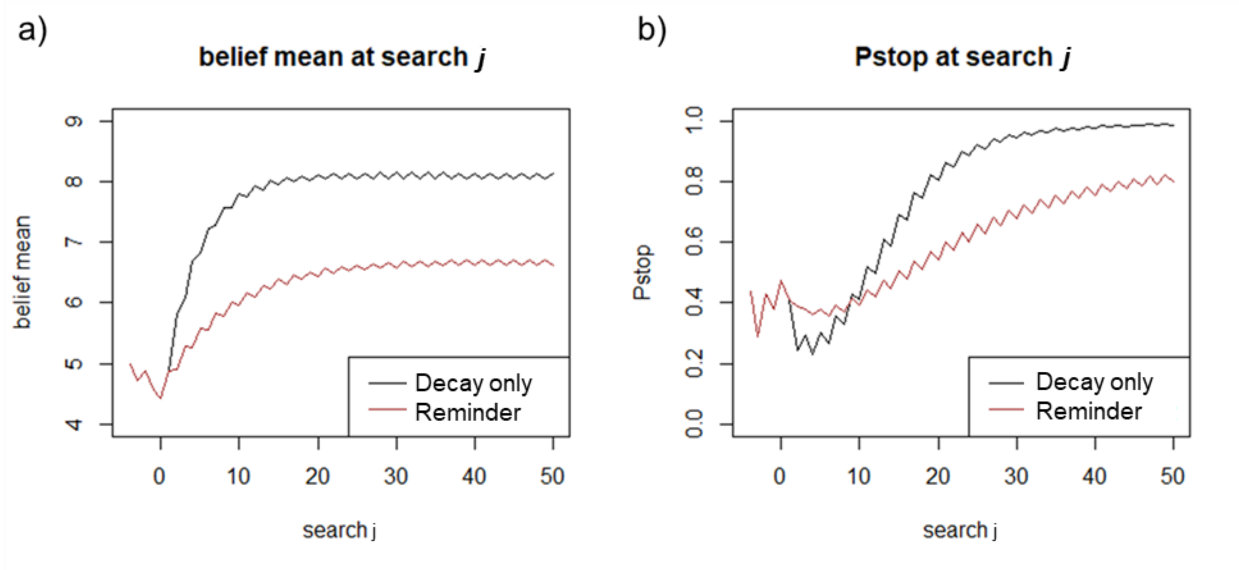
<u>Modelling of non-informative observations (information models)</u>

Table 83. Parameters used to generate model behaviour for both decay only and reminder model.

n_{bsl} / k_{bsl}	μ_{bsl}	$\psi^2{}_{bsl}$	ω	Qb_{max}	β	L
5	5	10	0.95	15	0.5	0.05

Impatience and ‘favourite number’ effects were not applied.

Figure 57. Model behaviour, a) belief mean and b) *P(j, d = stop)* for belief updating models.



Model behaviour is as expected as the decay only model would cause the effective *k* and *n* to be lower than in the reminder model. This causes the belief mean to increase faster as new information will form a larger proportion of the evidence accumulated. This also changes SEM faster, whether in the initial SEM increase due to a large difference between new information and existing beliefs (recall that '9's are observed on search while the initial faces provided are 5 3 6 2 3), or the eventual SEM decrease, as SEM is inversely proportional to effective k.

Impatience Models – Impatience Model 1

Table 84.

Parameters used to generate model behaviour when varying s_I.

n_{bsl} / k_{bsl}	μ_{bsl}	ψ^2_{bsl}	ω	Qb_{max}	β	L	S_I	I_t
5	5	10	0.95	25	1	0.05	0.35	1
5	5	10	0.95	25	1	0.05	0.25	1
5	5	10	0.95	25	1	0.05	0.15	1

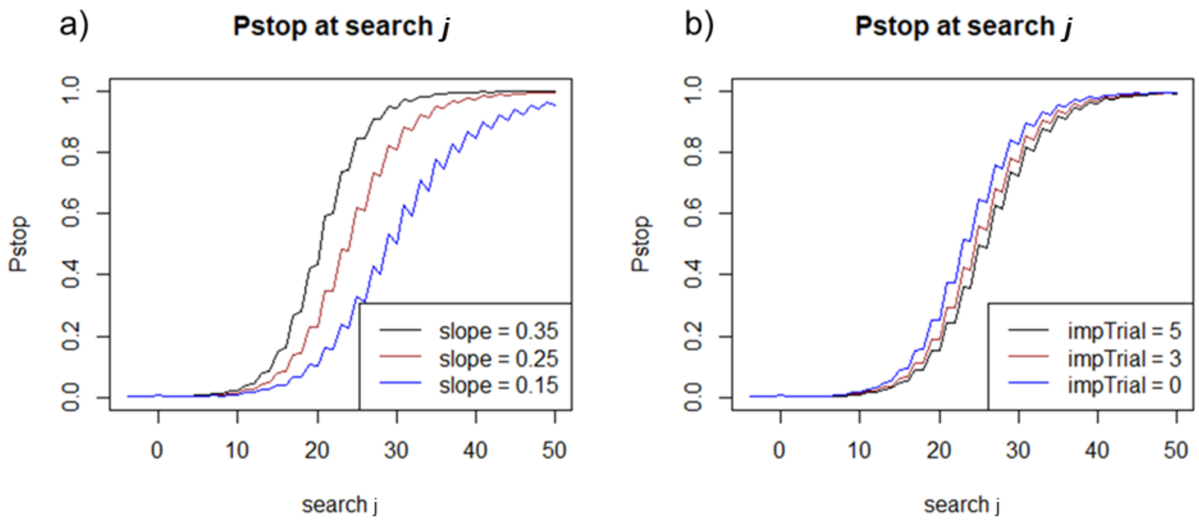
Table 85.

Parameters used to generate model behaviour when varying I_t.

n_{bsl} / k_{bsl}	μ_{bsl}	ψ^2_{bsl}	ω	Qb_{max}	β	L	S_I	I_t

5	5	10	0.95	25	1	0.05	0.25	5
5	5	10	0.95	25	1	0.05	0.25	3
5	5	10	0.95	25	1	0.05	0.25	0

Figure 58. ***P(j, d = stop)*** **with impatience model 1 at different values of** S_l **and** I_t**.**



As expected, a greater *slope* (S_l) in the impatience function correspondingly increases the steepness of the slope as *P(j, d = stop)* increases. As *impTrial* (I_t) increases, the timestep number at which the impatience function starts being applied, *P(j, d = stop)* increasing with a lower I_t also corresponds to expected model behaviour.

Impatience Models – Impatience Model 2

Table 86. Parameters used to generate model behaviour when varying *cs*.

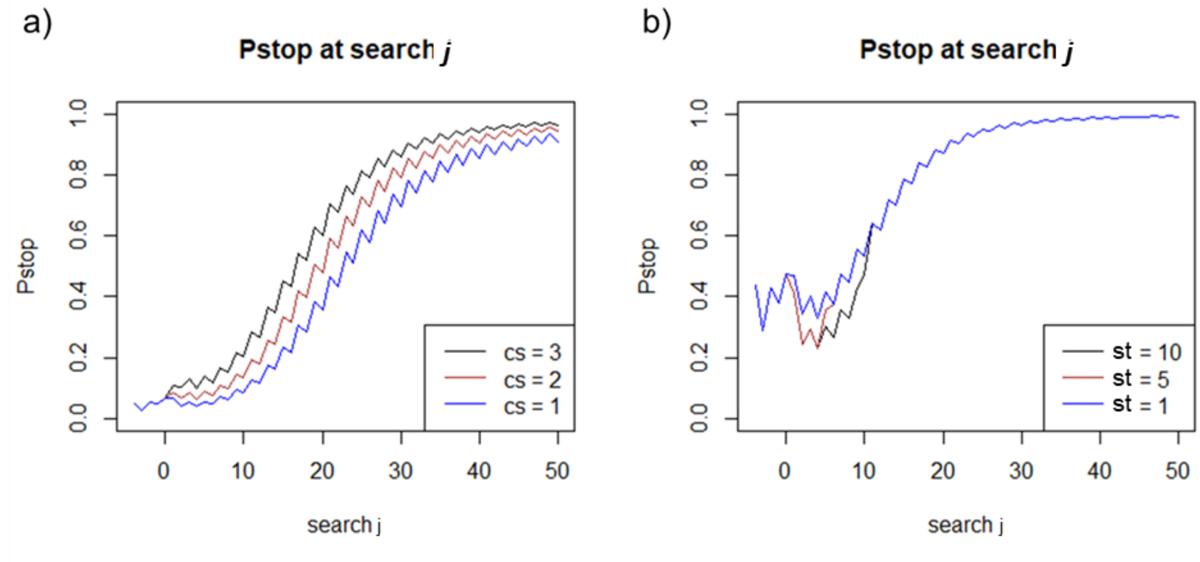
n_{bsl} / k_{bsl}	μ_{bsl}	ψ^2_{bsl}	ω	Qb_{max}	β	L	cs	St
5	5	10	0.95	20	1	0.05	3	1
5	5	10	0.95	20	1	0.05	2	1
5	5	10	0.95	20	1	0.05	1	1

Table 87. Parameters used to generate model behaviour when varying *st*.

n_{bsl} / k_{bsl}	μ_{bsl}	ψ^2_{bsl}	ω	Qb_{max}	β	L	cs	st

5	5	10	0.95	15	1	0.05	1	10
5	5	10	0.95	15	1	0.05	1	5
5	5	10	0.95	15	1	0.05	1	1

Figure 59. *P(j, d = stop)* with impatience model 1 at different values of *cs* and *st*.



As expected, a greater slope of the impatience function (*cs*) increases the slope of increasing *P(j, d = stop)* values. Next, as *st* corresponds to the timestep where the impatience function starts being applied, a larger value of p delays the increase in *P(j, d = stop)*.

<u>'Favourite Number' Model</u>

Table 88. Parameters used to generate model behaviour for 'favourite number' model.

a)

n_{bsl} / k_{bsl}	μ_{bsl}	ψ^2_{bsl}	ω	Qb_{max}	β	L	t_F	s_F
5	5	10	0.95	15	0.5	0.05	10	0.5
5	5	10	0.95	15	0.5	0.05	5	0.5
5	5	10	0.95	15	0.5	0.05	1	0.5

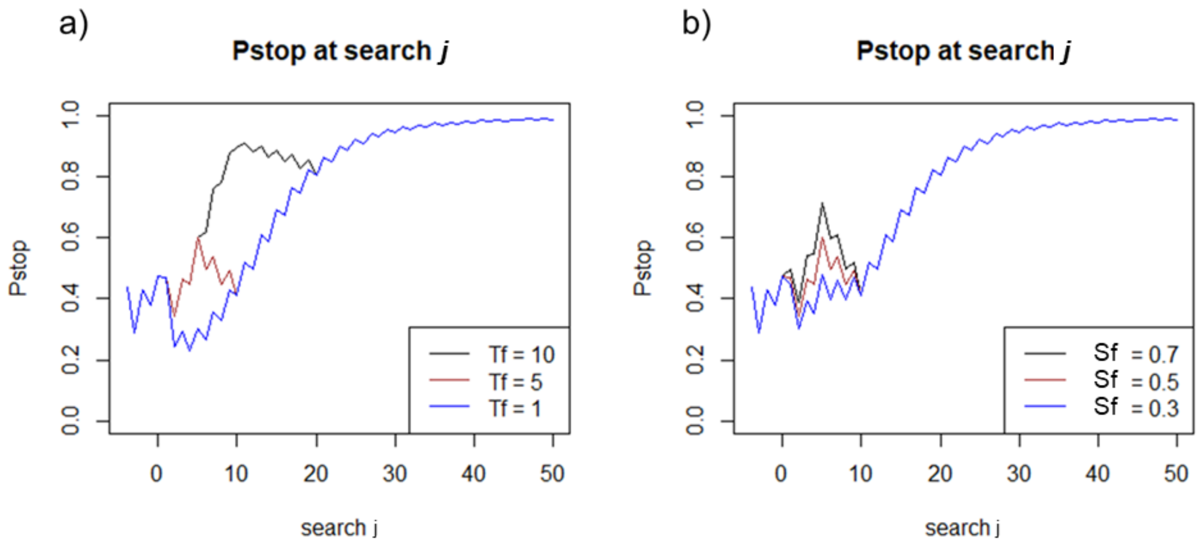
b)

n_{bsl} / k_{bsl}	μ_{bsl}	ψ^2_{bsl}	ω	Qb_{max}	B	L	t_F	s_F
5	5	10	0.95	15	0.5	0.05	5	0.7
5	5	10	0.95	15	0.5	0.05	5	0.5
5	5	10	0.95	15	0.5	0.05	5	0.3

Note. The set in a) was used to test the effects of t_F on behaviour and b) for s_F.

Figure 60.

***P(j, d = stop)* with 'favourite number' model at different values of t_F and s_F.**



As expected, in a) a greater value of T_F shifts the addition of the 'favourite number' bonus to a later timestep, as the parameter represents where the largest bonus should be added. In b) a greater S_F parameter increases the peak and slope of the 'favourite number' bonus, again as expected.

<u>Summary</u>

All model parameters affected the behaviour of the model as expected. Therefore, the model is performing with a degree of face validity. The next step is to generate synthetic data to further validate the model. In addition, this knowledge of how parameter variation corresponds to behaviour variation is useful in the model-validating process; specifically, it allows one to select the best parameters and ranges for an initial attempt at hand-generating data. In fact, this is what enabled the decision to vary Qb_{max} in the next section involving generating synthetic data, which will now be discussed.

6.5. Generating Synthetic Data

This section will demonstrate how the model can generate synthetic data, which was done via writing a function that computed the model in the programming language R (version 4.3.2; R Core Team, 2020). Synthetic data is crucial for validating the model; by simulating worry behaviour, the model can be assessed for whether it captures key aspects of empirical data. This process involves the following:

1. Select a probable set of model parameters based on prior analyses (i.e. the parameter variation analyses above).
2. Select a probable set of stimuli that the agent may receive.
3. Generate a graph of P(j, d = stop) over j to visually demonstrate model behaviour.
4. Generate the following specific synthetic data:
    a. number of relookings
    b. inferred underlying mood
    c. upper- and lower- emotion rating ranges.
5. Compare synthetic data patterns to experimental results.

Number of Re-lookings

At each search number, a sample is drawn from the following distribution, where D_{stop} refers to the decision to stop, based on the value of P(j, d = stop). Then, the timestep which the agent stops sampling on (j_{stop}) is determined by the first instance of $D_{stop} = 1$.

$$D_{stop} \sim Bernoulli(P(j, d = stop))$$

Equation 33

Emotion Declared and Uncertainty Reporting

As discussed previously, the emotion reported is generated by obtaining a single sample from a normal distribution (Equation 30)

The upper and lower limits of the 80% confidence interval are then generated by adding or subtracting a margin of error from the belief mean. This margin of error is calculated based on the 80% confidence interval, the standard deviation at that timestep, and the number of samples at that timestep (Equation Set 31).

Then, upper and lower limits in synthetic data are generated similarly to Equation 30 (Equation Set 32).

6.5.1. Synthetic Data Examples

Examples of synthetic data will be now shown.

First, the model's response to a predictable pattern of stimuli will be demonstrated (a series of 9s) in order to clearly observe patterns the model may generate without not obfuscation of any unexpected responses. Then, the model's response to a more realistic set of stimuli will be presented to demonstrate that the model can produce realistic data based on likely environmental cues. Including both sequences of stimuli (all 9s or realistic sequence) also allows for exploration of in what circumstances worry might be useful or not useful, especially with this exaggerated difference.

For this illustrative demonstration, Qb_{max} was selected as the parameter to vary as it represents the hypothesis that sampling, which represents worry, is over-valued; the higher the Qb_{max}, the more sampling is valued.

Table 90.

Parameters and model options used to generate this set of examples.

Example	n_{bsl} / k_{bsl}	μ_{bsl}	ψ^2_{bsl}	ω	Qb_{max}	β	L	t_F	s_F	Tr
High Worry	5	5	10	0.95	25	0.5	0.05	10	1	1
Low Worry	5	5	10	0.95	10	0.5	0.05	10	1	1

Impatience model	'Favourite number' model	Value model	Information model
2	present	1	1

Figure 61.

Model behaviour generated using the above parameters and model options.

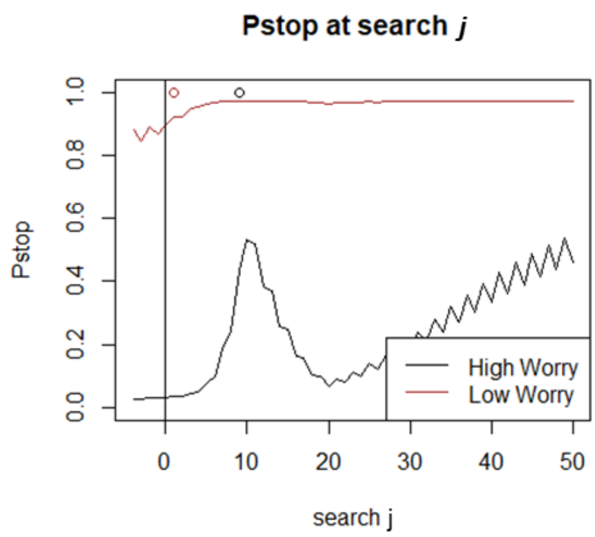


Table 91.

Data generated using the above parameters and model options.

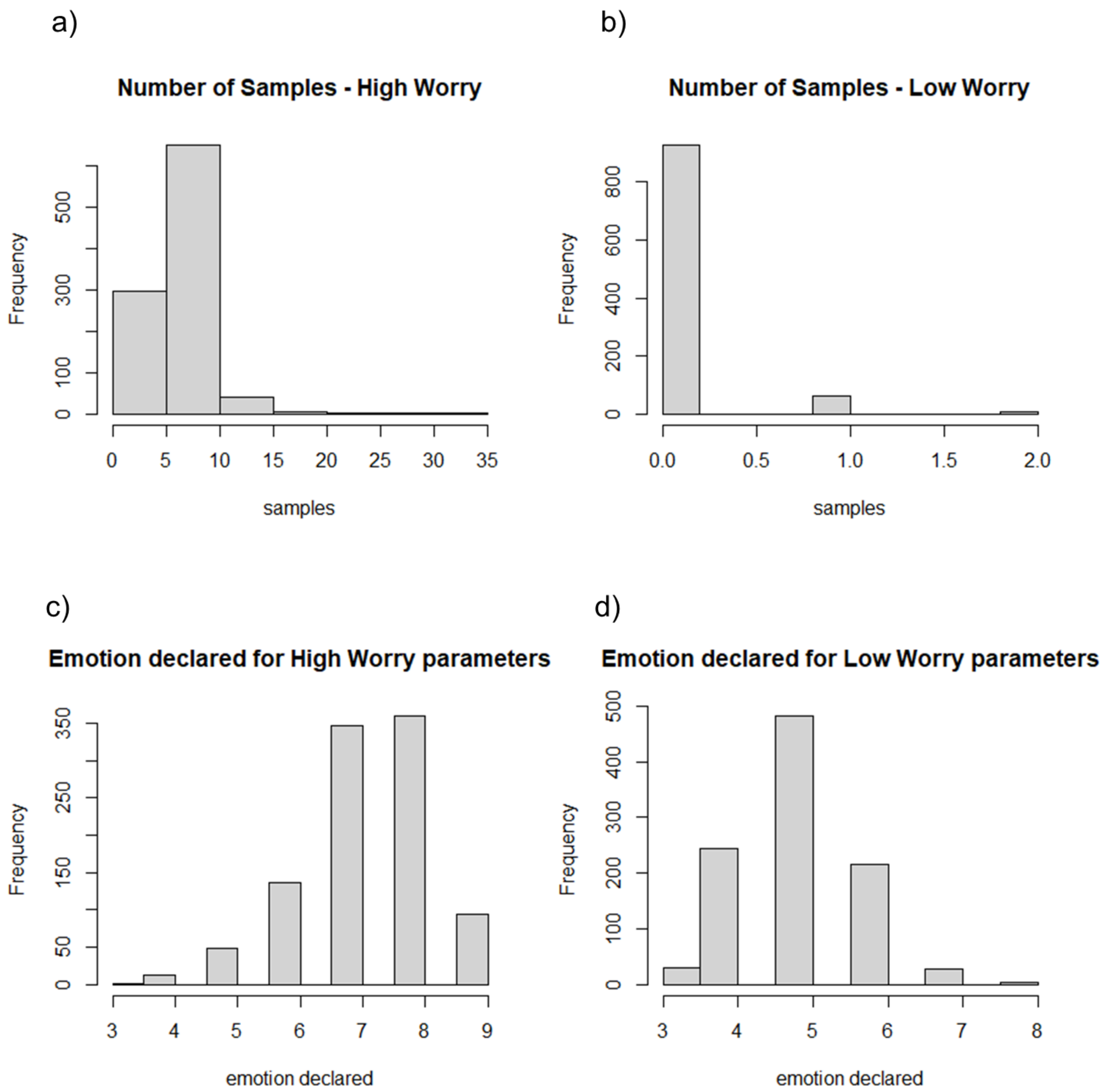
Type of Data	High Worry	Low Worry
Number of Re-lookings	9	1
Emotion Read Declared	7	6
Lower Limit of 80% CI	5.08	4.87
Upper Limit of 80% CI	9.00	6.79

6.5.2. Synthetic Data Example Overview

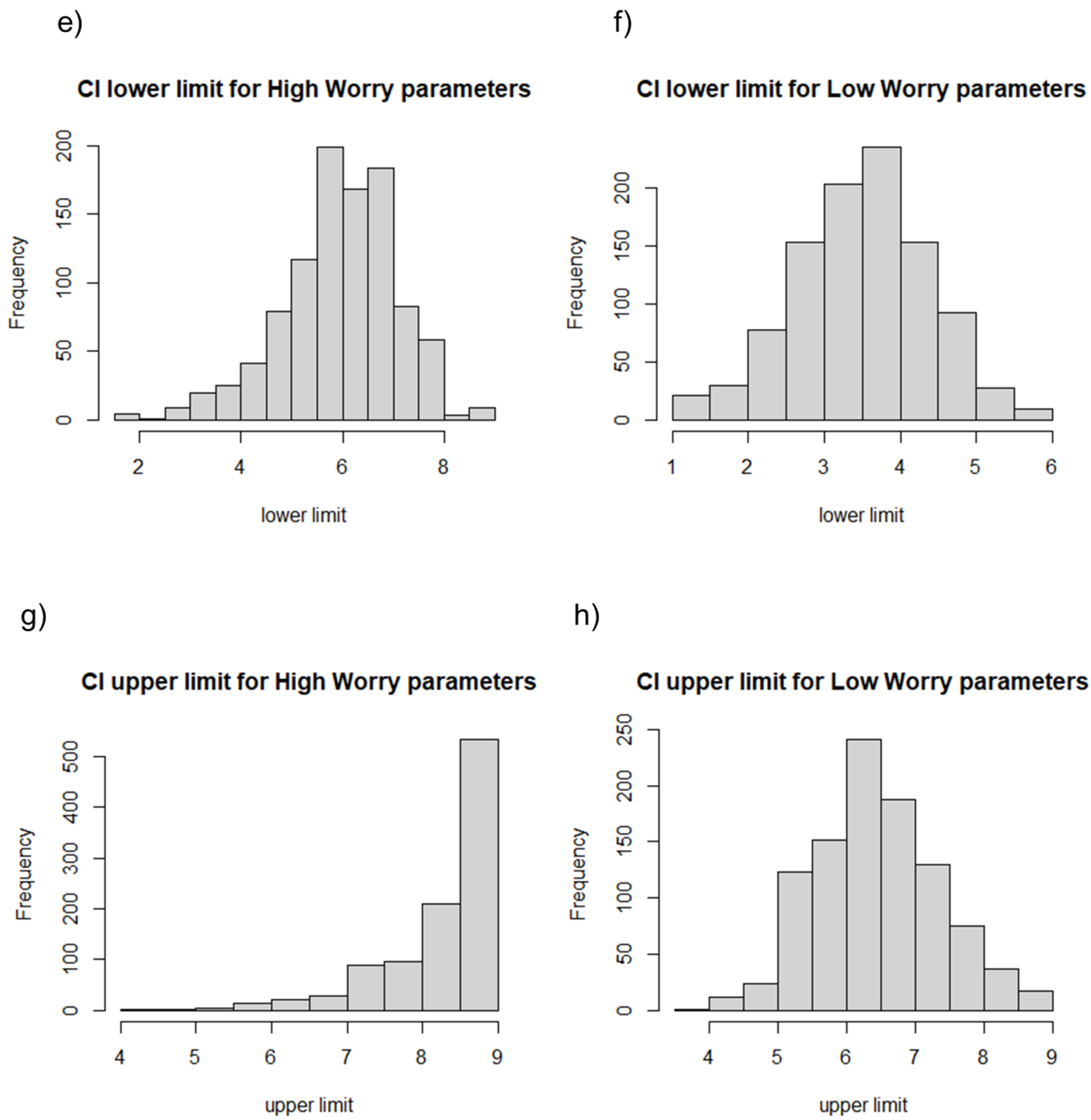
How accurately does this example above represent the parameters? To check this, a simulation approach can be conducted, where the above data generation process can be run 1000 times for the same set of parameters. Therefore, this was done for both sets of the parameters above.

Figure 62.

Histograms comparing generated data for parameters representing high and low worry.



a)
Number of Samples - High Worry
Frequency
samples
b)
Number of Samples - Low Worry
Frequency
samples
c)
Emotion declared for High Worry parameters
Frequency
emotion declared
d)
Emotion declared for Low Worry parameters
Frequency
emotion declared

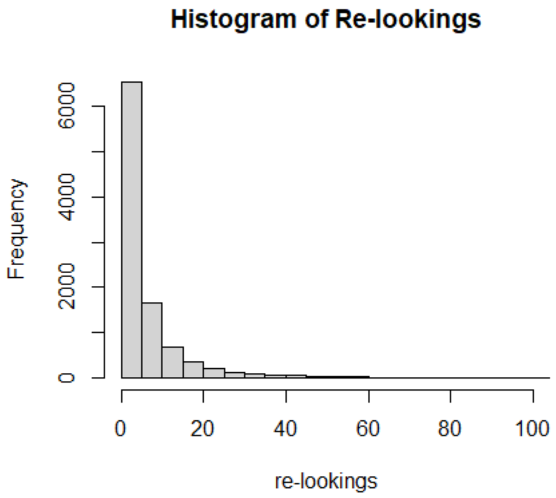


Note. a) and b) show the number of samples, i.e. re-lookings, taken by 1000 examples of agents with the given parameters. c) and d) show the emotion declared using the same; similarly, e) and f) show the lower limit of the confidence interval, and g) and h) the upper limit.

First, looking at a) and b), the number of samples are higher in the high worry than low worry representative parameters. Notably, the distribution of re-lookings looks similar to the data collected in the large scale online study, where the distribution is skewed towards 0, and there is a 'tail' of higher re-lookings (see Figure 63 below for reference). This suggests that the model is able to qualitatively capture features of the experimental data.

Figure 63.

Histogram of all re-looking numbers across the large online study dataset.



Similar to the generated data, the peak is at or very close to 0, with a long 'tail' of larger numbers of re-lookings.

For c)-h), the emotion read declared as well as its upper and lower 80% confidence interval limits are higher when generated with the high compared to low worry representative parameters. This is because more sampling happens with 'high worry' parameters, and since all searches returned '9' for easy data analysis during the testing stage, all values would be skewed towards 9.

6.5.3. Generating Synthetic Data for Realistic Observations

How, then, would the model behave when provided with a more realistic set of sampling outcomes? To find out, a more realistic set of observations was generated in the following way:

1. The 5 initial faces shown were repeated 10 times to form a string of known information which could be found from 50 samples.
2. 8 values from the original distribution of N(3.75,2.4) were randomly drawn in order to replace about 1/6 (to represent the 1 to 5 information ratio) of the information with new information.
3. 8 random numbers between 1-50 were drawn.
4. The information in the positions corresponding to the random numbers was replaced by the 8 values from Step 2.

5. All new information was labelled with 1 and already known information with 0 in a separate vector.

The process of generating 1000 sets of generative data was then repeated with the above set of more realistic observations.

Table 92. Parameters and model options used to generate this set of examples.

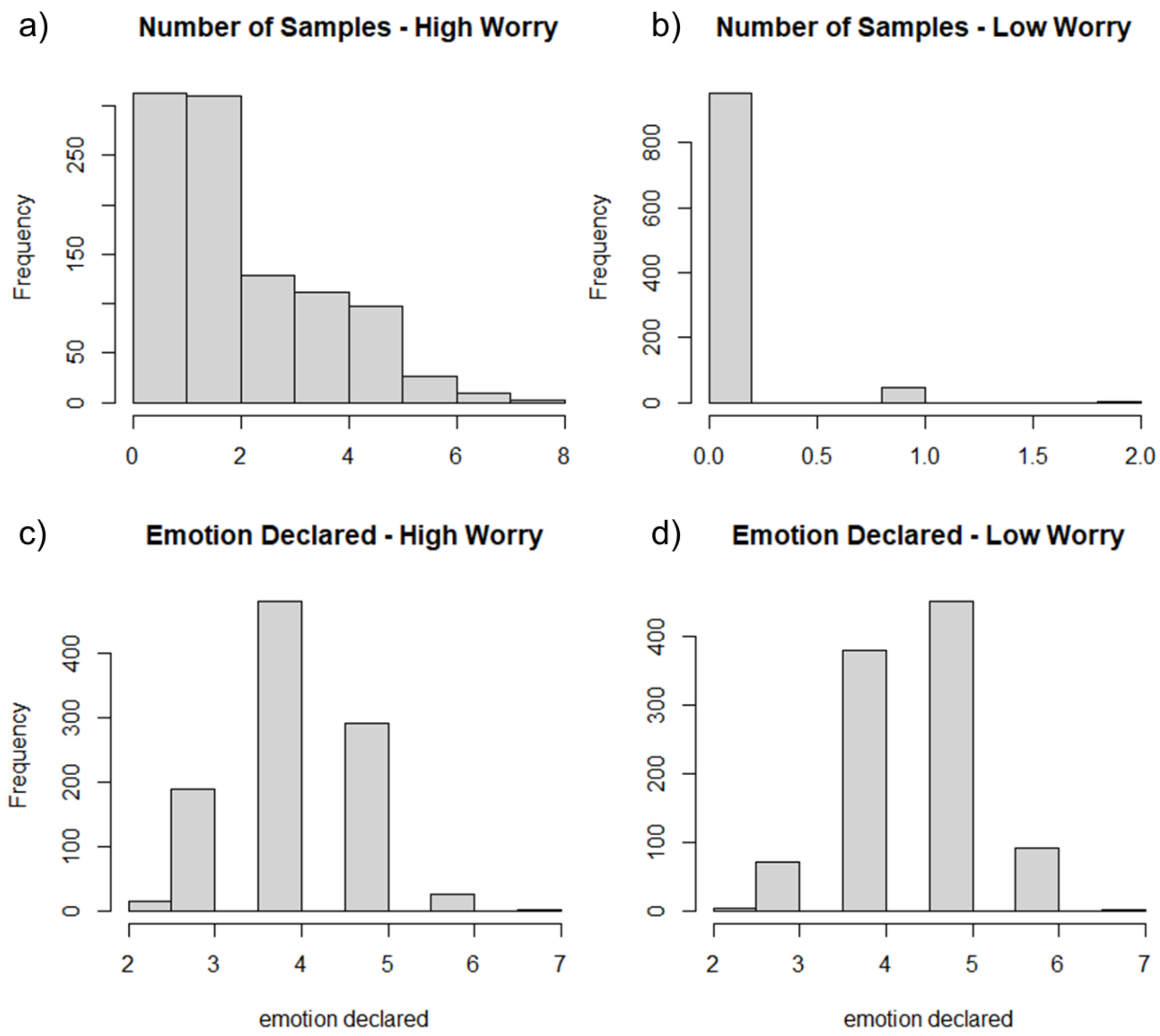
Example	n_{bsl} / k_{bsl}	μ_{bsl}	ψ^2_{bsl}	ω	Qb_{max}	β	L	t_f	s_F	t_F
High Worry	5	5	10	0.95	20	0.5	0.05	10	1	1
Low Worry	5	5	10	0.95	10	0.5	0.05	10	1	1

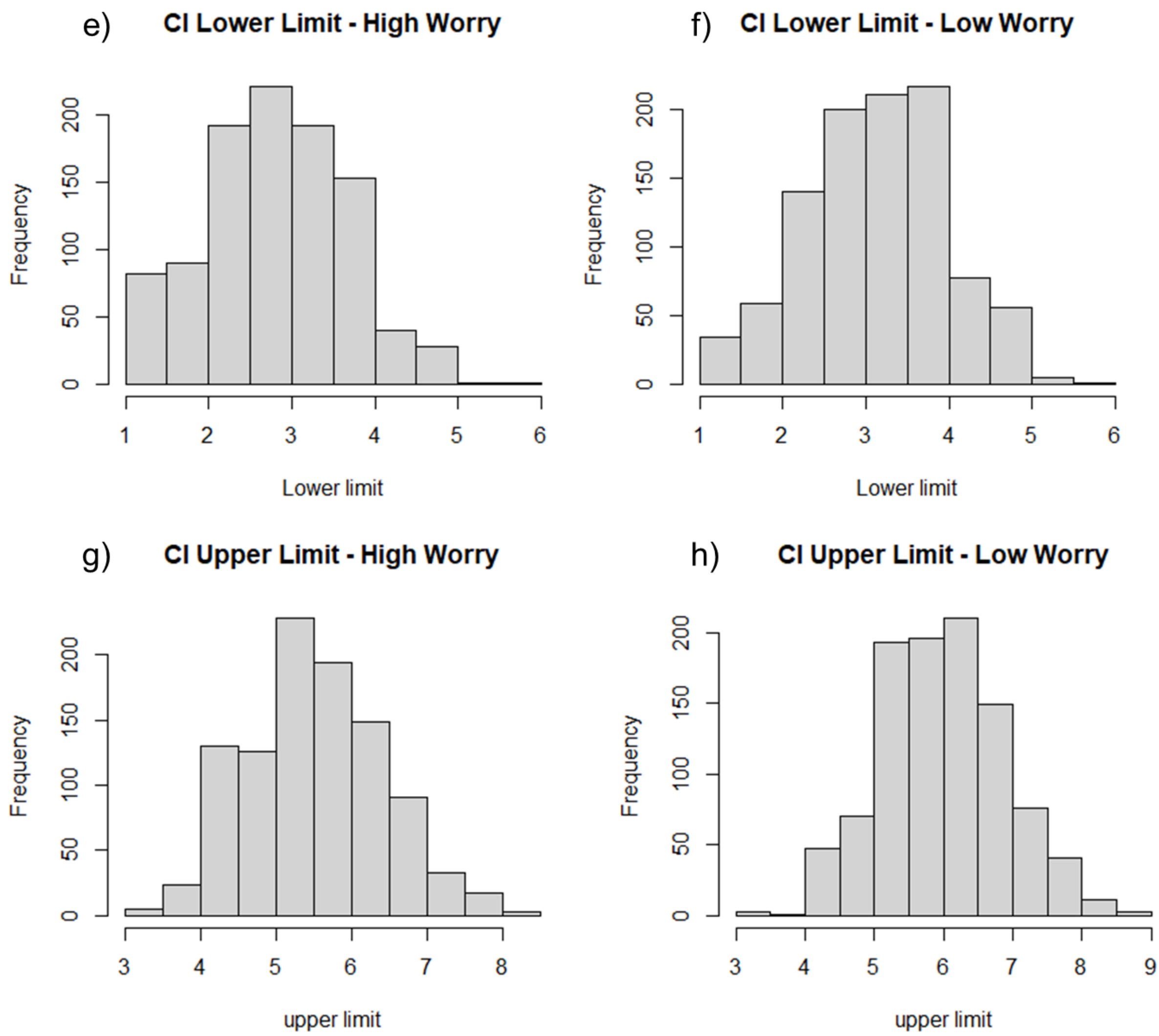
Impatience Model	'Favourite number' Model	Value Model	Information Model
2	2	1	1

The Qb_{max} values were lowered compared to the previous example while still being much higher in the high than low worry representative parameters as an initial test showed that the previous parameters often produced no instances of D_{stop} = 1 over 50 searches.

Figure 64.

Histograms comparing generated data for parameters representing high and low worry.





Note. a) and b) show the number of samples, i.e. re-lookings, taken by 1000 examples of agents with the given parameters. c) and d) show the emotion declared using the same; similarly, e) and f) show the lower limit of the confidence interval, and g) and h) the upper limit.

Figure 64a) and b) again show a similar pattern as re-lookings in behavioural data, where the set of parameters which represent high worry generate more sampling than those that represent low worry.

A comparison between Figure 62 (stimuli is all ‘9’s) and Figure 64 (stimuli is a more realistic set of numbers) also allows an exploration of when worry is more useful or less useful.

As can be seen, Figure 64 generally shows a smaller difference in behaviour produced by the ‘high worry’ and ‘low worry’ parameters compared to the differences shown in Figure 62. For instance, looking at 62c) and 62d), the modal reported emotion is 8 for the high worriers and 5 for the low worriers, the peak of the histogram being much more leftward in the low worry group. In contrast, while 64c) and 64d) still have different modal reported emotion values (4 compared to 5), most of the frequency weightage remains on both 4 and 5 for both low and high worriers, demonstrating more similar behaviour between them. This is more qualitatively representative of the data obtained from the large online study, where there was no significant difference in accuracy between the high and low worry groups despite the high worry group re-looking significantly more. This suggests that high worry behaviour produces more differences from low worry behaviour in the first (all 9s) compared to this second (realistic stimuli similar to original 5 faces) numerical environment.

To explore this further, there are two notable differences between the two numerical environments. First, provided information in the 'all 9s' environment very different from the initial 5 faces, whereas here the new information was very similar. As such, this suggests that high worry behaviour is more useful when new stimuli is different from initial stimuli, assuming that the new stimuli provides an accurate impression of the underlying state. Second, the ratio of new to old information was 1:1 in the previous environment, while the ratio is 1:5 in this one, making each search less useful. This could explain why worry-like behaviour was not useful in the large online study – as the ratio was 1:5 and the provided information was similar – providing an example of how modelling can explain behavioural data.

This suggests that an alternative experimental paradigm where re-lookings are more useful can be tested to reveal if there are situations where high worriers are more adaptive than their low worry counterparts. Specifically, if stimuli provided during re-lookings are closer to the correct answer *and* very different from initial stimuli provided, re-lookings are more useful, and therefore re-looking may be more adaptive. This would align with the concept that worry is problem-solving which is adaptive in certain situations.

6.5.4. Simulating Trait Worry

Although the above examples were generated by varying Qb_{max}, other parameters can also be varied to produce high trait worry like behaviour, i.e. a greater number of samples. While examples are not included for brevity, Table 93 below discusses some alternative ways that high trait worry like behaviour could occur.

Table 93.

Parameters that can simulate high trait worry i.e. sampling more.

Parameter	Explanation
n_{bsl} / k_{bsl}	A low n_{bsl} or k_{bsl} causes SEM to be higher; SEM is inversely proportional to *P(j, d = stop)*. (Figure 49)
μ_{bsl}	The larger the difference between μ_{bsl} and obtained evidence is, the larger the SEM, and the lower the *P(j, d = stop)*; however, the effect of μ_{bsl} fades quickly (in terms of timesteps). (Figure 50)
ψ^2_{bsl}	High ψ^2_{bsl} causes high SEM; SEM is inversely proportional to *P(j, d = stop)*. (Figure 51).
ω	Low ω causes more evidence decay, leading to lower n_{bsl} or k_{bsl} which causes SEM to be higher (Figure 52).
Qb_{max}	Shown and discussed above (Figure 53).
β	If *P(j, d = stop)* is between 0.5 and 1, a lower value of β shifts *P(j, d = stop)* to be closer to 0.5, reducing the chance of stopping. However, note that it would conversely increase the chance of stopping if *P(j, d = stop)* is between 0 and 0.5. (Figure 54)
L	Similar to the above, if *P(j, d = stop)* is between 0.5 and 1, a higher value of *L* shifts *P(j, d = stop)* to be closer to 0.5 and further away from 1. (Figure 55)
t_F	Timestep 'favourite number' function is centred around; as this increases, *P(j, d = stop)* increases at a greater timestep. (Figure 60)
s_F	Slope of 'favourite number' functions; decreasing the slope decreases the 'favourite number' bonus, decreasing *P(j, d = stop).* (Figure 60)
I_t	Timestep where impatience function starts to be applied for impatience models; hence, a higher value will cause the increase in *P(j, d = stop)* to occur at a later timestep. (Figure 58 and 59 respectively)
p	
S_I	Slope of function for impatience models; a lower slope decreases the effect of the impatience model on *P(j, d = stop)*, decreasing it (Figure 58 and 59 respectively)
cs	

Note. Note that the effect does not always happen, depending on the nature of the other parameters and provided observations. For example, if the effect of impatience has a much larger magnitude than the effect of SEM changing over timesteps such that it pushes *P(j, d = stop)* towards 1 quickly, it is likely that the first 3 parameters below would have no or minimal impact on *P(j, d = stop).*

Evidently, there are many ways that parameters can increase sampling, a key aspect of worry-like behaviour. These represent hypotheses about what cause worry. For example, if the impatience slope decrease is the main contributor to extended sampling, this suggests that there is a top-down process dictating the motivation to search longer, rather than an increase in the value of sampling; in contrast, if the increase in Q_{bound} is the main contributor to increased sampling, this suggests increased valuation of the process of sampling itself.

Furthermore, importantly, it is not just increased sampling that may differentiate low worry from high worry, which can be modelled by the parameters above, but particular patterns over the parameters in this model. For example, a classifier could differentiate between high and low worry using logistic regression based on the parameters; this approach has been shown to be suitable for computational modelling of psychiatric processes (Knolle et al., 2023).

An additional check that this model captures worry which can be done is that data generated from 'high worry' parameters should have the same relationship with questionnaire data that the empirical data does. This again extends beyond the number of samples, as questionnaires can be related to parameters via analyses such as a canonical correlation analysis, which can identify a combination of parameters and questionnaire data which describes aspects of behaviour (Will et al., 2017).

6.6. Likelihood Functions

A likelihood function represents the probability of obtaining the observed data given a specific set of model parameters (Myung, 2003). This helps to evaluate competing models and sets of parameters for what best accounts for the observed data. It serves as a way to quantify how well the hypotheses represented by the model are supported by empirical evidence. To this end, a likelihood function was written for this model in the programming language R and is described in detail below.

6.6.1. Likelihood of number of re-lookings

1. The vector of *P(j, d = stop)* values at each timestep is obtained; this has previously been calculated by the model at each timestep.
2. Each value in this vector is subtracted from 1 to produce a new vector which represents *P(j, o = continue)*.
3. A logarithmic transformation is applied to each value in both vectors. This is because joint probabilities calculated as is will cause underflow, as multiplying many probabilities will produce a very small value which cannot be represented accurately. Furthermore, given the probability of a decision P, log(P) scales to the motive behind it, e.g., as seen in the structure of softmax decision making functions in reinforcement learning.
4. To calculate the log-likelihood of each possible time-point at which samplings stop being taken, add the value of log(P(j, d = stop)) at that time-point to the sum of all log(P(j, o = continue)) values up to that time-point. This is because the probability of stopping sampling at this time-point includes the probability of not already having stopped at a previous time-point, i.e. the probability of all previous decisions being 'continue sampling'.
5. The log likelihood of *n* re-lookings is the log likelihood value of sampling stopping at time-point *n+1*. This is because if sampling stopped at that time-point, no samples were taken at that point, but samples were taken at every point up to it.

6.6.2. Likelihood of Lower and Upper Limits

1. Obtain the belief mean, n, effective sum squared deviation, and k from the timepoint where sampling stopped.
2. Calculate lower and upper bounds of the 80% confidence interval around the mean in t distribution, i.e. native space (since the belief is in the form of a t distribution).
3. Obtain the upper and lower bounds in the 1-9 interval space by multiplying the values above by the spread parameter of the t distribution, then adding the belief mean.
4. Set up 9 bins for a histogram, each corresponding to the 1-9.
5. Generate 1000 possible upper and lower bound values each by adding 1000 randomly sampled values from the normal distribution N~(0,Tr), where Tr is the

temperature parameter, to the value of the upper or lower bound obtained at Step 3.

6. Place each of the 1000 obtained values in a bin corresponding to the nearest integer value.
7. To find the probability of the participant's reported upper or lower bound given the model, divide the number of values in the corresponding bin by 1000.
8. Apply a log transform onto the obtained probability value to get the log likelihood.

6.6.3. Likelihood of Reported Emotion

1. Obtain the belief mean at the timepoint where sampling stopped.
2. Obtain the probability of the participant's reported emotion read by calculating the area under the curve in a normal distribution N(μ,Tr) bounded by +/-0.5 of the reported value.
3. Apply a log transform onto the obtained probability value to get the log likelihood.

These likelihood functions are written and are ready to be used to invert the generative models described in this chapter using the empirical data described in preceding chapters. This will enable empirically constrained estimates of the key mechanistic parameters above and, via Bayesian model comparison, furnish empirical evidence for the various hypotheses established in the current chapter.

6.7. Conclusion

An evidence accumulation model which captures worry-like behaviour in the form of re-lookings has been established and passed the key initial stages of validation, demonstrating that all parameters and parts of the model work as intended. The model was then used to generate synthetic data that qualitatively and quantitatively mirrors the behaviour of people with high worry, producing a pattern of high sampling. The distribution of number of samplings produced in both high worry and low worry representative parameters also had a similar distribution shape as the data obtained from the large online study, suggesting that the model can indeed capture real behavioural data. In sum, the model is able to capture worry in principle, and is in a position to provide insight into its mechanistic processes.

This, alongside the successful crafting of a likelihood function, places the model in good stead for further testing and eventual fitting to the data obtained from the large-scale online study. This will be discussed in the next chapter.

7. Overall Discussion and Future Work

7.1. Interim Overview

Chapter 1 highlighted the importance of studying worry in both anxiety and mental health as a whole, and explained how computational modelling is uniquely suited for uncovering the mechanisms of worry. Chapter 2 provided a systematic scoping review of the literature and found a lack of computational models of worry, revealing a key gap in the field and put forward evidence accumulation models as the best way to capture worry. Chapter 3 introduced a novel experimental paradigm which aims to make external and measurable the process of worry, and provided an overview of the piloting process, justifying key decisions for experimental design.

Chapter 4 introduced a large-scale online study of the novel paradigm, then provided an analysis of key factors. The analyses demonstrated that the key experimental outcome, re-lookings – known as samples to decision in the information gathering literature – are an appropriate proxy for worry. Importantly, it also provided a key insight that high worriers' re-looking behaviour is suboptimal compared to low worriers, in the sense that increased sampling did not lead to better outcomes – and this is likely driven by sampling even when chances of success are low. Chapter 5 built on this, finding that while between-subject factors such as perfectionism significantly predicted re-lookings in univariate analyses, their effects were completely mediated by momentary worry and trial-specific factors in multivariate analyses. This suggests that a mechanism by which these factors may increase worry is by increasing the type of sampling detected by this paradigm.

Chapter 6 introduced an evidence accumulation model of worry, demonstrating that it has passed key checks and can generate realistic data, providing a proof of concept that it could indeed capture the processes of worry and should undergo further testing.

This chapter will now discuss in further detail key aspects of the previous chapters as well as provide a roadmap for the path ahead.

7.2. Systematic Scoping Review

7.2.1. Strengths

The systematic review successfully identified key elements of existing models of worry, such as metacognition, beliefs, intolerance of uncertainty, experiential avoidance, attentional bias to threat, control and emotional dysregulation (Section 2.2; Table 5). It also highlighted a gap in the field, in that there are no computational models of worry. This enables an analysis of what to incorporate into a computational model of worry, concluding that evidence accumulation models are best suited for modelling worry. This informed both the design of the experimental paradigm and the crafting of the model in subsequent chapters.

Search was comprehensive, covering multiple databases and with alternative search terms for the key terms of “worry” and “model”. This is reflected by the large amount of records identified on initial search (n = 86673). Given this large number and therefore the resource intensiveness of filtering relevance by hand, ASReview was a highly suitable tool for the systematic scoping review.

While there is a chance that ASReview, being a new method of conducting a systematic review, may have yet unknown flaws, the papers that it suggested during the review process included models which were independently found via a conventional literature search, lending the process validity in this specific field. ASReview itself is also open-source, making its methods more easily interrogated, and has been independently shown to be effective (Campos et al., 2024).

Exclusions due to access reasons — such as the papers being non-English — were rare (only 17 out of a total of 985 papers screened via non-database methods, about 1.7%).

7.2.2. Limitations and Future Work

A key limitation is that systematic review searches are not designed for computational psychiatry. As seen from the large number of records initially returned, ‘model’ is a broad term which had to be used to ensure that no records are excluded, but is not specific enough to describe computational models alone. As such, many records were from conceptually similar fields, which do contribute to the understanding of worry but are not computational models of worry.

In addition, during the process of shortlisting papers via ASReview, search could have continued longer to account for the fact that papers may have been missed out.

However, there needs to be a trade-off between time and results, and it is relatively unlikely that a computational model of worry would be found in a paper further down the priority list produced by ASReview, as that would mean it is found in a paper which is more irrelevant at initial analysis. This is especially so when considering that even the relevant records did not include a single computational model of worry. Therefore, the key finding of the systematic scoping review that there are no computational models of worry remains highly likely.

In future work, to further verify the use of ASReview in this context, some records already known to be relevant can be pre-selected by hand and excluded ('held out') from the initial training data of key relevant papers. ASReview can then be tested by finding out if it can effectively retrieve these pre-selected records within a set number of searches, and if not, whether more records should be assessed than initially assumed.

Nevertheless, the findings of the scoping review provided a rich set of literature on worry models to analyse, and even if a computational model of worry were to be missed out, the scoping review has been sufficiently helpful in informing modelling directions. All in all, though more work can be done on the systematic review, as it stands it has sufficiently achieved its intended purpose of providing context and direction for modelling.

7.3. Experimental Paradigm and Piloting Process

7.3.1. Strengths

There were several rounds of piloting, which each brought improvement to the final experimental paradigm. Pilot 1 justified the inclusion of aversive stimuli, as feedback was that participants were not sufficiently convinced by the scenario alone and worry requires an aversive motivator to not simply be information sampling. Pilot 2 checked that comprehension, attentional and headphone checks for the threat of scream paradigm were effective and revealed the need to generate samples from a distribution rather than via hand-selection. Pilot 3 demonstrated the need for information to be provided separately and sequentially, as well as refined how self-reported worry was collected. Apart from this, technical issues were also resolved during the course of piloting, which would have occurred too late to be fixed in the large-scale online study e.g. audio issues which would have strongly reduced the effectiveness of the threat of scream.

Each of these pilots had approximately n = 30 participants, which was enough to observe the main effect of information ratio, revealing that it should be a key focus in the large-scale online study, while being of a sufficiently small number to pilot quickly and efficiently. This enabled multiple piloting rounds despite time and funding limitations. The findings also allowed hypotheses to be made about the findings of the large-scale online study before any analysis was conducted, as some insight into behaviour was already known. In particular, the counterintuitive finding that sampling occurred more in the low chance of success condition was hypothesised to occur again in the large-scale online study, and it would not have been hypothesised without the piloting results. The consistency of this finding across 2 out of 3 pilots, the excluded one being of a significantly different design, as well as the eventual final analysis, also suggests that it is a relatively robust result and less likely to have occurred due to a fluke. Furthermore, even though this result did not occur in Pilot 3, its lack of occurrence itself provides insight; as Pilot 3 alone had a 6 second long 'worry period' prior to re-lookings, this suggests that the 'worry period' removed the need for re-lookings, and therefore that re-looking is indeed a representation of the internal processes which would have happened if the opportunity to re-look was not presented.

7.3.2. Limitations

For clarity, the piloting process and experimental paradigm itself is discussed here, rather than its results (which will be discussed in the next subsection).

A key issue found across the piloting process was that re-lookings were skewed towards 0 and attempts to increase them were not effective. This reduced the discriminability of the number of re-lookings by increasing that chance that changes to an effect of interest do not change number of re-lookings. Qualitative feedback during the piloting process included that people chose not to re-look as they already felt sufficiently certain. Therefore, a potential change that could target this would be reducing the number of facial expressions presented at the start (the minimum would be 2 in order to be able to vary precision). While re-lookings in theory would depend on SEM alone, and the same SEM can be provided regardless of number of faces, more information itself can provide a feeling of greater certainty, or having gathered sufficient information. This can be seen experimentally in the numbers of people who used the ‘favourite number’ heuristic, where they based their decision on the amount, rather than nature, of information they have obtained. More faces also increases the working memory load and the mental demands of ‘calculating’ the overall facial expression, which participants may wish to avoid. A test about whether reducing the number of faces provided or increasing the SEM would be more effective at increasing re-lookings can be conducted and the result used to inform which method should be used. Another change that could increase the number of re-lookings would be to further decrease the chance of success, based on the finding that people re-looked more in the low success condition; however, there is a chance that this effect may have occurred in comparison to the high success condition, and it is possible that the numerical chance of success matters less than the relative chance of success between the two conditions available. Other potential changes include increasing the strictness of the criteria needed to have a definite chance of avoiding a scream – i.e. they only definitely avoid the scream if they choose the exact correct emotion read, whereas now they can still avoid it by being one unit off – to more strongly punish errors.

7.4. Large Scale Online Study

7.4.1. Discussion of Results

There were two key takeaways from the large-scale online study. First, the paradigm successfully captured worry. Second, high worriers were less adaptive than low worriers, demonstrating persistent worry-like sampling even when doing so was ineffectual, and possible reasons for this can be explored.

First, it was demonstrated that the paradigm successfully captured both state and trait worry through re-lookings, as results across both chapters provided empirical support for its validity. For state worry, trial-to-trial momentary worry significantly predicted re-lookings; for trait worry, high worriers engaged in significantly more re-lookings than low worriers. Further support for re-lookings capturing state worry was evident in how momentary worry was the best psychological predictor of re-lookings, over factors such as perfectionism, mood-related symptoms, and demographic factors.

Then, with regards to the adaptiveness of worry-like behaviour, a crucial behavioural pattern emerged: high worriers re-looked significantly more than low worriers, but importantly this did not change their accuracy, there being no significant difference in error magnitudes between the two groups. This suggests that that the effortful increase in sampling, alongside a higher level of mental distress as captured by higher self-rated worry, did not lead to any improvement in outcomes. Therefore, in the cost-benefit framework as discussed in Chapter 1, the behaviour of high worriers is maladaptive. This was unexpected as it was hypothesized that high worriers would perform better due to obtaining more information. (Alternative frameworks will be discussed subsequently.)

A further finding from this study sheds light on the mechanism behind this. It was found that high worriers re-looked significantly *more* when there was a low chance of success compared to a high chance of success, and this did not occur in low worriers. This suggests that high worriers persist despite environmental cues which indicate that doing so would be unhelpful. The fact that this only occurs in high worriers points towards it being a behaviour which may characterise them and drive worry.

This is backed up by evidence that sampling differences may be how person-specific factors cause worry. In multivariate analyses, it was found that the effects of demographics, perfectionism and depressive symptoms were no longer significant after trial-specific momentary worry and information ratio were controlled for (and had significant effects), meaning that their effects were completely mediated. This means that these factors, now rendered non-significant, are likely to exert their effect via the mechanisms captured in the paradigm – i.e. by changing how people sample. This suggests that, indeed, sampling is a key way in which to understand worry.

A possible comment that some of the results may have occurred due to attributes of the experimental paradigm rather than being potentially generalisable. For example, while high worriers' behaviour is maladaptive here, it may be argued that the experimental paradigm is too specific a situation to provide insight into maladaptive worry in general. While it is true that this paradigm cannot cover every possible situation – and nor does it claim to – experimental decisions have enabled it to reflect real worry as much as possible. For example, the section mentioned above discussed that re-lookings may be ineffectual because even new information obtained is randomly drawn from an underlying distribution and therefore may not necessarily point the participant in the correct direction. This is not to mention the fact that the chance of obtaining new information is low. It was therefore briefly discussed that, if the green-bordered facial expression had been not merely a sample but the correct answer, the greater tendency of high worriers to re-look would have been more favoured, and therefore more adaptive and useful.

This begs the question of: if worry is a sampling process aimed at solution-finding, would a successful solution be more like gathering a set of useful samples, or finding a single extremely useful answer? The decision was made to choose the former due to the associative nature of worry (T. D. Borkovec et al., 1998; Vasey & Borkovec, 1992), which would imply that thinking about an unpleasant situation would cause memories or thoughts from the same situation to surface. Similarly, the chance of success is low because in real worry, one often does not find a satisfactory solution. It could be arguable that these trials are too short to capture worry episodes, which are often prolonged; however, these can still capture single worrisome thoughts, or alternatively, the full experiment could even be a single worry episode, as the topic of concern remains consistent throughout the experiment (worries about the emotions of other people in the workplace).

Next, with regards to the specific finding that high worriers are less adaptive, this was indicated by the fact that increased re-lookings came with no corresponding decrease in mean magnitude of errors. However, it must be acknowledged that this could be “adaptive” to high worriers’ preferences; perhaps accuracy matters less to them than, for example, a feeling that they have done all they can, or avoiding a sense of discomfort that comes with making a decision before they are ready. Neurodiversity acknowledges that what is adaptive is what allows someone to achieve their individual wants, even if they prioritise, in this case, potentially something else over accuracy and efficiency. The key issue, then, is to understand the future patient’s perspective, and what their overall goals are, which may lead to difficult decision-making. For example, if one speaks of being willing to ‘put up’ with temporary high worry to feel better afterwards, does this type of worry warrant concern? Could this perception be false, however, given that results (Figure 31, Chapter 4) show that worry does not decrease even after one acts based on it? Evidently, a view which takes into account each person’s unique value systems – which may not simply be to maximise reward and minimise punishment – is important.

Lastly, the finding from the multivariate analysis demonstrates that as a signal, the number of re-lookings sensitively captures changes in worry without getting drowned out by the effects of person-specific attributes, indicating its usefulness as a measure. This highlights the paradigm's capacity to capture moment-to-moment fluctuations in worry as participants respond to environmental changes (e.g., shifting success probabilities). This allows for the phenomenology of worry to be captured – as it fluctuates naturally over time in relation to the environment – adding to more static measures of worry tendency captured by questionnaires. Furthermore, intriguingly, it enables links to the study of the brain as a dynamic system which may have attributes such as early warning signs for mental decompensation (J. Cui et al., 2025; Dablander et al., 2023), as being able to quantify worry or worry-like behaviour allows a look into what is 'under the hood'.

This, together with key findings from Chapter 4 which highlight the role of worry in re-lookings (e.g. high trait worriers also re-looking significantly more), demonstrate the primacy of worry to re-lookings, and how this particular measure could be useful in further studies for gaining understanding of worry.

7.4.2. Clinical implications

Some key findings from the large-scale online study have clinical implications. The fact that high worriers respond to a lower chance of success by sampling more suggests a possible driver for worry. Specifically, responding to worry not producing a satisfactory solution is responded to with 'this means I need to search harder' rather than 'this means I need to stop worrying'. This is an example of a metacognitive belief that high worriers may hold. Literature has documented that positive beliefs that worry is helpful increases worry (Davey, 2008; Hebert et al., 2014; Wells, 2006), and targeting these beliefs can reduce worry (Laberge et al., 2000). This therefore provides further evidence that these are a valid target for talking therapies such as cognitive behavioural therapy, where beliefs are explicitly inferred and analysed (Moutoussis et al., 2018; Nair et al., 2020). Talking therapies which specifically target metacognitions (Wells, 2010) may be especially relevant. This study has contributed by uncovering evidence for a metacognitive belief that lack of success necessitates persistent worry, a belief may be present broadly across high worriers.

Furthermore, the finding that people may have difficulty accurately perceiving precision when under threat, as evidenced by there being no difference in re-lookings between high and low precision conditions (Section 3.7.), as well as their number of re-lookings being based on perceived rather than actual uncertainty, suggests a potential target for intervention. This reduction in executive function could impair their ability to stop worrying, or even other forms of repetitive negative thinking such as rumination, as executive function has been shown to be impaired in both depression and anxiety (RP Alves et al., 2014; Shields et al., 2016). Existing CBT approaches target maladaptive responses to intolerance to uncertainty (Bomyea et al., 2015), but it is unclear if difficulty in estimating uncertainty itself has been targeted. If future work reveals this to be a cause of worry, it could be a novel target for talking therapies. This could be a further development of the 'probability of catastrophe' module in Danger Ideation Reduction Therapy, which addresses unrealistic estimates of danger (Maqbool et al., 2017). Exposure-therapy-like interventions where patients are guided to maintain executive function under stressful or aversive circumstances could also reduce the occurrence of worry; for example, a possible pathway is to combine calming techniques with practicing thought processes that assist with executive function. Interestingly, this may already happen naturally during the course of talking therapy, as clients bring anxiety-causing problems to their therapist and are guided to think through them.

Next, the finding that perfectionism predicts between-subject differences re-lookings – as found in univariate analyses – has psychoeducational and therapeutic implications, as this suggests that targeting perfectionism can reduce worry. CBT for perfectionism has been shown to be efficacious in reducing symptoms of anxiety in a recent meta-analysis (Galloway et al., 2022), and novel therapies such as group dynamic-relational therapy have been proposed (Mikail et al., 2022). Therefore, this supports findings which show that perfectionism-focused therapy can be an avenue for reducing worry.

Lastly, the concept of re-lookings indicating worry could pave a way to technologically detect mental states in real time. In the current world, interactions often involve information search e.g. checking inboxes, monitoring values, or visually inspecting for changes. As such, understanding what these naturally occurring 're-lookings' represent could allow them to be evaluated as markers of mental states, providing information seamlessly without actions being interrupted (as self-reporting would require). This allows for real-time, and seamless, detection of mental states, via system integration e.g. built into the software of smartphones or work laptops. This is akin to wearable technologies providing monitoring of mental health (Morris & Aguilera, 2012; Yen, 2021), except without needing one to actively interact with it, potentially increasing compliance and uptake. This has potential in tracking signs of mental distress in disorders where a worsening trend could be reflected by an increase in worry, such as GAD or OCD. This could be used not just by clinicians but by the user themselves in a self-empowering way akin to integrating assistive technology into daily life. This aligns with recent interest in preventative mental health such as interventions for subthreshold depression (Buntrock et al., 2024), while avoiding the stigma of overdiagnosis. Indicators can be self-calibrated, perhaps suggesting that one may need to take a break, do relaxation exercises, or seek social support; this can help prevent a worsening of one's mental health and the precipitation of a mental health crisis, helping to relieve some load on already strained mental health services.

In general, as worry is present in a large range of mental health disorders, as discussed in the introduction, the findings in this study present transdiagnostic targets for intervention – potentially having a large impact on the field of mental health.

7.4.3. Strengths

The large-scale online study has key strengths which enabled it to produce the fruitful findings discussed above.

First, as discussed in Chapter 4, limiting participation to people who scored in the top and bottom 10% of the PSWQ increased the power of the study, allowing for a more sensitive study of interpersonal differences. This structure akin to a case-control study set up a direct comparison of the processes in maladaptive compared to adaptive worry, which was very useful in analyses. Differences between high and low worriers were found on multiple fronts, from overall re-lookings to responsiveness to the information ratio condition to changes in state worry before and after re-lookings, demonstrating the efficacy of this selection method. This allows us to potentially pick apart which processes are present – or amplified– in maladaptive worry only, adaptive worry only, and worry in general. This is crucial to understanding the nature of worry, especially in the context of it being intended to be helpful, and being an optimum stopping problem.

Second, questionnaire selection was a strength, as they were selected to be able to capture nuances such as the difference between state and trait anxiety, enabling them to be analysed separately. This was also seen in how the perfectionism scale chosen had 4 subscales, each capturing a different aspect of perfectionism. This is especially important as this is a novel paradigm, and as such there may be unexpected associations with questionnaires, which would shed light on what exactly is being measured and if the paradigm captures a psychological process which was not intended to be captured. This is especially difficult, and crucial, in mental health, due to the interconnectedness of many processes, as alluded to in the discussion about a general vulnerability factor in the introduction. This is also important for checking the discriminant validity of the measure, which is defined as “measur(ing) the construct that it was supposed to measure but not any other construct of interest” (Rönkkö & Cho, 2022).

Third, the experimental paradigm aims to mirror real processes of worry as much as possible, providing it ecological validity. The purpose of worry – a forward-thinking phenomenon to avoid an aversive outcome – lies at the core of the paradigm. The stimuli, which is of course central, reflects how the most common worry topic is interpersonal relationships, as well as how the experience of avoiding punishment by reading mood can be a core, painful memory which carries into future relationships. Faces themselves are also very salient stimuli. Lastly, as discussed in the section directly before this, the very structure of the paradigm mirrors the associative, and persistent, nature of worry. These decisions were informed by the systematic scoping review (Chapter 2) as well as a general review of the field of research on worry.

Lastly, and importantly, the robustness checks conducted throughout data analysis increased support for the validity of the results. This was especially important given that there were demographic differences between the high and low worry group (age, gender and SES). While these differences were explainable by known demographic trends e.g. that worry decreases with age, checking that the results were still valid after controlling for these factors ensured that they were not due to these factors.

7.4.4. Future Work

While the selection process evidently had benefits, there are some key drawbacks. First, the participants are unlikely to be representative of the general population, given that they were selected precisely for being at the extreme deciles for a questionnaire for trait worry. Clinical worry was also not examined, as participants with mental health diagnoses were excluded. This means that variation across the full spectrum of trait worry was not examined, limiting 'dose-response curve' analyses of worry, and findings may not be applicable to the population as whole or clinical population specifically. However, the fact that re-looking distribution patterns mirror that of the pilots where there was no selection process based on trait worry, and the key result that re-lookings are significantly higher in the low success condition remained consistent throughout piloting and in the eventual large scale study, suggest that these results are likely to be valid. In addition, the direction of effects of individual differences captured by questionnaires were generally as expected. There is also some evidence that a continuum exists between normal and pathological worry, rather than being entirely qualitatively different (Goring & Papageorgiou, 2008), suggesting that these results would not be inapplicable, especially since people with formal diagnoses of psychological and neurological disorders were excluded. Future work can check if the findings here are applicable across the entire spectrum of trait worry, both by testing the general population and by testing clinical populations which were excluded.

Next, while n = 306 is sufficient for finding some between subject differences, it is still relatively underpowered compared to other studies aimed at finding individual differences e.g. Bach and Moutoussis (2020) tested 781 participants (Bach et al., 2020). This may explain why multiple fixed effects were hypothesised to have a significant effect but were just above the corrected significance threshold – the study was slightly underpowered overall. Therefore, future work would be to expand the study to more participants to increase its power, providing more certainty about relationships found.

For questionnaires, while it would be impossible to include every possible questionnaire that could be associated with re-lookings, it was noted that elements of the experiment could be associated with compulsivity, and as such a compulsivity questionnaire could be included in future work. Compulsivity is defined as performing "repetitive, unwanted, and functionally impairing overt or covert behaviour without adaptive function" (Hollander et al., 2016) in a stereotyped or habitual way, based on either rigid rules or to avoid perceived negative outcomes. As such, the character of re-lookings being a repetitive action, found to be maladaptive in high worriers, and in order to avoid aversive stimuli, clearly shares some characteristics. The phenomenon of a ‘favourite number’ of re-lookings as discussed in the modelling chapter (Chapter 6) also suggests the possibility of a rigid rule, unchanging despite variation in conditions. Future work could examine the contribution of compulsivity to re-lookings e.g. by the inclusion of a transdiagnostic compulsivity questionnaire (Hook et al., 2021).

Mediation analyses can also be improved by a bootstrap test, calculating the size of the mediation effect as well as a significance value; an accessible R package is available and it claims to be robust even for data which deviates from an assumption of normality, making it a viable option (Alfons et al., 2022).

7.5. Modelling

7.5.1. Discussion of Model

The model successfully captured empirical data both qualitatively and quantitatively, as demonstrated by the similarities between experimental and model-generated data. It passed key initial validation tests such as mathematical checks and parameter behaviour checks, placing it in good stead for further testing and eventual fitting to data.

Given that the model has not yet been tested on the data, discussion will focus on the principles, crafting and in-silico testing of the model. Empirical testing will be discussed in the future work subsection (7.5.3.). First, the utility of the model in distinguishing different types of worry will be discussed, and next, the model will be compared with an existing computational model of rumination, which is strongly related to though not exactly worry.

As seen in Chapter 6, many parameters in the model can potentially increase worry-like behaviour. A possible way to divide them is into parameters which affect worry in a top-down (affecting worry via cognitive control e.g. smaller impatience parameters) or bottom-up (affecting worry by affecting the value of sampling directly e.g. increasing Qb_{max}) way. This could shed light on the relative contributions of bottom-up threat perception and top down positive and negative beliefs about worry, as has been discussed in some cognitive models of worry, e.g. Hirsch & Matthews’ (2012) cognitive model of pathological worry. It could also differentiate between different forms of worry, as it may manifest differently in different disorders, as a transdiagnostic symptom present not just in Generalised Anxiety Disorder but heightened in many disorders e.g. Post-Traumatic Stress Disorder (PTSD) (Tull et al., 2011) and Obsessive Compulsive Disorder (OCD) (Calleo et al., 2010). For example, worry that occurs due to increase in a parameter related to the 'favourite number' bonus could be associated with OCD, due to the repetitive behaviour in OCD sometimes being characterized by rigid rules (Hollander et al., 2016). This can shed light on the key mechanisms behind different types of worry, whether in different disorder types or in maladaptive compared to adaptive worry especially, allowing the targeting of these processes in treatments such as talking therapy.

Next, as the Bedder et al (2023) rumination model is the most similar computational model to this model, a compare-and contrast-will be discussed, although some points have already been addressed in Chapter 6. First, recall that worry is defined as uncontrollable distressing thoughts due to concern about an impending threat (Hirsch & Mathews, 2012), while rumination is defined as "thoughts that revolve around a common instrumental theme that recur in the absence of immediate environmental demands" (Martin & Tesser, 2013). Conventionally, rumination considers the past, worry considers the future. Both are considered forms of repetitive negative thinking.

Both models posit that the purpose of repetitive negative thinking is to infer an underlying state, and the models structurally reflect this. Both are in the form of a Partially Observed Markov Decision Process (POMDP). This is explicitly discussed in the rumination model, while in the worry model this can be seen by how it is a decision problem, the underlying emotion is partially observable via sampling, and it is Markovian. In both models, decision-making is determined by the values of each action, but they are calculated differently. In the rumination model, the value of sampling is determined recursively based on values of each subsequent belief, weighed by transition probabilities, and a sampling cost, whereas in the worry model, the value of sampling is a logistic function which increases over searches, characterized by participant-specific parameters. For the value of terminating sampling, the rumination model calculates this using the outcome of stopping in each possible state weighed by its likelihood based on current beliefs, while the worry model calculates this by either the inverse of the SEM or the probability of avoiding a scream – which, while also calculating the outcome based on current beliefs, is more paradigm-specific. Notably, although one model is used to describe rumination and one worry, this alone does not differentiate them.

The key difference here is that the rumination model assumes that the agent is an ideal Bayesian reinforcement learner, while the worry model does not. The worry model has elements such as an impatience parameter and 'favourite number' parameter which reflects possible heuristics. This is important as the empirical data suggests that uncertainty has less of an effect on behaviour than expected, given the lack of effect precision has on re-lookings, meaning that an ideal Bayesian model, which incorporates uncertainty at its core, would not be representative. Instead, impatience or a 'favourite number' heuristic, which are not related to uncertainty at all, could prove to be the best way to capture worry-like behaviour. These may be approximations the brain uses, which may be inaccurate but simplify decision-making, being less complex and resource-intensive to compute.

Incorporating both elements in the same model – certainty dependent and certainty independent behaviour – allows for testing of which has a stronger effect on decision-making. This can shed light on whether worry is indeed optimum in some contexts – represented by ideal Bayesian learning – or whether it is a phenomenon that persists unrelated to reducing uncertainty and avoiding aversive outcomes, even if worriers perceive this to be their purpose. If the latter is true, this would reflect a 'malfunctioning' of the brain system which produces and selects approximations in maladaptive worriers, as it is causing them more distress than being helpful. It would also provide support that positive beliefs about worry are in fact false, placing it as an ideal target for interventions which involve examining held beliefs.

Nevertheless, given the similarities between the models and in the underlying concept that repetitive negative thinking could be optimal in some circumstances, although it is a rumination model, future work could involve testing a modified version of the rumination model on experimental data obtained here. Comparing which model fits better will allow insights into the structure of worry, demonstrating how an experimental paradigm can provide rich data for testing even models it was not initially designed for.

7.5.2. Strengths

First, the model draws from a rich body of literature, as seen from the scoping review (Chapter 2), which concluded that evidence accumulation models are particularly well-suited to model worry. This means that it is grounded in the phenomenology of worry, as well as existing computational models of decision-making under aversive circumstances and non-computational models of worry.

Next, due to the incorporation of elements such as an impatience parameter and lapse rate, the model is well-suited for being tested on experimental data. It is also of course designed to fit data from a particular experimental paradigm. This is important as this enables the hypotheses in the model to be tested to checked for validity. Without empirical testing, its predictable validity is unknown.

Finally, the model has undergone several checks that it functions as intended, even though it has not yet undergone empirical testing. It has been both mathematically and conceptually checked that model parameters change beliefs and decision-making as expected. Furthermore, importantly, it could generate data qualitatively and quantitatively similar to data collected in the experimental paradigm for both high and low worry. This supports the face validity of the model.

7.5.3. Limitations and Future Work

There are some ways in which the model is limited in representing worry. First, in this model samples are independent of each other, but in real worry, chronological thoughts are likely to be related to each other, i.e. associative (T. D. Borkovec et al., 1998), and therefore not independent. Although the infrequency of new information causes most of the information obtained on re-looking to be correlated with each other, being drawn from the first 5 faces only, the sampling process itself is random. Second, in real worry sampling is likely to be biased towards negative thoughts or memories, as cognitive biases towards interpreting stimuli as concerning, as well as increased hypervigilance, are well-documented in anxiety disorders (Goodwin et al., 2017; Kimble et al., 2014; S. Milne et al., 2019; Wessing et al., 2017). These elements, while not in the experiment, could be accounted for in modelling e.g. by having a higher learning rate for learning from facial expressions with negative affect (Kishida & Sands, 2021; Montague et al., 2016). However, given that the emotion of the person presented did not have a significant effect on re-lookings, the negative bias may not be relevant in this context.

Third, while the model captures worry in a single trial, it does not take into account trial-to-trial dynamics. This is important as recent aversive stimuli i.e. hearing a scream may naturally cause one to be in a more anxious state immediately after, increasing worry and re-lookings. Learning may also occur over trials. In other words, worry could affect decision-making over and above information provided by the paradigm e.g. by mediating the effect of factors such as information ratio on future trials.

To check for an order effect, analysis of the earlier and later halves of the experiment can be conducted, and to check for an effect of a recent scream, trials with a scream played immediately before it and trials which do not have this can be compared. This behavioural analysis will inform whether taking into account cross-trial elements would be a good use of model development time. Once a model-fitting pipeline is in place, this could also be modelled, and potentially provide more sensitivity than descriptive behavioural analyses. A model which takes into account trial-to-trial dynamics can also study feedback loops such as worry causing further worry, whether through metacognitive beliefs ('I worry that I am worrying too much') or by increasing the anxiety of the participant. The effect of anxiety induced by previous trials can be incorporated into parameters of the model, such as by using delta-learning e.g. the Rescorla-Wagner rule (Rescorla & Wagner, 1972) on the Qb_{max} or simply multiplying Qb_{max} by a coefficient greater than 1 if a scream occurred

Lastly, while the model predicts number re-lookings, the emotion declared, and the upper and lower bound of the 80% confidence interval, it does not yet have components which predict self-reported worry itself. To do this, the exact relationship between re-lookings and worry needs to be considered. For example, worry may be a function of expected re-lookings specifically in the '1 to 40' information ratio condition alone, as evidence suggests that this is where behavioural differences are the most apparent (e.g. Section 4.4.1.). Structurally, it could be calculated similarly to self-esteem (Low et al., 2022) or emotion (Emanuel & Eldar, 2023). Predicting self-reported worry, if successful, will further validate the model.

Immediate future work will focus on testing the model empirically. As discussed in Chapter 6, likelihood functions for number of re-lookings, emotion read reported, and upper and lower bound of the 80% confidence interval have been written. The next steps are therefore as follows, based on previous work by the author (Low et al., 2022). As the model has multiple variants, but all steps apply to each variant of the model.

1. Write function which fits model to data based on likelihood functions, generating parameters which are most likely to produce this data.
2. Parameter Recovery: Produce synthetic data using a variety of parameters and re-fit it to the model. Check if parameters are recovered appropriately, i.e. parameters recovered are similar to those used to generate the model; otherwise, modify model or fitting procedure until this occurs successfully. For example, priors may be added to the likelihood function to confine parameters to their most likely distribution, or the starting parameters for the fitting process may be modified. The removal of some parameters can also be considered.
3. Fit model to empirical data. Check for signs that the model is not functioning as intended e.g. extremely high values of parameters. Once more, modify model or fitting procedure as necessary.
4. Model Comparison: Evaluate how well each model fits the data e.g. by using the Bayesian Information Criterion (BIC) (Raftery, 1995).

7.6. Conclusion

This thesis has provided support for the key hypothesis: worry is the internal sampling of thoughts and memories aimed to problem-solve, becoming maladaptive when persisting beyond usefulness. Key results from the large-scale testing of a novel experimental paradigm which captures worry showed that both trait and state worry predicts sampling robustly, and that high worriers are less adaptive in their sampling processes, being driven to sample more even when chances of success are low. This hypothesis will by further tested by fitting a computational model to the data which has already been shown to be able to generate synthetic data similar to empirical data. It is hoped that this will pave the way for a better understanding of worry, providing transdiagnostic insight into the many mental health conditions that worry characterizes, eventually providing treatments which make a crucial difference to individuals and society.

Bibliography

Adams, R. A., Huys, Q. J. M., & Roiser, J. P. (2016). Computational Psychiatry: Towards a mathematically informed understanding of mental illness. *Journal of Neurology, Neurosurgery and Psychiatry*. https://doi.org/10.1136/jnnp-2015-310737

Alfons, A., Ateş, N. Y., & Groenen, P. J. (2022). A robust bootstrap test for mediation analysis. *Organizational Research Methods*, *25*(3), 591–617.

Anderson, C., & Galinsky, A. D. (2006). Power, optimism, and risk-taking. *European Journal of Social Psychology*, *36*(4), 511–536.

Ardizzi, M., Martini, F., Umiltà, M. A., Sestito, M., Ravera, R., & Gallese, V. (2013). When early experiences build a wall to others' emotions: An electrophysiological and autonomic study. *PLoS One*, *8*(4), e61004.

Bach, D. R., Moutoussis, M., Bowler, A., & Dolan, R. J. (2020). Predictors of risky foraging behaviour in healthy young people. *Nature Human Behaviour*, *4*(8), 832–843. https://doi.org/10.1038/s41562-020-0867-0

Balderston, N. L., Hsiung, A., Ernst, M., & Grillon, C. (2017). Effect of threat on right dlPFC activity during behavioral pattern separation. *Journal of Neuroscience*, *37*(38), 9160–9171.

Bandelow, B., & Michaelis, S. (2015). Epidemiology of anxiety disorders in the 21st century. *Dialogues in Clinical Neuroscience*, *17*(3), 327–335. https://doi.org/10.1016/j.siny.2015.10.004

Bar-Haim, Y., Lamy, D., Pergamin, L., Bakermans-Kranenburg, M. J., & Van Ijzendoorn, M. H. (2007). Threat-related attentional bias in anxious and nonanxious individuals: A meta-analytic study. *Psychological Bulletin*, *133*(1), 1.

Basevitz, P., Pushkar, D., Chaikelson, J., Conway, M., & Dalton, C. (2008). Age-Related Differences in Worry and Related Processes. *International Journal of Aging & Human Development*, *66*, 283–305. https://doi.org/10.2190/AG.66.4.b

Baxter, A. J., Vos, T., Scott, K. M., Ferrari, A. J., & Whiteford, H. A. (2014). The global burden of anxiety disorders in 2010. *Psychological Medicine*, *44*(11), 2363–2374. https://doi.org/10.1017/S0033291713003243

Beaurenaut, M., Tokarski, E., Dezecache, G., & Grèzes, J. (2020). The 'Threat of Scream' paradigm: A tool for studying sustained physiological and subjective anxiety. *Scientific Reports*, *10*(1), 1–11. https://doi.org/10.1038/s41598-020-68889-0

Bedder, R. L., Pisupati, S., & Niv, Y. (2023). *Modelling rumination as a state-inference process*. *45*(45).

Bomyea, J., Ramsawh, H., Ball, T., Taylor, C., Paulus, M., Lang, A., & Stein, M. (2015). Intolerance of uncertainty as a mediator of reductions in worry in a cognitive behavioral treatment program for generalized anxiety disorder. *Journal of Anxiety Disorders*, *33*, 90–94.

Borkovec, T. (1985). Worry: A potentially valuable concept. *Behaviour Research and Therapy*, *23*(4), 481–482.

Borkovec, T. D., Ray, W. J., & Stober, J. (1998). Worry: A cognitive phenomenon intimately linked to affective, physiological, and interpersonal behavioral processes. *Cognitive Therapy and Research*, *22*(6), 561–576.

Bottesi, G., Marchetti, I., Sica, C., & Ghisi, M. (2020). What is the internal structure of intolerance of uncertainty? A network analysis approach. *Journal of Anxiety Disorders*, *75*, 102293.

Bradley, B. P., Mogg, K., White, J., Groom, C., & De Bono, J. (1999). Attentional bias for emotional faces in generalized anxiety disorder. *British Journal of Clinical Psychology*, *38*(3), 267–278.

Brenes, G. A. (2006). Age differences in the presentation of anxiety. *Aging and Mental Health*, *10*(3), 298–302.

Brunswik, E. (2023). *Perception and the representative design of psychological experiments*. Univ of California Press.

Buhr, K., & Dugas, M. J. (2002). The intolerance of uncertainty scale: Psychometric properties of the English version. *Behaviour Research and Therapy*, *40*(8), 931–945.

Buntrock, C., Harrer, M., Sprenger, A. A., Illing, S., Sakata, M., Furukawa, T. A., Ebert, D. D., Cuijpers, P., Adriaanse, M. C., & Albert, S. M. (2024). Psychological interventions to prevent the onset of major depression in adults: A systematic review and individual participant data meta-analysis. *The Lancet Psychiatry*, *11*(12), 990–1001.

Çalıyurt, O. (2022). The Mental Health Consequences of the Global Housing Crisis. *Alpha Psychiatry*, *23*(6), 264.

Calleo, J. S., Hart, J., Björgvinsson, T., & Stanley, M. A. (2010). Obsessions and worry beliefs in an inpatient OCD population. *Journal of Anxiety Disorders*, *24*(8), 903–908.

Calmes, C. A., & Roberts, J. E. (2007). Repetitive thought and emotional distress: Rumination and worry as prospective predictors of depressive and anxious symptomatology. *Cognitive Therapy and Research*, *31*, 343–356.

Campos, D. G., Fütterer, T., Gfrörer, T., Lavelle-Hill, R., Murayama, K., König, L., Hecht, M., Zitzmann, S., & Scherer, R. (2024). Screening Smarter, Not Harder: A Comparative Analysis of Machine Learning Screening Algorithms and Heuristic Stopping Criteria for Systematic Reviews in Educational Research. *Educational Psychology Review*, *36*(1), 19.

Carhart-Harris, R., Chandaria, S., Erritzoe, D., Gazzaley, A., Girn, M., Kettner, H., Mediano, P., Nutt, D., Rosas, F., & Roseman, L. (2023). Canalization and plasticity in psychopathology. *Neuropharmacology*, *226*, 109398.

Carleton, R. N. (2016). Into the unknown: A review and synthesis of contemporary models involving uncertainty. *Journal of Anxiety Disorders*, *39*, 30–43. https://doi.org/10.1016/j.janxdis.2016.02.007

Carleton, R. N., Duranceau, S., Freeston, M. H., Boelen, P. A., McCabe, R. E., & Antony, M. M. (2014). “But it might be a heart attack”: Intolerance of uncertainty and panic disorder symptoms. *Journal of Anxiety Disorders*, *28*(5), 463–470.

Carleton, R. N., Norton, M. P. J., & Asmundson, G. J. (2007). Fearing the unknown: A short version of the Intolerance of Uncertainty Scale. *Journal of Anxiety Disorders*, *21*(1), 105–117.

Casella, G., & Berger, R. (2002). *Regression models. Statistical inference*.

Cervin, M., Norris, L. A., Ginsburg, G., Gosch, E. A., Compton, S. N., Piacentini, J., Albano, A. M., Sakolsky, D., Birmaher, B., & Keeton, C. (2021). The p factor consistently predicts long-term psychiatric and functional outcomes in anxiety-disordered youth. *Journal of the American Academy of Child & Adolescent Psychiatry*, *60*(7), 902–912.

Cisler, J. M., Bacon, A. K., & Williams, N. L. (2009). Phenomenological characteristics of attentional biases towards threat: A critical review. *Cognitive Therapy and Research*, *33*, 221–234.

Cisler, J. M., & Koster, E. H. W. (2010). Mechanisms of attentional biases towards threat in anxiety disorders: An integrative review. *Clinical Psychology Review*, *30*(2), 203–216. https://doi.org/10.1016/j.cpr.2009.11.003

Clauss, J. (2019). *Extending the neurocircuitry of behavioural inhibition: A role for the bed nucleus of the stria terminalis in risk for anxiety disorders*. https://doi.org/10.1136/gpsych-2019-100137

Colquhoun, H. L., Levac, D., O'Brien, K. K., Straus, S., Tricco, A. C., Perrier, L., Kastner, M., & Moher, D. (2014). Scoping reviews: Time for clarity in definition, methods, and reporting. *Journal of Clinical Epidemiology*, *67*(12), 1291–1294.

Costello, E. J., & Angold, A. (1988). Scales to assess child and adolescent depression: Checklists, screens, and nets. *Journal of the American Academy of Child and Adolescent Psychiatry*, *27*(6), 726–737. https://doi.org/10.1097/00004583-198811000-00011

Cui, J., Olthof, M., Hasselman, F., & Lichtwarck-Aschoff, A. (2025). Examining the research methods of early warning signals in clinical psychology through a theoretical lens. *BMC Psychiatry*, *25*, 261.

Cui, X., Dickhaus, T., Ding, Y., & Hsu, J. C. (2021). *Handbook of multiple comparisons*. CRC Press.

Dablander, F., Pichler, A., Cika, A., & Bacilieri, A. (2023). Anticipating critical transitions in psychological systems using early warning signals: Theoretical and practical considerations. *Psychological Methods*, *28*(4), 765.

Davey, G. C. L. (1994). Pathological worrying as exacerbated problem-solving. In *Worrying: Perspectives on theory, assessment and treatment.* (pp. 35–59). John Wiley & Sons.

Davey, G. C. L. (2008). A Mood-as-Input Account of Perseverative Worrying. *Worry and Its Psychological Disorders: Theory, Assessment and Treatment*, 217–237. https://doi.org/10.1002/9780470713143.ch13

de Leon, J. (2014). Focusing on drug versus disease mechanisms and on clinical subgrouping to advance personalised medicine in psychiatry. *Acta Neuropsychiatrica*, *26*(6), 327–333.

Diefenbach, G., Stanley, M., & Beck, J. (2001). Worry content reported by older adults with and without generalized anxiety disorder. *Aging & Mental Health*, *5*(3), 269–274.

Dinno, A., & Dinno, M. A. (2017). Package 'dunn. Test.' *CRAN Repos*, *10*, 1–7.

Dubois, D., Rucker, D. D., & Galinsky, A. D. (2012). Retracted: Super Size Me: Product Size as a Signal of Status. *Journal of Consumer Research*, *38*(6), 1047–1062.

Dugas, M. J., Freeston, M. H., & Ladouceur, R. (1997). Intolerance of uncertainty and problem orientation in worry. *Cognitive Therapy and Research*, *21*, 593–606.

Dugas, M. J., Gosselin, P., & Ladouceur, R. (2001). Intolerance of uncertainty and worry: Investigating specificity in a nonclinical sample. *Cognitive Therapy and Research*, *25*, 551–558.

Dugas, M. J., Sexton, K. A., Hebert, E. A., Bouchard, S., Gouin, J.-P., & Shafran, R. (2022). Behavioral experiments for intolerance of uncertainty: A randomized clinical trial for adults with generalized anxiety disorder. *Behavior Therapy*, *53*(6), 1147–1160.

Duttweiler, P. C. (1984). The Internal Control Index: A Newly Developed Measure of Locus of Control. *Educational and Psychological Measurement*, *44*(2), 209–221. https://doi.org/10.1177/0013164484442004

Eichstaedt, K. E., Kovatch, K., & Maroof, D. A. (2013). A less conservative method to adjust for familywise error rate in neuropsychological research: The Holm's sequential Bonferroni procedure. *NeuroRehabilitation*, *32*(3), 693–696.

Emanuel, A., & Eldar, E. (2023). Emotions as computations. *Neuroscience & Biobehavioral Reviews*, *144*, 104977.

Etkin, A., Egner, T., Peraza, D. M., Kandel, E. R., & Hirsch, J. (2006). Resolving emotional conflict: A role for the rostral anterior cingulate cortex in modulating activity in the amygdala. *Neuron*, *51*(6), 871–882.

Evans, J. S. B. (2008). Dual-processing accounts of reasoning, judgment, and social cognition. *Annu. Rev. Psychol.*, *59*(1), 255–278.

Evans, N. J., & Wagenmakers, E.-J. (2019). *Evidence accumulation models: Current limitations and future directions*.

Finch, T. (2009). Incremental calculation of weighted mean and variance. *University of Cambridge*, *4*(11–5), 41–42.

Flett, G. L., Nepon, T., & Hewitt, P. L. (2016). Perfectionism, worry, and rumination in health and mental health: A review and a conceptual framework for a cognitive theory of perfectionism. *Perfectionism, Health, and Well-Being*, 121–155.

Fox, A. B., & Earnshaw, V. A. (2023). The relationship between mental illness stigma and self-labeling. *Psychiatric Rehabilitation Journal*, *46*(2), 127.

Fox, J. (2015). *Applied regression analysis and generalized linear models*. Sage publications.

Freeston, M. H., Rhéaume, J., Letarte, H., Dugas, M. J., & Ladouceur, R. (1994). Why do people worry? *Personality and Individual Differences*, *17*(6), 791–802.

Frost, R. O., Marten, P., Lahart, C., & Rosenblate, R. (1990). The dimensions of perfectionism. *Cognitive Therapy and Research*, *14*(5), 449–468. https://doi.org/10.1007/BF01172967

Gagne, C., & Dayan, P. (2022). Peril, prudence and planning as risk, avoidance and worry. *Journal of Mathematical Psychology*, *106*, 102617.

Galinsky, A. D., Gruenfeld, D. H., & Magee, J. C. (2003). From power to action. *Journal of Personality and Social Psychology*, *85*(3), 453.

Galloway, R., Watson, H., Greene, D., Shafran, R., & Egan, S. J. (2022). The efficacy of randomised controlled trials of cognitive behaviour therapy for perfectionism: A systematic review and meta-analysis. *Cognitive Behaviour Therapy*, *51*(2), 170–184.

Galvan, M. J., Payne, B. K., Hannay, J., Georgeson, A. R., & Muscatell, K. A. (2023). What does the MacArthur scale of subjective social status measure? Separating economic circumstances and social status to predict health. *Annals of Behavioral Medicine*, *57*(11), 929–941.

Giacalone, M., Agata, Z., Cozzucoli, P. C., & Alibrandi, A. (2018). Bonferroni-Holm and permutation tests to compare health data: Methodological and applicative issues. *BMC Medical Research Methodology*, *18*, 1–9.

Gibb, B. E., Schofield, C. A., & Coles, M. E. (2009). Reported history of childhood abuse and young adults' information-processing biases for facial displays of emotion. *Child Maltreatment*, *14*(2), 148–156.

Glöckner, A., Hilbig, B. E., & Jekel, M. (2014). What is adaptive about adaptive decision making? A parallel constraint satisfaction account. *Cognition*, *133*(3), 641–666.

Goodwin, H., Eagleson, C., Mathews, A., Yiend, J., & Hirsch, C. (2017). Automaticity of Attentional Bias to Threat in High and Low Worriers. *Cognitive Therapy and Research*, *41*(3), 479–488. https://doi.org/10.1007/s10608-016-9818-5

Goring, H. J., & Papageorgiou, C. (2008). Rumination and worry: Factor analysis of self-report measures in depressed participants. *Cognitive Therapy and Research*, *32*, 554–566.

Granier, K. L., & Segal, D. L. (2021). Diverse aspects of worry among younger and older adults: A multifaceted approach. *Psychology*, *12*(03), 441.

Gruenfeld, D. H., Inesi, M. E., Magee, J. C., & Galinsky, A. D. (2008). Power and the objectification of social targets. *Journal of Personality and Social Psychology*, *95*(1), 111.

Haddaway, N. R., Page, M. J., Pritchard, C. C., & McGuinness, L. A. (2022). PRISMA2020: An R package and Shiny app for producing PRISMA 2020-compliant flow diagrams, with interactivity for optimised digital transparency and Open Synthesis. *Campbell Systematic Reviews*, *18*(2), e1230.

Hadwin, J. A., Donnelly, N., Richards, A., French, C. C., & Patel, U. (2009). Childhood anxiety and attention to emotion faces in a modified stroop task. *British Journal of Developmental Psychology*, *27*(2), 487–494.

Handley, A. K., Egan, S. J., Kane, R. T., & Rees, C. S. (2014). The relationships between perfectionism, pathological worry and generalised anxiety disorder. *BMC Psychiatry*, *14*, 1–8.

Hauser, T. U., Moutoussis, M., Dayan, P., & Dolan, R. J. (2017). Increased decision thresholds trigger extended information gathering across the compulsivity spectrum. *Translational Psychiatry*. https://doi.org/10.1038/s41398-017-0040-3

Hebert, E. A., Dugas, M. J., Tulloch, T. G., & Holowka, D. W. (2014). Positive beliefs about worry: A psychometric evaluation of the Why Worry-II. *Personality and Individual Differences*, *56*(1), 3–8. https://doi.org/10.1016/j.paid.2013.08.009

Hilbe, J. M. (2011). *Negative binomial regression*. Cambridge University Press.

Hirsch, C. R., & Mathews, A. (2012). A cognitive model of pathological worry. *Behaviour Research and Therapy*, *50*(10), 636–646. https://doi.org/10.1016/j.brat.2012.06.007

Hoehn-Saric, R., & McLeod, D. R. (1985). Locus of control in chronic anxiety disorders. *Acta Psychiatrica Scandinavica*, *72*(6), 529–535. https://doi.org/10.1111/j.1600-0447.1985.tb02650.x

Holland, C. A., Ebner, N. C., Lin, T., & Samanez-Larkin, G. R. (2019). Emotion identification across adulthood using the Dynamic FACES database of emotional expressions in younger, middle aged, and older adults. *Cognition and Emotion*, *33*(2), 245–257.

Hollander, E., Doernberg, E., Shavitt, R., Waterman, R. J., Soreni, N., Veltman, D. J., Sahakian, B. J., & Fineberg, N. A. (2016). The cost and impact of compulsivity: A research perspective. *European Neuropsychopharmacology*, *26*(5), 800–809.

Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics*, 65–70.

Hook, R. W., Grant, J. E., Ioannidis, K., Tiego, J., Yücel, M., Wilkinson, P., & Chamberlain, S. R. (2021). Trans-diagnostic measurement of impulsivity and compulsivity: A review of self-report tools. *Neuroscience & Biobehavioral Reviews*, *120*, 455–469.

Hopkins, A. K. (2021). *The neuro-computational role of uncertainty in anxiety*.

Horsfield, P., Stolzenburg, S., Hahm, S., Tomczyk, S., Muehlan, H., Schmidt, S., & Schomerus, G. (2020). Self-labeling as having a mental or physical illness: The effects of stigma and implications for help-seeking. *Social Psychiatry and Psychiatric Epidemiology*, *55*, 907–916.

Jackson-Koku, G. (2016). Beck depression inventory. *Occupational Medicine*, *66*(2), 174–175.

Jonason, P. K., & Perilloux, C. (2012). Domain-specificity and individual differences in worry. *Personality and Individual Differences*, *52*(2), 228–231.

Kazinka, R., Vilares, I., & MacDonald III, A. W. (2022). A computational model of non-optimal suspiciousness in the Minnesota Trust Game. *Computational Psychiatry*, *6*(1), 60.

Kimble, M., Boxwala, M., Bean, W., Maletsky, K., Halper, J., Spollen, K., & Fleming, K. (2014). The impact of hypervigilance: Evidence for a forward feedback loop. *Journal of Anxiety Disorders*, *28*(2), 241–245. https://doi.org/10.1016/j.janxdis.2013.12.006

Kishida, K. T., & Sands, L. P. (2021). A dynamic affective core to bind the contents, context, and value of conscious experience. In *Affect Dynamics* (pp. 293–328). Springer.

Knolle, F., Sterner, E., Moutoussis, M., Adams, R. A., Griffin, J. D., Haarsma, J., Taverne, H., Goodyer, I. M., Fletcher, P. C., & Murray, G. K. (2023). Action selection in early stages of psychosis: An active inference approach. *Journal of Psychiatry and Neuroscience*, *48*(1), E78–E89.

Kruskal, W. H., & Wallis, W. A. (1952). Use of ranks in one-criterion variance analysis. *Journal of the American Statistical Association*, *47*(260), 583–621.

Kwon, M.-K., Setoodehnia, M., Baek, J., Luck, S. J., & Oakes, L. M. (2016). The development of visual search in infancy: Attention to faces versus salience. *Developmental Psychology*, *52*(4), 537.

Laberge, M., Dugas, M. J., & Ladouceur, R. (2000). Modification des croyances relatives aux inquiétudes après traitement du trouble d'anxiété généralisée. *Canadian Journal of Behavioural Science/Revue Canadienne Des Sciences Du Comportement*, *32*(2).

Lavie, N., Beck, D. M., & Konstantinou, N. (2014). Blinded by the load: Attention, awareness and the role of perceptual load. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *369*(1641), 20130205.

Lilienfeld, S. O. (2007). Psychological treatments that cause harm. *Perspectives on Psychological Science*, *2*(1), 53–70.

Llera, S. J., & Newman, M. G. (2010). Effects of Worry on Physiological and Subjective Reactivity to Emotional Stimuli in Generalized Anxiety Disorder and Nonanxious Control Participants. *Emotion*, *10*(5), 640–650. https://doi.org/10.1037/a0019351

Low, A. A. Y., Hopper, W. J. T., Angelescu, I., Mason, L., Will, G.-J., & Moutoussis, M. (2022). Self-esteem depends on beliefs about the rate of change of social approval. *Scientific Reports*, *12*(1), 1–15. https://doi.org/10.1038/s41598-022-10260-6

Lyyra, P., & Parviainen, T. (2018). Behavioral Inhibition Underlies the Link Between Interoceptive Sensitivity and Anxiety-Related Temperamental Traits. In *Frontiers in Psychology* (Vol. 9). https://www.frontiersin.org/article/10.3389/fpsyg.2018.01026

Maas, C. J., & Hox, J. J. (2004). The influence of violations of assumptions on multilevel parameter estimates and their standard errors. *Computational Statistics & Data Analysis*, *46*(3), 427–440.

Macintyre, A., Ferris, D., Gonçalves, B., & Quinn, N. (2018). What has economics got to do with it? The impact of socioeconomic factors on mental health and the case for collective action. *Palgrave Communications*, *4*(1), 1–5.

Maqbool, M., Sengar, K., Vikas, Kumar, M., & Uparikar, P. D. (2017). Efficacy of danger ideation reduction therapy in obsessive-compulsive disorder washer with poor insight: A case study and literature review. *Indian Journal of Psychological Medicine*, *39*(4), 523–526.

Martin, L. L., & Tesser, A. (2013). Some ruminative thoughts. In *Ruminative thoughts* (pp. 1–47). Psychology Press.

McFadyen, J., Smout, C., Tsuchiya, N., Mattingley, J. B., & Garrido, M. I. (2019). Surprising threats accelerate evidence accumulation for conscious perception. *bioRxiv*, 525519.

McNally, R. J. (2019). Attentional bias for threat: Crisis or opportunity? *Advances in Cognitive Science and Psychopathology*, *69*, 4–13. https://doi.org/10.1016/j.cpr.2018.05.005

McNally, R. J., Kaspi, S. P., Riemann, B. C., & Zeitlin, S. B. (1990). Selective processing of threat cues in posttraumatic stress disorder. *Journal of Abnormal Psychology*, *99*(4), 398.

Meyer, T. J., Miller, M. L., Metzger, R. L., & Borkovec, T. D. (1990). Development and validation of the penn state worry questionnaire. *Behaviour Research and Therapy*, *28*(6), 487–495. https://doi.org/10.1016/0005-7967(90)90135-6

Mikail, S. F., Hewitt, P. L., Flett, G. L., & Ge, S. (2022). Group dynamic-relational therapy for perfectionism. *Research in Psychotherapy: Psychopathology, Process, and Outcome*, *25*(3).

Milne, A. E., Bianco, R., Poole, K. C., Zhao, S., Oxenham, A. J., Billig, A. J., & Chait, M. (2021). An online headphone screening test based on dichotic pitch. *Behavior Research Methods*, *53*, 1551–1562.

Milne, S., Lomax, C., & Freeston, M. H. (2019). A review of the relationship between intolerance of uncertainty and threat appraisal in anxiety. *The Cognitive Behaviour Therapist*, *12*, e38. Cambridge Core. https://doi.org/10.1017/S1754470X19000230

Miloff, A., Savva, A., & Carlbring, P. (2015). Cognitive bias measurement and social anxiety disorder: Correlating self-report data and attentional bias. *Internet Interventions*, *2*(3), 227–234.

Montague, P. R., Kishida, K. T., Moran, R. J., & Lohrenz, T. M. (2016). An efficiency framework for valence processing systems inspired by soft cross-wiring. *Current Opinion in Behavioral Sciences*, *11*, 121–129.

Morris, M. E., & Aguilera, A. (2012). Mobile, social, and wearable computing and the evolution of psychological practice. *Professional Psychology: Research and Practice*, *43*(6), 622.

Moss, R. H., Kelly, B., Bird, P. K., & Pickett, K. E. (2023). Examining individual social status using the MacArthur Scale of Subjective Social Status: Findings from the Born in Bradford study. *SSM-Population Health*, *23*, 101463.

Moutoussis, M., Shahar, N., Hauser, T. U., & Dolan, R. J. (2018). Computation in Psychotherapy, or How Computational Psychiatry Can Aid Learning-Based Psychological Therapies. *Computational Psychiatry*, *2*, 50–73. https://doi.org/10.1162/cpsy_a_00014

Myung, I. J. (2003). Tutorial on maximum likelihood estimation. *Journal of Mathematical Psychology*, *47*(1), 90–100. https://doi.org/10.1016/S0022-2496(02)00028-7

Nair, A., Rutledge, R. B., & Mason, L. (2020). Under the Hood: Using Computational Psychiatry to Make Psychological Therapies More Mechanism-Focused. *Frontiers in Psychiatry*, *11*. https://doi.org/10.3389/fpsyt.2020.00140

Nasirpour, N., Jafari, K., Habibi Asgarabad, M., Salehi, M., Amin-Esmaeili, M., Rahimi-Movaghar, A., & Motevalian, S. A. (2024). The mediating role of subjective social status in the association between objective socioeconomic status and mental health status: Evidence from Iranian national data. *Frontiers in Psychiatry*, *15*, 1427993.

Neacsiu, A. D., Bohus, M., & Linehan, M. M. (2014). Dialectical behavior therapy: An intervention for emotion dysregulation. *Handbook of Emotion Regulation*, *2*, 491–507.

Newby, J. M., McKinnon, A., Kuyken, W., Gilbody, S., & Dalgleish, T. (2015). Systematic review and meta-analysis of transdiagnostic psychological treatments for anxiety and depressive disorders in adulthood. *Clinical Psychology Review*, *40*, 91–110. https://doi.org/10.1016/j.cpr.2015.06.002

Newman, M. G., & Llera, S. J. (2011). A novel theory of experiential avoidance in generalized anxiety disorder: A review and synthesis of research supporting a contrast avoidance model of worry. *Clinical Psychology Review*, *31*(3), 371–382.

Notebaert, L., Tilbrook, M., Clarke, P. J. F., & MacLeod, C. (2017). When a Bad Bias Can Be Good: Anxiety-Linked Attentional Bias to Threat in Contexts Where

Dangers Can Be Avoided. *Clinical Psychological Science*, *5*(3), 485–496. https://doi.org/10.1177/2167702616681295

Ociskova, M., Prasko, J., Latalova, K., Sedlackova, Z., Kamaradova, D., Sandoval, A., & Grambal, A. (2017). F* ck your care if you label me! Borderline personality disorder, stigma, and self-stigma. *Activitas Nervosa Superior Rediviva*, *59*(1), 16–22.

Oppong, F. B., & Agbedra, S. Y. (2016). Assessing univariate and multivariate normality. A guide for non-statisticians. *Mathematical Theory and Modeling*, *6*(2), 26–33.

Passardi, S. (2018). *Emotion processing in posttraumatic stress disorder: Emotion recognition, interpretation of neutral facial expressions, and facial mimicry*.

Pedersen, M. L., Frank, M. J., & Biele, G. (2017). The drift diffusion model as the choice rule in reinforcement learning. *Psychonomic Bulletin & Review*, *24*, 1234–1251.

Penney, A. M., Mazmanian, D., & Rudanycz, C. (2013). Comparing positive and negative beliefs about worry in predicting generalized anxiety disorder symptoms. *Canadian Journal of Behavioural Science/Revue Canadienne Des Sciences Du Comportement*, *45*(1), 34.

Perneger, T. V. (1998). What's wrong with Bonferroni adjustments. *Bmj*, *316*(7139), 1236–1238.

Pfister, R. (2022). Operationalization and generalization in experimental psychology: A plea for bold claims. In *Experimental Psychology: Ambitions and Possibilities* (pp. 45–60). Springer.

Pike, A. C., & Robinson, O. J. (2022). Reinforcement learning in patients with mood and anxiety disorders vs control individuals: A systematic review and meta-analysis. *JAMA Psychiatry*, *79*(4), 313–322.

Pinheiro, J., & Bates, D. (2000). *Mixed-effects models in S and S-PLUS*. Springer science & business media.

Pollak, S. D. (2008). Mechanisms linking early experience and the emergence of emotions: Illustrations from the study of maltreated children. *Current Directions in Psychological Science*, *17*(6), 370–375.

Price, M. A., Butow, P. N., Lo, S. K., Wilson, J., & Kathleen Cuningham Consortium for Research into Familial Breast Cancer (kConFab) Psychosocial Group. (2007). Predictors of cancer worry in unaffected women from high risk breast cancer families: Risk perception is not the primary issue. *Journal of Genetic Counseling*, *16*, 635–644.

Raftery, A. E. (1995). Bayesian Model Selection in Social Research. *Sociological Methodology*, *25*(1995), 111–163.

Ratcliff, R. (1988). *Continuous versus discrete information processing: Modeling accumulation of partial information.*

Ratcliff, R., & Rouder, J. N. (1998). Modeling response times for two-choice decisions. *Psychological Science*, *9*(5), 347–356.

Rescorla, R. A., & Wagner, A. R. (1972). A theory of Pavlovian Conditioning: Variations in the Effectiveness of Reinforcement and Nonreinforcement. In A. H. Black & ProkasyW F (Eds.), *Classical Conditioning II: current research and theory* (pp. 64–99). Appleton-Century Crofts. https://doi.org/10.1101/gr.110528.110

Richter, P., Werner, J., Heerlein, A., Kraus, A., & Sauer, H. (1998). On the validity of the Beck Depression Inventory: A review. *Psychopathology*, *31*(3), 160–168.

Rinck, M., Reinecke, A., Ellwart, T., Heuer, K., & Becker, E. S. (2005). Speeded detection and increased distraction in fear of spiders: Evidence from eye movements. *Journal of Abnormal Psychology*, *114*(2), 235.

Robichaud, M., Koerner, N., & Dugas, M. J. (2019). *Cognitive behavioral treatment for generalized anxiety disorder: From science to practice*. Routledge.

Robinson, O. C. (2011). The idiographic/nomothetic dichotomy: Tracing historical origins of contemporary confusions. *History & Philosophy of Psychology*, *13*(2), 32–39.

Robinson, O. J., Vytal, K., Cornwell, B. R., & Grillon, C. (2013). The impact of anxiety upon cognition: Perspectives from human threat of shock studies. *Frontiers in Human Neuroscience*, *7*, 203.

Roemer, L., Molina, S., & Borkovec, T. D. (1997). An investigation of worry content among generally anxious individuals. *The Journal of Nervous and Mental Disease*, *185*(5), 314–319.

Rönkkö, M., & Cho, E. (2022). An updated guideline for assessing discriminant validity. *Organizational Research Methods*, *25*(1), 6–14.

Rosenberg, M. (1965). *Society and the adolescent self-image*. Princeton university press.

Ross, S. M. (2014). *Introduction to probability models*. Academic press.

Rothman, K. J. (1990). No adjustments are needed for multiple comparisons. *Epidemiology*, *1*(1), 43–46.

RP Alves, M., Yamamoto, T., Arias-Carrión, O., BF Rocha, N., E Nardi, A., Machado, S., & Cardoso, A. (2014). Executive function impairments in patients with depression. *CNS & Neurological Disorders-Drug Targets (Formerly Current Drug Targets-CNS & Neurological Disorders)*, *13*(6), 1026–1040.

Rubin, D. B. (2016). Evaluations of the optimal discovery procedure for multiple testing. *The International Journal of Biostatistics*, *12*(1), 21–29.

Salehi, B., Cordero, M. I., & Sandi, C. (2010). Learning under stress: The inverted-U-shape function revisited. *Learning & Memory*, *17*(10), 522–530.

Santos, A., Mier, D., Kirsch, P., & Meyer-Lindenberg, A. (2011). Evidence for a general face salience signal in human amygdala. *Neuroimage*, *54*(4), 3111–3116.

Schaerer, M., Du Plessis, C., Yap, A. J., & Thau, S. (2018). Low power individuals in social power research: A quantitative review, theoretical framework, and empirical test. *Organizational Behavior and Human Decision Processes*, *149*, 73–96.

Shields, G. S., Moons, W. G., Tewell, C. A., & Yonelinas, A. P. (2016). The effect of negative affect on cognition: Anxiety, not anger, impairs executive function. *Emotion*, *16*(6), 792.

Smith, P. K., Jostmann, N. B., Galinsky, A. D., & Van Dijk, W. W. (2008). Lacking power impairs executive functions. *Psychological Science*, *19*(5), 441–447.

Snedecor, G. W., & Cochran, W. G. (1968). *Statistical methods: By george w. Snedecor and william g. Cochran*. Iowa State University Press.

Sowislo, J. F., & Orth, U. (2013). Does low self-esteem predict depression and anxiety? A meta-analysis of longitudinal studies. *Psychological Bulletin*, *139*(1), 213–240. https://doi.org/10.1037/a0028931

Spielberger, C. D., Gonzalez-Reigosa, F., Martinez-Urrutia, A., Natalicio, L. F., & Natalicio, D. S. (1971). The state-trait anxiety inventory. *Revista Interamericana de Psicologia/Interamerican Journal of Psychology*, *5*(3 & 4).

Spinhoven, P., Van der Veen, D., Voshaar, R. O., & Comijs, H. (2017). Worry and cognitive control predict course trajectories of anxiety in older adults with late-life depression. *European Psychiatry*, *44*, 134–140.

Stöber, J., & Joormann, J. (2001). Worry, procrastination, and perfectionism: Differentiating amount of worry, pathological worry, anxiety, and depression. *Cognitive Therapy and Research*, *25*, 49–60.

Stoklosa, J., Blakey, R. V., & Hui, F. K. (2022). An overview of modern applications of negative binomial modelling in ecology and biodiversity. *Diversity*, *14*(5), 320.

Svihra, M., & Katzman, M. A. (2004). *Behavioural inhibition: A predictor of anxiety*. *9*(8), 547–550.

Szabó, M., & Lovibond, P. F. (2002). The cognitive content of naturally occurring worry episodes. *Cognitive Therapy and Research*, *26*, 167–177.

Szeto, A. C., Luong, D., & Dobson, K. S. (2013). Does labeling matter? An examination of attitudes and perceptions of labels for mental disorders. *Social Psychiatry and Psychiatric Epidemiology*, *48*, 659–671.

Tabachnick, B. G., & Fidell, L. S. (2013). Using multivariate statistics (6. Baskı). *MA: Pearson*.

Taylor, M. M., & Snyder, H. R. (2021). Repetitive negative thinking shared across rumination and worry predicts symptoms of depression and anxiety. *Journal of Psychopathology and Behavioral Assessment*, *43*(4), 904–915.

Tinbergen, N. (1963). On aims and methods of ethology. *Zeitschrift Für Tierpsychologie*, *20*(4), 410–433.

Topper, M., Emmelkamp, P. M., Watkins, E., & Ehring, T. (2014). Development and assessment of brief versions of the Penn State Worry Questionnaire and the Ruminative Response Scale. *British Journal of Clinical Psychology*, *53*(4), 402–421.

Tull, M. T., Hahn, K. S., Evans, S. D., Salters-Pedneault, K., & Gratz, K. L. (2011). Examining the role of emotional avoidance in the relationship between posttraumatic stress disorder symptom severity and worry. *Cognitive Behaviour Therapy*, *40*(1), 5–14.

van der Heiden, C., Muris, P., Bos, A. E., van der Molen, H., & Oostra, M. (2009). Normative data for the Dutch version of the Penn State Worry Questionnaire. *Netherlands Journal of Psychology*, *65*, 69–75.

Vander Haegen, M., & Etienne, A. M. (2016). Cognitive processes across anxiety disorders related to intolerance of uncertainty: Clinical review. *Cogent Psychology*, *3*(1). https://doi.org/10.1080/23311908.2016.1215773

Vasey, M. W., & Borkovec, T. D. (1992). A catastrophizing assessment of worrisome thoughts. *Cognitive Therapy and Research*, *16*(5), 505–520.
Venables, W. N., & Ripley, B. D. (2013). *Modern applied statistics with S-PLUS*. Springer Science & Business Media.
Ver Hoef, J. M., & Boveng, P. L. (2007). Quasi-Poisson vs. Negative binomial regression: How should we model overdispersed count data? *Ecology*, *88*(11), 2766–2772.
Verstraeten, K., Bijttebier, P., Vasey, M. W., & Raes, F. (2011). Specificity of worry and rumination in the development of anxiety and depressive symptoms in children. *British Journal of Clinical Psychology*, *50*(4), 364–378.
Vieta, E. (2015). Personalised medicine applied to mental health: Precision psychiatry. *Rev Psiquiatr Salud Ment*, *8*(3), 117–118.
Vytal, K. E., Cornwell, B. R., Letkiewicz, A. M., Arkin, N. E., & Grillon, C. (2013). The complex interaction between anxiety and cognition: Insight from spatial and verbal working memory. *Frontiers in Human Neuroscience*, *7*, 93.
Weber, E. U., & Johnson, E. J. (2009). Mindful judgment and decision making. *Annual Review of Psychology*, *60*(1), 53–85.
Wells, A. (2006). The metacognitive model of worry and generalised anxiety disorder. In G. C. L. Davey & A. Wells (Eds.), *Worry and its Psychological Disorders: Theory, Assessment and Treatment* (pp. 179–200). Wiley Publishing.
Wells, A. (2010). Metacognitive Theory and Therapy for Worry and Generalized Anxiety Disorder: Review and Status. *Journal of Experimental Psychopathology*, *1*(1), jep.007910. https://doi.org/10.5127/jep.007910
Wessing, I., Romer, G., & Junghöfer, M. (2017). Hypervigilance-avoidance in children with anxiety disorders: Magnetoencephalographic evidence. *Journal of Child Psychology and Psychiatry, and Allied Disciplines*, *58*(1), 103–112. https://doi.org/10.1111/jcpp.12617
West, D. (1979). Updating mean and variance estimates: An improved method. *Communications of the ACM*, *22*(9), 532–535.
Westfall, P. H., & Young, S. S. (1993). *Resampling-based multiple testing: Examples and methods for p-value adjustment*. John Wiley & Sons.
White, L. K., McDermott, J. M., Degnan, K. A., Henderson, H. A., & Fox, N. A. (2011). Behavioral inhibition and anxiety: The moderating roles of inhibitory control

and attention shifting. *Journal of Abnormal Child Psychology*, *39*(5), 735–747. https://doi.org/10.1007/s10802-011-9490-x

Wilkinson, G., & Rogers, C. (1973). Symbolic description of factorial models for analysis of variance. *Journal of the Royal Statistical Society Series C: Applied Statistics*, *22*(3), 392–399.

Will, G., Rutledge, R. B., Moutoussis, M., & Dolan, R. J. (2017). *Neural and computational processes underlying dynamic changes in self- esteem*. 1–21.

Windelband, W. (1998). History and natural science. *Theory & Psychology*, *8*(1), 5–22.

Wise, T., Liu, Y., Chowdhury, F., & Dolan, R. J. (2021). Model-based aversive learning in humans is supported by preferential task state reactivation. *Science Advances*, *7*(31), eabf9616.

Xie, Y., Kong, Y., Yang, J., & Chen, F. (2019). Perfectionism, worry, rumination, and distress: A meta-analysis of the evidence for the perfectionism cognition theory. *Personality and Individual Differences*, *139*, 301–312.

Yang, X., Fang, Y., Chen, H., Zhang, T., Yin, X., Man, J., Yang, L., & Lu, M. (2021). Global, regional and national burden of anxiety disorders from 1990 to 2019: Results from the Global Burden of Disease Study 2019. *Epidemiology and Psychiatric Sciences*, *30*, e36. https://doi.org/10.1017/S2045796021000275

Yen, H.-Y. (2021). Smart wearable devices as a psychological intervention for healthy lifestyle and quality of life: A randomized controlled trial. *Quality of Life Research*, *30*, 791–802.

Yilmaz, A. E. (2015). The Role of Worry and Rumination in the Symptoms of Anxiety and Depression. *Turkish Journal of Psychiatry*, *26*(2).

Ying, X. (2019). *An overview of overfitting and its solutions*. *1168*, 022022.

Yirga, A. A., Melesse, S. F., Mwambi, H. G., & Ayele, D. G. (2020). Negative binomial mixed models for analyzing longitudinal CD4 count data. *Scientific Reports*, *10*(1), 16742.

Yıldırım, J. C., & Bahtiyar, B. (2022). The association between metacognitions and worry: The mediator role of experiential avoidance strategies. *The Journal of Psychology*, *156*(8), 552–567.

Yook, K., Kim, K. H., Suh, S. Y., & Lee, K. S. (2010). Intolerance of uncertainty, worry, and rumination in major depressive disorder and generalized anxiety disorder. *Journal of Anxiety Disorders*, *24*(6), 623–628. https://doi.org/10.1016/j.janxdis.2010.04.003

Young, C. C., & Dietrich, M. S. (2015). Stressful life events, worry, and rumination predict depressive and anxiety symptoms in young adolescents. *Journal of Child and Adolescent Psychiatric Nursing*, *28*(1), 35–42.

Yu, Y., & Williams, D. (1999). *Handbook of Sociology of Mental Health. Handbooks of Sociology and Social Research*.

APPENDIX

Appendix Table 1.

Full list of papers identified in systematic scoping review (Chapter 2).

Index	**Authors**	**Year**	**Title**	**Specificity**	**Population**	**Model Components**	**Concept Mapping**	**Computational?**
1	Dugas & Koerner	2005	Cognitive-behavioral treatment for generalized anxiety disorder: Current status and future directions	GAD	General	intolerance of uncertainty, positive beliefs about worry, negative problem orientation, and cognitive avoidance.	intolerance of uncertainty, beliefs, experiential avoidance	No
2	Rist	2015	Metacognitions, worry and sleep in everyday life: Studying bidirectional pathways using Ecological Momentary Assessment in GAD patients	Worry	General vs Clinical	Sleep, Negative metacognitions	metacognition	No
3	Wells	1999	A cognitive model of generalized anxiety disorder	Worry but part of GAD model	General	"usage of worrying as a coping strategy and subsequent negative evaluation of worrying", positive metabeliefs about worry, negative appraisal of worry	metacognition, beliefs	No

4	Wells	2004	A Cognitive Model of GAD: Metacognitions and Pathological Worry	Worry but part of GAD model	General	"usage of worrying as a coping strategy and subsequent negative evaluation of worrying", positive metabeliefs about worry, negative appraisal of worry	metacognition, beliefs	No
5	Kusec, Tallon & Koerner	2016	Intolerance of uncertainty, causal uncertainty, causal importance, self-concept clarity and their relations to generalized anxiety disorder	GAD	General	causal uncertainty, causal importance, and self-concept clarity	intolerance of uncertainty	No
6	Penney, Dwight & Rudanycz	2013	Comparing Positive and Negative Beliefs About Worry in Predicting Generalized Anxiety Disorder Symptoms	GAD	General	positive and negative beliefs about worry	metacognition, beliefs	No
7	Wells	2005	The metacognitive model of GAD: Assessment of meta-worry and relationship with DSM-IV generalized anxiety disorder	GAD	Clinical (GAD)	meta-worry frequency, belief, and GAD	metacognition, beliefs	No

8	Langlois et al	2007	Les variables cognitives impliquées dans l'inquiétude face à la maladie.	Illness worry	General	cognitive avoidance and negative problem orientation	experiential avoidance, beliefs	No
9	Norton et al	2005	Hierarchical model of vulnerabilities for anxiety: replication and extension with a clinical sample	Anxiety (various)	Clinical: outpatients seeking treatment for affective disorders (including anxiety disorders)	intolerance of uncertainty	intolerance of uncertainty	No
10	Wells	1995	Meta-cognition and worry: A cognitive model of generalized anxiety disorder	GAD	General	usage of worrying as a coping strategy and subsequent negative evaluation of worrying, positive metabeliefs about worry, negative appraisal of worry	metacognition, beliefs	No
11	Nordahl, Vollset & Hjemdal	2022	An empirical test of the metacognitive model of generalized anxiety disorder	GAD	General	usage of worrying as a coping strategy and subsequent negative evaluation of worrying, positive metabeliefs about worry, negative appraisal of worry	metacognition, beliefs	No
12	Chen, Yao & Qian	2018	The influence of uncertainty and intolerance of uncertainty on anxiety	Anxiety (trait)	General (non clinical)	trait intolerance of uncertainty and uncertainty	intolerance of uncertainty	No

13	Sexton et al	2003	Hierarchical model of generalized and specific vulnerabilities in anxiety	Anxiety (various)	General (non clinical)	neuroticism, intolerance of uncertainty, anxiety sensitivity	intolerance of uncertainty, anxiety sensitivity, neuroticism	No
14	van der Heiden et al	2010	A hierarchical model for the relationships between general and specific vulnerability factors and symptom levels of generalized anxiety disorder	GAD	Clinical (GAD)	intolerance of uncertainty, negative metacognitions, neuroticism	intolerance of uncertainty, metacognition, neuroticism	No
15	Chapman, Kertz & Woodruff-Borden (L. Kevin Chapman, Sarah J. Kertz, Janet Woodruff-Borden)	2009	A structural equation model analysis of perceived control and psychological distress on worry among African American and European American young adults	Worry	General	psychological distress, perceived control	control, psychological distress	No

16	McEvoy & Mahoney et al	2013	Intolerance of uncertainty and negative metacognitive beliefs as transdiagnostic mediators of repetitive negative thinking in a clinical sample with anxiety disorders	Worry (and repetitive negative thinking)	Clinical (diagnosed with principal anxiety disorder)	negative metacognitions, intolerance of uncertainty	metacognition, intolerance of uncertainty	No
17	Dugas, Laugeson & Bukowski	2012	Intolerance of uncertainty, fear of anxiety, and adolescent worry	Worry	Adolescents	intolerance of uncertainty, fear of anxiety	intolerance of uncertainty, metacognition, beliefs	No
18	Ruggiero et al	2012	Beliefs over control and meta-worry interact with the effect of intolerance of uncertainty on worry	Worry	Clinical (GAD) vs controls	metacognitive beliefs about worry, intolerance of uncertainty, perceptions of control over events and reactions	metacognition, beliefs, control	No
19	Esbjørn et al	2014	Meta-worry, worry, and anxiety in children and adolescents: relationships and interactions	Worry (and repetitive negative thinking)	Youth (Danish) (study 1), Youth (Danish, GAD vs non-GAD	metacognitive processes, negative beliefs about worry, age	metacognition, beliefs	No

					anxiety vs healthy participants) (study 2)			
20	Fisher & Noble	2017	Anxiety and depression in people with epilepsy: The contribution of metacognitive beliefs	Anxiety and depression	People with specific physical health conditions	Metacognitive beliefs	metacognition, beliefs	No
21	Fergus & Wheless	2018	Examining incremental explanatory power in accounting for worry severity: negative metacognitive beliefs uniquely predict worry severity following a worry episode	Worry	Participants endorsing frequent worry	baseline worry severity, negative metacognitive beliefs surrounding the dangerousness and uncontrollability of worry	metacognition, beliefs	No
22	Jong-Meyer, Beck & Riede	2009	Relationships between rumination, worry, intolerance of uncertainty and metacognitive beliefs.	Worry	General vs Clinical	intolerance of uncertainty and metcognitive beliefs	intolerance of uncertainty, metacognition, beliefs	No
23	Ellis & Hudson	2010	The Metacognitive Model of Generalized	Worry but part of GAD model	Children & adolescents	"usage of worrying as a coping strategy and subsequent negative evaluation of	metacognition, beliefs	No

			Anxiety Disorder in Children and Adolescents			worrying", positive metabeliefs about worry, negative appraisal of worry		
24	Yang, Wang, Chen & Ding	2015	Personality and Worry: The Role of Intolerance of Uncertainty	Worry	General	Personality (extroversion and neuroticism), mediated by intolerance of uncertainty	neuroticism, intolerance of uncertainty	No
25	Thielsch, Andor & Ehring	2015	Do Metacognitions and Intolerance of Uncertainty Predict Worry in Everyday Life? An Ecological Momentary Assessment Study	Worry		negative metacognitive beliefs, positive metacognitive beliefs, intolerance of uncertainty, trait worry, daily hassles	metacognition, intolerance of uncertainty	No
26	Koerner & Wells	2006	A Cognitive Model of Generalized Anxiety Disorder: the Role of Intolerance of Uncertainty	Worry	General	"usage of worrying as a coping strategy and subsequent negative evaluation of worrying", positive metabeliefs about worry, negative appraisal of worry	metacognition, beliefs	No

27	Kertz, Stevens, McHugh & Björgvinsson	2013	Distress intolerance and worry: the mediating role of cognitive variables	Worry	General vs Clinical	distress intolerance, mediators: intolerance of uncertainty [IU], cognitive avoidance, metacognitive beliefs about worry, and negative problem orientation	emotional dysregulation, anxiety sensitivity, intolerance of uncertainty, experiential avoidance, metacognition, beliefs	No
28	Anderson et al (Rebecca Anderson 1, Lora Capobianco 1, Peter Fisher 2, David Reeves 3, Calvin Heal 4, Cintia L Faija 1, Hannah Gaffney 5, Adrian Wells)	2019	Testing relationships between metacognitive beliefs, anxiety and depression in cardiac and cancer patients: Are they transdiagnostic?	Anxiety and depression	People with specific physical health conditions	Uncontrollability, danger, positive beliefs (metacognitive)	control, beliefs, metacognition	No

29	de Bruin, Rassin & Muris	2007	The prediction of worry in non-clinical individuals: The role of intolerance of uncertainty, meta-worry, and neuroticism.	Worry	General	IU, meta-worry, and neuroticism (to various extents in idiosyncratic vs trait worry)	intolerance of uncertainty, metacognition, neuroticism	No
30	Rovella, A., González, M., Peñate, W., & Ibáñez, I.	2011	Worry trait and generalized anxiety disorder in a sample of general population: The differential role of intolerance of uncertainty, cognitive, avoidance, negative problem orientation, and meta-beliefs	GAD	General	intolerance to uncertainty, the negative orientation towards the problem, the cognitive avoidance and the meta-beliefs	intolerance of uncertainty, beliefs, experiential avoidance	No
31	Price et al	2007	Predictors of cancer worry in unaffected women from high risk breast cancer families: risk perception is not the primary issue	Illness worry	unaffected women from high risk breast cancer families	General anxiety, perceived risk, the stressful impact of recent cancer related events, a relative risk greater than 10, being closer in age to the youngest breast cancer diagnosis in family, and knowledge of personal mutation status	neuroticism	No

32	Laugesen, Dugas & Bukowski	2003	Understanding adolescent worry: the application of a cognitive model	Worry	Adolescents	intolerance of uncertainty, positive beliefs about worry (metacognitive), negative problem orientation, and cognitive avoidance	intolerance of uncertainty, beliefs, metacognition, experiential avoidance	No
33	Kertz & Woodruff-Borden	2012	The role of metacognition, intolerance of uncertainty, and negative problem orientation in children's worry	Worry	Children	positive and negative beliefs about worry (metacognitive), intolerance of uncertainty, and problem orientation	beliefs, metacognition, intolerance of uncertainty	No
34	Kertz	2011	Worry in children : proposal and test of a cognitive model	Worry	Children	cognitive development will predict the cognitive variables of threat interpretation, metacognitive beliefs about worry, negative problem orientation, and intolerance of uncertainty (IU)	metacognition, beliefs, intolerance of uncertainty	No
35	Geronimi et al	2019	A Preliminary Investigation of Cognitive Features Associated With Worry Among	Worry	Children	metacognitive negative beliefs about worry	metacognition, beliefs	No

			African American Youth					
36	DiLorenzo et al	2006	A model of disease-specific worry in heritable disease: The influence of family history, perceived risk and worry about other illnesses	Illness worry	General	family history, disease-specific perceived risk, and perceived risk for and worry about other diseases	-	No
37	Fitzpatrick	2014	Exploring the relationships between neuroticism, experiential avoidance, and worry: A test of a mediational model	Worry	General	experiential avoidance is the pathway through which the relationship between neuroticism and worry is transmitted	neuroticism, experiential avoidance	No
38	Hirsch & Matthews	2012	A cognitive model of pathological worry	Worry	General	involuntary (bottom-up) processes, such as habitual biases in attention and interpretation favouring threat content, and voluntary (top-down) processes, such as attentional control	attentional bias to threat, metacognition	No

39	Yıldırım & Bahtiyar	2022	The Association between Metacognitions and Worry: The Mediator Role of Experiential Avoidance Strategies	Worry	General	experiential avoidance	experiential avoidance	No
40	Mennin et al	2005	Preliminary evidence for an emotion dysregulation model of generalized anxiety disorder	GAD	General vs Clinical	emotion dysregulation	emotional dysregulation	No
41	Berenbaum, H	2010	An initiation–termination two-phase model of worrying	Worry	General	experiential avoidance, intolerance of uncertainty	experiential avoidance, intolerance of uncertainty	No
42	Einstein, D. A.	2014	Extension of the transdiagnostic model to focus on intolerance of uncertainty: A review of the literature and implications for treatment	Anxiety	General	intolerance of uncertainty	intolerance of uncertainty	No

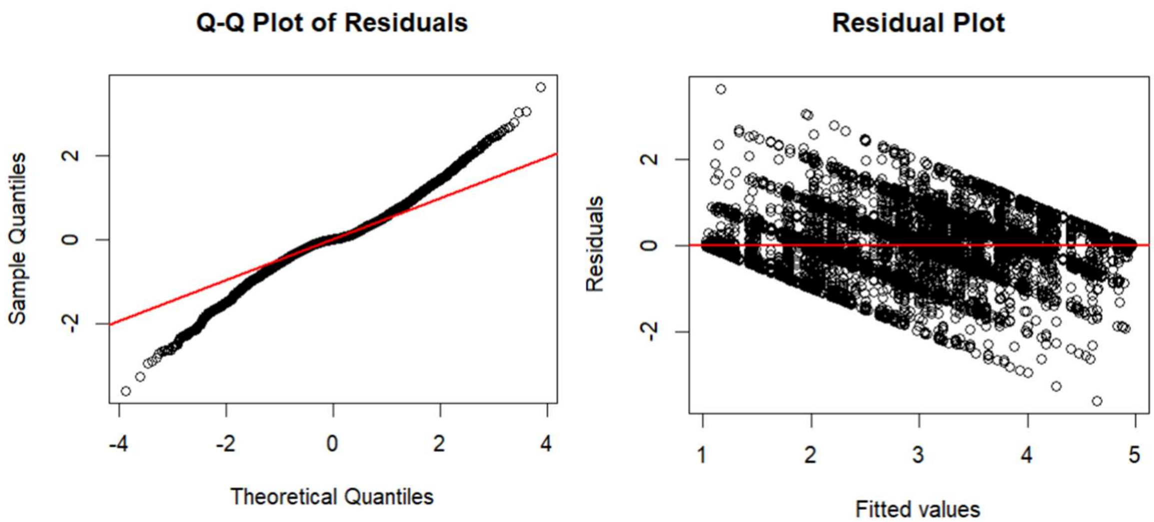
43	Ouellet et al	2019	Intolerance of uncertainty and difficulties in emotion regulation: Proposal for an integrative model of generalized anxiety disorder	Worry but part of GAD model	General	intolerance of uncertainty, emotional dysregulation, negative problem orientation (beliefs)	intolerance of uncertainty, emotional dysregulation, beliefs	No
44	Songco, Hudson & Fox	2020	A Cognitive Model of Pathological Worry in Children and Adolescents: A Systematic Review	Worry	Children	attention, memory and interpretation bias, attentional control, verbal aspect (metacognition)	attentional bias to threat, metacognition	No
45	Riskind	2024	Unscrambling the Dynamics of Danger: Scientific Foundations and Evidence for the Looming Vulnerability Model and Looming Cognitive Style in Anxiety.	Anxiety (various)	General	1) the stimuli are more easily detected and prioritized in attentional capture, and more salient, (2), amplify the appraisal of threat (3) induce more anxiety and negative emotional reactions, particularly fear, and (4) evoke maladaptive emotion regulation and behavior	attentional bias to threat, emotional dysregulation	No
46	Topper et al	2014	Are Rumination and Worry Two Sides of the Same Coin? A	Worry	General	repetitive negative thinking	beliefs, metacognition	No

			Structural Equation Modelling Approach					
47	LaFreniere, L. S. and M. G. Newman	2019	The impact of uncontrollability beliefs and thought-related distress on ecological momentary interventions for generalized anxiety disorder: A moderated mediation model	GAD	Clinical (GAD)	distress and uncontrollability beliefs	beliefs, control	No
48	M. W. Eysenck, N. Derakshan, R. Santos and M. G. Calvo	2007	Anxiety and cognitive performance: Attentional control theory	Anxiety (various)	General	metacognition (specifically inhibition and shifting of the goal-directed attentional system), attention to threat-related stimuli.	metacognition, attentional bias to threat	No
49	Grant et al	2013	An Examination of the Reciprocal Relationship Between Avoidance Coping and Symptoms of Anxiety and Depression	Anxiety and depression	General	cognitive and behavioural avoidance coping (metacognition)	metacognition	No

50	Brodbeck et al	2013	General distress, hopelessness—suicidal ideation and worrying in adolescence: Concurrent and predictive validity of a symptom-level bifactor model for clinical diagnoses	Worry	Clinical (GAD)	hopelessness—suicidal ideation, generalised worrying, restlessness	beliefs, psychological distress	No
51	A. Heeren, C. Mouguiama-Daouda and R. J. McNally	2022	A network approach to climate change anxiety and its key related features	Climate anxiety	General	general worry, the experience of climate change, pro-environmental behaviors, and the functional impairments associated with climate anxiety	-	No

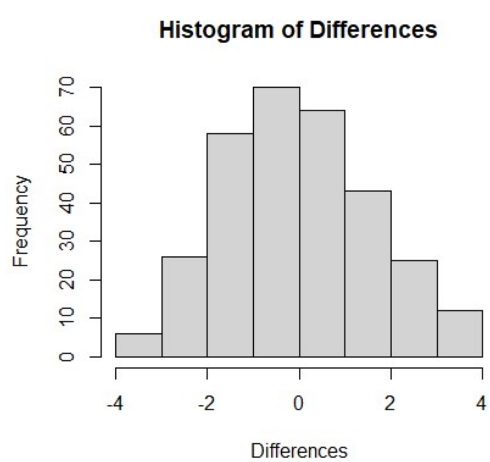
Appendix Figure 1.

Q-Q plot and residual plot for initial fitting of trial-to-trial worry data (Chapter 4).



Appendix Figure 2.

Normal distribution of differences for self-reported worry before and after re-lookings.



Appendix Equation Set 1.

Derivation of $update_r$, i.e. u_r (Chapter 6).

$$n_5 = n_{bsl} + \omega(n_5 - n_{bsl}) + update_r$$
$$n_5 = n_{bsl} + \omega n_5 - \omega n_{bsl} + update_r$$
$$update_r = n_5 - n_{bsl} - \omega n_5 + \omega n_{bsl}$$
$$update_r = (1 - w) * (n5 - n_b sl)$$

Equation Set 1. Derivation of $update_r$.