

# The value of non-instrumental information in anxiety: insights from a resource-rational model of planning

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## Abstract

Anxiety is intimately related to the desire for information and, under some accounts, thought to arise from the intolerance of uncertainty. Here, we seek to test this hypothesis by studying the relationship between trait anxiety and the willingness to pay for non-instrumental information (i.e., information that reveals whether an event will happen but cannot be used to change the outcome). We model behavior with a resource-rational model of planning, according to which non-instrumental information is useful for planning ahead, but paying for this information only makes sense if the anticipated benefits of planning outweigh the cognitive and financial costs. We find that individuals with high trait somatic anxiety, but not other anxiety factors (cognitive anxiety, negative affect, or low self-esteem), consistently exhibit a stronger preference for non-instrumental information, regardless of the valence of the outcome, the probability of the outcome, or the cost to know if the outcome will happen (when it is nonzero). By fitting the resource-rational model, we find that the desire for information arises from a decreased subjective cost of information: subjects with high somatic anxiety behave as if the disutility of paying for information is relatively small. Our findings lend support to the intolerance of uncertainty hypothesis and highlight the specificity of trait somatic anxiety in modulating the desire for information.

**Keywords:** anxiety, resource rationality, decision making, uncertainty

## Introduction

Anxiety has been conceptualized as an ‘epistemic’ emotion, intimately related to the pursuit of information (Miceli and Castelfranchi, 2005). Anxiety increases in response to uncertainty, and its aversive nature motivates the resolution of uncertainty (Caplin and Leahy 2001; though not all forms of uncertainty are associated with displeasure, see Loewenstein 1987). When anxiety becomes pathological, its effects can generalize across domains, such that seemingly innocuous circumstances give rise to intolerable distress (Szuhany and Simon, 2022). These baseline levels of anxiety define trait anxiety (i.e., stable, enduring anxiety irrespective of contextual factors), which vary across individuals and will become the focus of this paper. One influential perspective states that pathological trait anxiety arises from the intolerance of uncertainty (Dugas et al., 1998, 2001; Carleton et al., 2007, 2012).

In this paper, we explore the epistemic view of trait anxiety through the lens of non-instrumental information preferences (see also Bennett et al., 2020). These preferences appear in scenarios where a person can gather information about a future outcome but cannot change the outcome (e.g., watching a tense sports game, anticipating the outcome of a job interview, or awaiting the results of a diagnostic medical test). At first glance, learning about an outcome in these scenarios can only reduce uncertainty (although we will shortly argue that there is more going on). It seems irrational to want to know whether an outcome will happen in these scenarios, yet people act on these desires, frequently choosing to pay money (Pierson and Goodman, 2014; Jiwa et al., 2021), sacrifice a proportion of future earnings (Bennett et al., 2016, 2020; Brydevall et al., 2018), expend physical effort (Goh et al., 2021), and even endure pain (Bode et al., 2023) to gain non-instrumental information. These preferences are typically amplified by the degree of uncertainty reduction (Charpentier et al., 2018; Van Lieshout et al., 2018; Kobayashi et al., 2019; Sharot and Sunstein, 2020). Why do people value non-instrumental information?

Pierson and Goodman (2014) proposed that non-instrumental information preferences arise from the utility of planning ahead: even if information doesn’t affect the outcome itself, it can affect what you will do with the outcome. For example, learning about the outcome of a job interview earlier provides more time to think about what projects to take on in the new job. According to Pierson and Goodman’s model, such information is in fact instrumental. Importantly, the value of information depends both on the expected utility of planning ahead and the disutility of devoting limited cognitive resources to planning. The “resource-rational” decision balances these factors to optimize expected utility (Lieder and Griffiths, 2020; Bhui et al., 2021). Consistent with the model predictions, Pierson and Goodman showed that people generally have a stronger desire for information when the probability of the outcome is higher, except for a slight reduction in desire when the probability of the outcome is very high and the information is costly. The intuition for this result is that the utility of planning is higher when the outcome is more likely to occur (if the outcome is not going to occur, there’s no point planning for it). When information is costly, people may be deterred from paying to learn about outcomes that are highly likely to occur anyway; the expected utility of planning doesn’t outweigh the cost of information.

In this paper, we use the experimental task and resource-rational model of Pierson and Goodman to better understand decision making in trait anxiety. The model offers one way of formalizing an intolerance of uncertainty account, according to which high trait anxiety promotes stronger desire for information. In the model, this could arise through several possible pathways: higher utility for the outcome, lower cost of planning, lower cost of information, lower utility of leisure, or weaker loss aversion. We assess the evidence for each of these pathways by analyzing parameter estimates.

Importantly, recent work has argued that anxiety is not a unitary construct, and that different anxiety factors influence behavior in distinct ways (Wise and Dolan, 2020; Fan et al., 2023; Witte et al., 2024). This is consistent with the multifactorial nature of anxiety, which can manifest with a number of psychological (e.g., feelings of apprehension, impaired concentration, irritability) and physical (e.g., elevated heart rate, rapid breathing, and tremulousness) symptoms. We build

upon previous work (Fan et al., 2023) and decompose trait anxiety into four distinct components: somatic anxiety, cognitive anxiety, negative affect, and low self-esteem. This allows us to develop a more fine-grained and clinically meaningful picture of the relationship between trait anxiety and information preferences.

## Methods

### Subjects

We recruited 80 subjects (mean age  $\pm$  SD, 42.9 years  $\pm$  12.8, range 23 to 73; 54 male, 25 female, 1 non-binary) from Amazon Mechanical Turk and hosted the experiment on Qualtrics. Subjects gave informed consent and the Harvard University Committee on the Use of Human Subjects approved the experiment. The experiment took approximately 5 minutes and subjects were paid \$1.50 (a rate of \$18 per hour).

### Task

Subjects read the following prompt (Figure 1A):

Imagine you will be locked in a room for an hour. At the end of the hour, you will be allowed to leave the room. There is a chance that something will happen to you when you leave. In each of the following situations, you will have to decide whether you want to be told at the beginning of the hour what will happen to you when you leave the room.

and were then given the following example scenario (Figure 1B):

You could win \$1000 with a chance of 90%. Would you pay \$100 to know now?

They responded on a Likert scale with one of the following answers: definitely not, probably not, no preference, probably yes, definitely yes. They then completed 30 scenarios in random order that differed by outcome (lose \$1000, win \$1000), probability of outcome at 1 hour (1%, 10%, 50%, 90%, 99%), and the cost to know now (\$0, \$5, \$100). They were explicitly provided this information and instructed that their answers would not affect their payout.

### Anxiety inventories and factors

After finishing the task, subjects completed two anxiety inventories: the State-Trait Anxiety Inventory-Trait version (STAIT; Spielberger, 1983) and the State-Trait Inventory of Cognitive and Somatic Anxiety-Trait version (STICSAT) (STICSAT; Grös et al., 2007).

The STAIT consists of 20 questions, each with 4 possible responses: almost never, sometimes, often, and almost always (Table S1). The STICSAT consists of 21 questions, each with 4 possible responses: not at all, a little, moderately, very much so (Table S2). Individual items were coded from 1 to 4, where 1 corresponded to no anxiety and 4 corresponded to high anxiety. For the anxiety-present questions on the STAIT (questions 2, 4, 5, 8, 9, 11, 12, 15, 17, 18, 20) and for all questions on the STICSAT, 1 corresponded to ‘almost never’/‘not at all’ responses and 4 corresponded to ‘almost always’/‘very much so’ responses. Anxiety-absent questions on the STAIT (questions 1, 3, 6, 7, 10, 13, 14, 16, 19) were reverse coded so a score of 1 corresponded to ‘almost always’ responses and a score of 4 corresponded to ‘almost never’ responses.

Following Fan et al. (2023), we used responses on the STAIT and STICSAT (41 total responses) and calculated scores on four factors for each subject. These oblique factors were identified on the basis of exploratory factor analysis and confirmatory factor analysis in an independent sample. These factors were labeled somatic anxiety, cognitive anxiety, negative affect, and low self-esteem

on the basis of item loadings. We used the factor loading structure from [Fan et al. \(2023\)](#) and calculated factor scores with the Bartlett method ([Bartlett, 1937](#)) using the psych package (version 2.4.3) in R (version 4.2.2).

## Resource-rational model of planning

We adapted the resource-rational model from [Pierson and Goodman \(2014\)](#). This model is based on the premise that people have limited cognitive resources and therefore seek information to determine whether they should devote resources to planning for outcomes. If an event is going to happen, then time and resources can be devoted to planning for it. If the event is not going to happen, then no resources need to be wasted planning for it. The agent is assumed to have three choices:

1. Obtain information: To obtain information, the agent pays a utility ( $C_{\text{info}}$ ) which we assume scales linearly with the cost to know now,  $c$ . If the outcome is going to occur, with probability  $p$ , the agent gains a utility associated with planning for the outcome ( $U_{\text{outcome}}$ ) minus a planning cost ( $C_{\text{plan}}$ ). To account for gain/loss asymmetries ([Kahneman and Tversky, 1979](#)), we scale  $U_{\text{outcome}}$  by  $s_{\text{gain}}$  when the outcome is positive and  $s_{\text{loss}}$  when the outcome is negative. If the outcome does not occur, with probability  $1 - p$ , the agent does not pay a planning cost and gains utility of 0.

$$U_{\text{info}} = p(s \cdot U_{\text{outcome}} - C_{\text{plan}}) - C_{\text{info}} \cdot c \quad (1)$$

where  $U_{\text{info}}$  is the net utility associated with obtaining information.

2. Plan in uncertainty: The agent can choose to plan without paying for information. In this case, the agent always pays a planning cost ( $C_{\text{plan}}$ ) and gains a utility associated with the outcome ( $U_{\text{outcome}}$ ) with probability  $p$ , scaled by  $s_{\text{gain}}$  or  $s_{\text{loss}}$ .

$$U_{\text{plan}} = p \cdot s \cdot U_{\text{outcome}} - C_{\text{plan}} \quad (2)$$

where  $U_{\text{plan}}$  is the net utility associated with planning in uncertainty.

3. Live in denial: Finally, the agent can choose neither to obtain information nor to plan for the outcome. We assume this frees up computational resources and the agent gains utility  $U_{\text{leisure}}$ .

The agent makes a choice in accordance with the value of information, VOI, which is the difference between the utility of paying for information ( $U_{\text{info}}$ ) and the utility of not paying for information (the better of  $U_{\text{plan}}$  and  $U_{\text{leisure}}$ ; see Figure S3 for an intuition):

$$\text{VOI} = U_{\text{info}} - \max(U_{\text{plan}}, U_{\text{leisure}}) \quad (3)$$

We constructed hierarchical models to estimate each parameter. For  $U_{\text{outcome}}$ ,  $C_{\text{plan}}$ ,  $C_{\text{info}}$ , and  $U_{\text{leisure}}$ , parameters were drawn from  $\mathcal{N}(\mu, 1)$  (parameterized as mean and standard deviation), where  $\mu \sim \mathcal{N}(0, 5)$  for each parameter. The scale parameters,  $s_{\text{gain}}$  and  $s_{\text{loss}}$ , were each drawn from  $\mathcal{N}(1, 1)$ . All parameters were constrained to be greater than 0 and were drawn separately for each subject. To map the value of information onto Likert responses, we used an ordered linear regression with 4 cut points corresponding to the 5 Likert categories. Given the apparent linear relationship between cost and responses, cost was rank transformed and recentered ( $[\$0 \$5 \$100] \rightarrow [0 1 2]$ ) prior to model fitting. This simplification is generally consistent with concave utility functions ([Pratt, 1978](#)) used to model risk aversion.

We compared the model presented above to two reduced models: one with no outcome scaling ( $s_{\text{gain}} = s_{\text{loss}} = 1$ ) and one with a single shared  $C_{\text{info}}$  parameter across all subjects. We performed

model comparison using Pareto-smoothed importance sampling leave-one-out cross-validation to estimate the expected log predictive density, an established technique for Bayesian model comparison (Vehtari et al., 2017). Our ‘full’ model above was strongly favored (Table S3).

We performed posterior predictive checks by using the mean of the posterior distribution of parameter values of each subject to generate a full, synthetic dataset on the exact task performed by subjects. These simulations are presented in solid lines in Figures 1, 2, S1, and S3.

To ensure parameter identifiability, we used the synthetic dataset above and fit the ‘full’ model again. We computed Pearson’s correlations between the ground-truth and recovered parameters (with bootstrapped 95% confidence intervals), which revealed good recoverability of all parameters in the model (Table S4).

Models were fit using R (version 4.2.2; accessed with RStudio 2022.12.0+353) using the Rstan package (version 2.26.13). We performed model comparison using the loo package (version 2.5.1).

## Statistical analyses

For purposes of visualization, Likert responses were integer scored from -2 (for ‘definitely not’) to +2 (for ‘definitely yes’). To explore the relationship between task parameters and anxiety factor scores (without a process model), we fit a mixed-effects ordered logistic model predicting response (one of the 5 ordered Likert categories) with fixed effects of outcome at 1 hour, probability, cost to know now (and their interactions), and each of the four anxiety factor scores, and a random intercept per subject. Each input was  $z$ -scored prior to model fitting and we rank-transformed and recentered the cost to know now (same procedure as for the resource-rational model). We used the ordinal package (version 2023.12-4) in R (version 4.2.2). To determine the relationship between anxiety factor scores and model variables/parameters, we took the mean variable/parameter estimate for each participant and fit linear regressions predicting model variables/parameters as a function of the four anxiety factor scores. We used the fitlm function in MATLAB R2021b and standardized model inputs and outputs by  $z$ -scoring. To determine the relationship between anxiety factor scores and the strategy of seeking no information, we fit a logistic regression using the fitglm function in MATLAB R2021b, standardizing the anxiety factor scores by  $z$ -scoring. Error bars are standard errors of the mean unless stated otherwise.

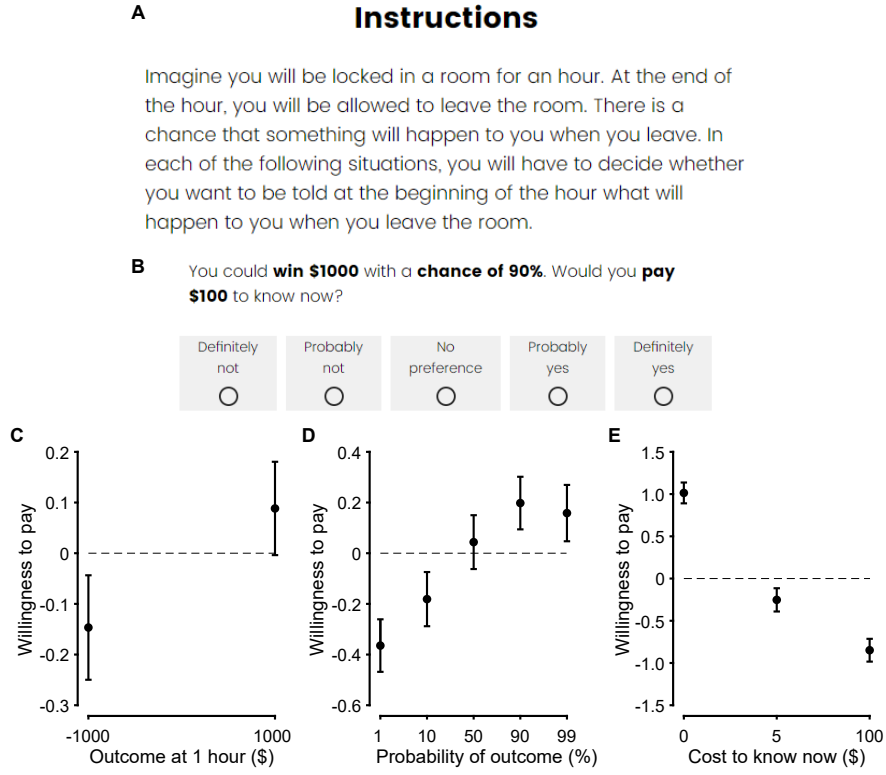
## Data availability

Data and code are available at <https://osf.io/6zyxg/>.

## Results

We replicated prior findings (Pierson and Goodman, 2014), finding that subjects generally desired to learn the outcome, even though it had no objective, instrumental value (Figure 1C). Across outcomes, subjects wanted to know more when the outcome was positive ( $\beta = 0.196$ ,  $p < 10^{-5}$ ), when the probability was high ( $\beta = 0.323$ ,  $p < 10^{-13}$ ), and when the cost was low ( $\beta = -1.211$ ,  $p < 10^{-15}$ ). The relationship between willingness to pay and probability of outcome was slightly flatter for losses than for gains (interaction between outcome and probability,  $\beta = 0.135$ ,  $p = 1.60 \times 10^{-3}$ ; Figure S1D-G).

Based on the intolerance of uncertainty account of anxiety, we hypothesized that subjects with high trait anxiety would have a greater willingness to pay for information, since access to this information reduces uncertainty. After performing the experiment, subjects completed two validated trait anxiety scales, the STAIT and STICSAT. On the basis of prior work, we extracted four anxiety factor scores for each participant: somatic anxiety, cognitive anxiety, negative affect, and low self-esteem (Fan et al., 2023). These labels were chosen on the basis of item loadings (Tables S1, S2). For each factor, the item with the highest loading was as follows: for somatic anxiety, ‘My face feels hot’; for cognitive anxiety, ‘I can’t get some thought out of my mind’; for negative affect,



**Figure 1: Task instructions and general findings.**

A) Task instructions.

B) Example scenario.

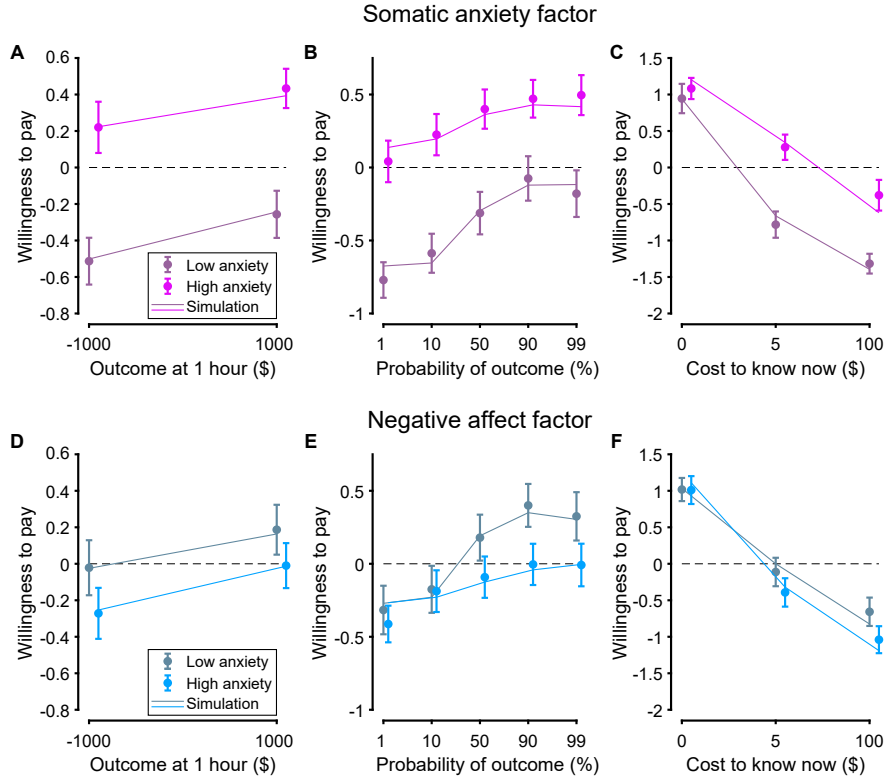
C,D,E) Average willingness to pay as a function of outcome at 1 hour (C), probability (D), and cost to know now (E) for the  $N = 80$  subjects across 30 scenarios each. Willingness to pay is the Likert response for each scenario, scored from -2 for ‘definitely not’ to +2 for ‘definitely yes.’

‘I am content’; for low self-esteem ‘I lack self-confidence.’ In Figure 2, we highlight somatic anxiety and negative affect, as these two factors were the least correlated (Figure S2).

Consistent with our hypothesis, we identified a significant effect of somatic anxiety on willingness to pay, such that those with high anxiety were more willing to pay ( $\beta = 0.895$ ,  $p = 3.15 \times 10^{-4}$ ; Figure 2A,B,C). This was evident as an increased willingness to pay regardless of outcome, probability, and cost to know. The willingness to pay more was only evident when cost was nonzero, an insight we will build on further when modeling the cognitive processes underlying these decisions. The increased willingness to pay was specific to somatic anxiety; we did not identify a significant effect of negative affect ( $\beta = -0.090$ ,  $p = 0.604$ ; Figure 2D,E,F), cognitive anxiety ( $\beta = -0.379$ ,  $p = 0.207$ ; Figure S3A,B,C), or low self-esteem ( $\beta = 0.159$ ,  $p = 0.365$ ; Figure S3D,E,F).

To gain insight into the underlying cognitive computations, we adapted a resource-rational model of planning developed by Pierson and Goodman (2014). Central to this model is the idea that brains are resource-limited and planning is costly: it makes sense to pay for apparently useless information if one wants to use that information to plan for future outcomes. Framed this way, the non-instrumental nature of information in our task is an illusion since the information can be used for planning. The model distinguishes 3 different choices for each scenario: subjects can pay for information (and then decide whether they should plan), they can plan in uncertainty (i.e., commit to planning but without paying to know the outcome), or they can live in denial (i.e., neither planning nor paying for information). The key decision variable in this model is the value of information—the difference between the utility that can be gained by paying for information and the utility that can be gained by ignoring information (Figure 3). The model contains several





**Figure 2: Willingness to pay as a function of somatic anxiety and negative affect.**

A,B,C) For somatic anxiety, willingness to pay as a function of outcome at 1 hour (A), probability of outcome (B), and cost to know now (C).

D,E,F) For negative affect, willingness to pay as a function of outcome at 1 hour (D), probability of outcome (E), and cost to know now (F).

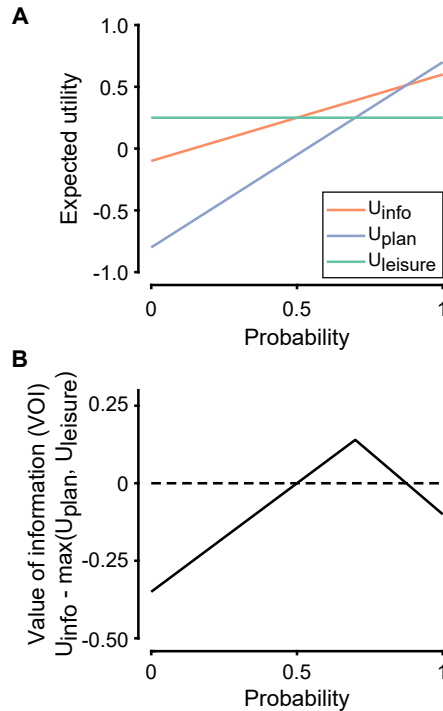
Solid lines model simulations. For visualization only, data are median split into high anxiety (bright colors) and low anxiety (dull colors).

parameters that govern the utility of the outcome, the cost of planning, the cost of information, the utility of leisure, and scaling of gains vs losses. We fit the model and found that it captured key features of behavior, including variation across anxiety factors (Figures 1, 2, S1, and S3).

We next constructed linear regression models to identify the association between anxiety factor scores and the variables/parameters in the cognitive model (Figure 4). Consistent with our behavioral data, there was a significant increase in the value of information only for the somatic anxiety factor ( $\beta = 0.571$ ,  $p = 2.76 \times 10^{-3}$ ). We identified no significant changes in the other two model variables (the utility of information and utility of planning).

To gain insight into how the value of information was increased in somatic anxiety, we next regressed anxiety factor scores onto the model parameters. We identified a significant decrease in the cost of information in somatic anxiety ( $\beta = -0.443$ ,  $p = 0.0145$ ), suggesting this is a major driver of the increased value of information. This is consistent with our observation that there was no difference in willingness to pay for the cost = \$0 condition in somatic anxiety (Figure 2C). To confirm the importance of this parameter, we fit a simplified model where a single cost of information parameter,  $C_{\text{info}}$ , was shared across all subjects. Model comparison strongly favored the model where  $C_{\text{info}}$  was allowed to vary across subjects (Table S3).

Interestingly, we identified an increase in the cost of information as a function of negative affect ( $\beta = 0.297$ ,  $p = 0.0197$ ), as well as a decrease in the utility of leisure ( $\beta = -0.290$ ,  $p = 0.0437$ ). Because an increase in the cost of information (which decreases the utility of information) decreases the value of information, and a decrease in the utility of leisure increases the value of information, these two effects largely cancel one another out, leaving the value of information, and therefore



**Figure 3: Example calculation of the value of information.**

A) Expected utilities of information ( $U_{\text{info}}$ ), planning in uncertainty ( $U_{\text{plan}}$ ), and living in denial ( $U_{\text{leisure}}$ ) as a function of probability of the outcome. For this simulation, we used  $s = 1$ ,  $U_{\text{outcome}} = 1.5$ ,  $C_{\text{plan}} = 0.8$ ,  $C_{\text{info}} = 0.1$ ,  $c = 1$ , and  $U_{\text{leisure}} = 0.25$ .

B) The value of information as a function of probability. Here, there is an inverted-U relationship between the value of information and the probability of the outcome.

overall behavior, unchanged as a function of negative affect.

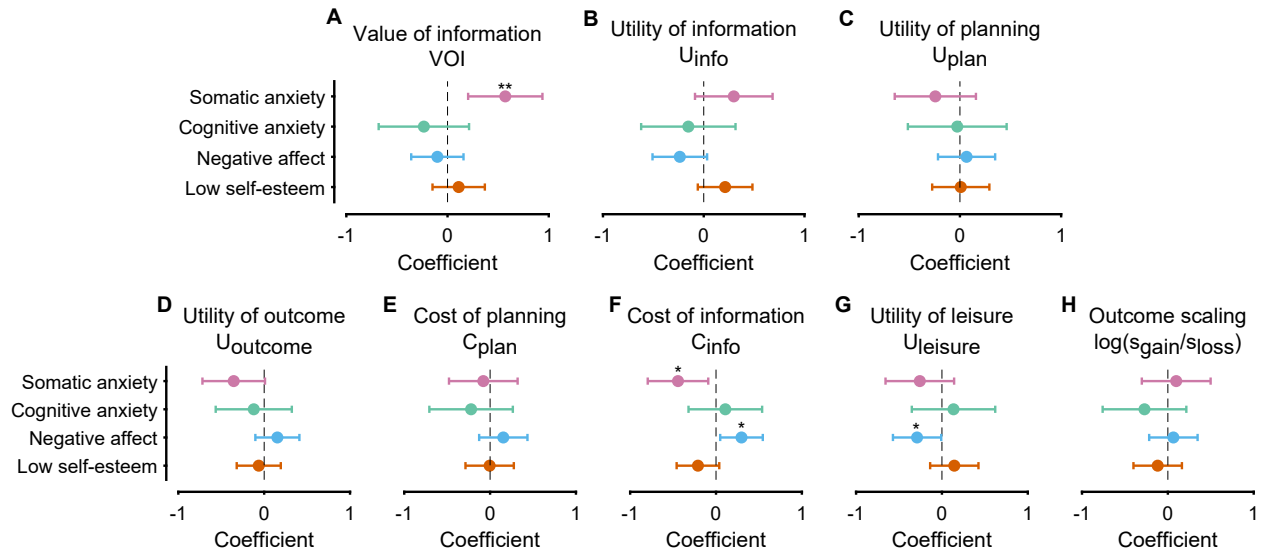
Finally, we sought to identify whether anxiety could predict utility-maximizing behavior, or the ‘optimal’ strategy under a framework that ignores resource constraints. We identified a subset of participants who were unwilling to pay when the cost was non-zero ( $N = 13$  of the 80 subjects, 16.25%). These subjects are the most averse to paying for information in the task, and should therefore place relatively low utility on information. Consistent with our previous findings, we found that only low somatic anxiety was associated with utility-maximizing behavior ( $\beta = -7.21$ ,  $p = 0.0265$ ).

## Discussion

We studied the relationship between trait anxiety and the desire for non-instrumental information, finding that subjects with high trait somatic anxiety consistently exhibited a stronger desire for non-instrumental information. Using a resource-rational model of planning, we found that subjects high in trait somatic anxiety placed higher utility on information, and that this arose from a decreased subjective cost of information. Finally, we found that only low trait somatic anxiety predicted the utility-maximizing strategy.

Prior work has found marked heterogeneity in preferences for non-instrumental information (Bennett et al., 2016). Our work shows that some of this heterogeneity reflects previously unmeasured structure due to trait anxiety. A key strength of our work is in teasing apart multiple facets of anxiety and showing that somatic anxiety is uniquely associated with preferences for non-instrumental information. At first blush, one would think cognitive anxiety should be the key factor driving changes in information seeking, since changes in the process of thinking itself should en-





**Figure 4: Relationship between anxiety factor scores and cognitive model variables and parameters.**

A,B,C) Standardized regression coefficients between anxiety factors and model variables. The model variables listed here are the value of information (A), the utility of information (B), and utility of planning (C).

D,E,F,G,H) Standardized regression coefficients between anxiety factors and model parameters. The model parameters listed here are the utility of outcome (D), cost of planning (E), cost of information (F), utility of leisure (G), and the outcome scaling, represented as the log of the ratio between gains and losses (H).

Error bars are bootstrapped 95% confidence intervals. \* denotes  $p < 0.05$ . \*\* denotes  $p < 0.005$ .

gender changes in decision making. Our observation that trait somatic anxiety, not trait cognitive anxiety, correlates with preference for information is a strength of our approach, since it shows that this approach can allow us to draw seemingly counter-intuitive conclusions. We do not yet have a good foundational understanding of why somatic anxiety should be linked with changes in information preference. Note also that some previous studies have found no evidence for a relationship between somatic anxiety and information preferences (Witte et al., 2024), or even effects in the opposite direction (Fan et al., 2023). We discuss the latter finding more below.

Our study fails to provide evidence for the loss aversion account of anxiety, which states that anxiety arises from overestimating the consequences of negative events (Butler and Mathews, 1983; Hartley and Phelps, 2012; Paulus and Angela, 2012). If loss aversion were the primary driver of trait anxiety, we would have captured it as a stronger preference towards negative outcomes and a change in the loss scaling parameter. Our findings generally favor intolerance of uncertainty, consistent with recent work suggesting the same (Charpentier et al., 2017).

While loss aversion does not provide a good account of our results, intolerance of uncertainty is more promising. We began with the premise that if anxiety is a consequence of intolerance of uncertainty, then it should manifest with increased value of non-instrumental information. The resource-rational model should therefore not be interpreted as modeling the *cause* of trait anxiety, but rather capturing its consequences: The decreased subjective cost of information in trait somatic anxiety is likely a consequence of anxiety, which motivates subjects to acquire information in order to reduce uncertainty.

Our support for the intolerance of uncertainty hypothesis is a bit more nuanced than it might appear. One point of contention is the recent finding that somatic anxiety is associated with *decreased* exploration of uncertain options (directed exploration) in a bandit task which appears at odds with our findings of *increased* information-seeking in a non-instrumental task. Bennett

et al. (2020) offer a potential resolution. In a non-instrumental task, these authors found that subjects with high anxiety had increased preference for costly information *and*, independently, decreased preference for high-variance outcomes. The aversion towards high-variance outcomes may therefore be consistent with decreased directed exploration in Fan et al. (2023). Although this reconciles our disparate findings, it suggests nuance to the intolerance of uncertainty hypothesis which would predict increased directed exploration in anxiety. Separately, the fact that our findings of increased information-seeking in anxiety is consistent with Bennett et al. (2020) argues for the robustness of this finding. This is especially important in light of work arguing that findings from description-based scenarios (ours) vs learning through experience (Bennett et al., 2020) can lead to different conclusions (Lejarraga and Hertwig, 2021).

Increased value of information in trait somatic anxiety is consistent with the behavior of high-anxiety people more generally. For example, an anxious student with an upcoming exam might endlessly ask questions of their professor to reduce uncertainty, or an anxious patient might ask numerous questions about potential medication side effects before deciding whether they want to take the medication. Clinically, somatic and cognitive anxiety are so highly correlated (Figure S2) that it is not typical in clinical practice to attempt to disambiguate the two to understand how much of a patient’s distress can be attributed to each symptom cluster. The high correlation between these symptoms is reflected in diagnostic criteria; in generalized anxiety disorder, for example, both physical and cognitive symptoms make up the diagnostic criteria. In contrast, negative affect is much less correlated with somatic and cognitive anxiety, and more easily disambiguated in the clinical setting from the typical symptoms of anxiety. This is consistent with work demonstrating that the items comprising the negative affect factor map closely to depression (Bieling et al., 1998).

The relationship between negative affect and depression provides some insight into our observation that negative affect is associated with increased cost of information ( $C_{\text{info}}$ ) and decreased utility of leisure ( $U_{\text{leisure}}$ ). In our task, changes in these two parameters largely cancel each other out, leading to no change in behavior. However, to the extent that changes in these parameters generalize to more ecologically-relevant settings, a decrease in  $U_{\text{leisure}}$ , for example, could reflect the subjective intolerability of depressive states.

In summary, by applying a resource-rational model of planning, we find that trait somatic anxiety correlates with an increased desire for information, driven by reduced subjective cost of information. Intriguingly, we did not identify a relationship between trait somatic anxiety and the parameters in the model related to the allocation of cognitive resources ( $U_{\text{outcome}}$ ,  $C_{\text{plan}}$ ,  $U_{\text{leisure}}$ ). This finding is consistent with work demonstrating that the quality of planning does not vary as a function of anxiety (Robinson et al., 2013). Perhaps, then, the fatigue and poor concentration that are common to anxiety disorders (e.g., Bishop, 2009; Hallion et al., 2018) arise not from inefficient planning, but from engaging in planning more often, taxing cognitive resources. The relationship between trait anxiety and planning is a rich area for future work.

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## Competing interests

The authors have no competing interests to declare.

## Author contributions

B.A.B. contributed to conceptualization, methodology, data curation, formal analysis, investigation, project administration, visualization, and writing—original draft. S.J.G contributed to conceptualization, methodology, supervision, funding acquisition, and writing—review & editing.

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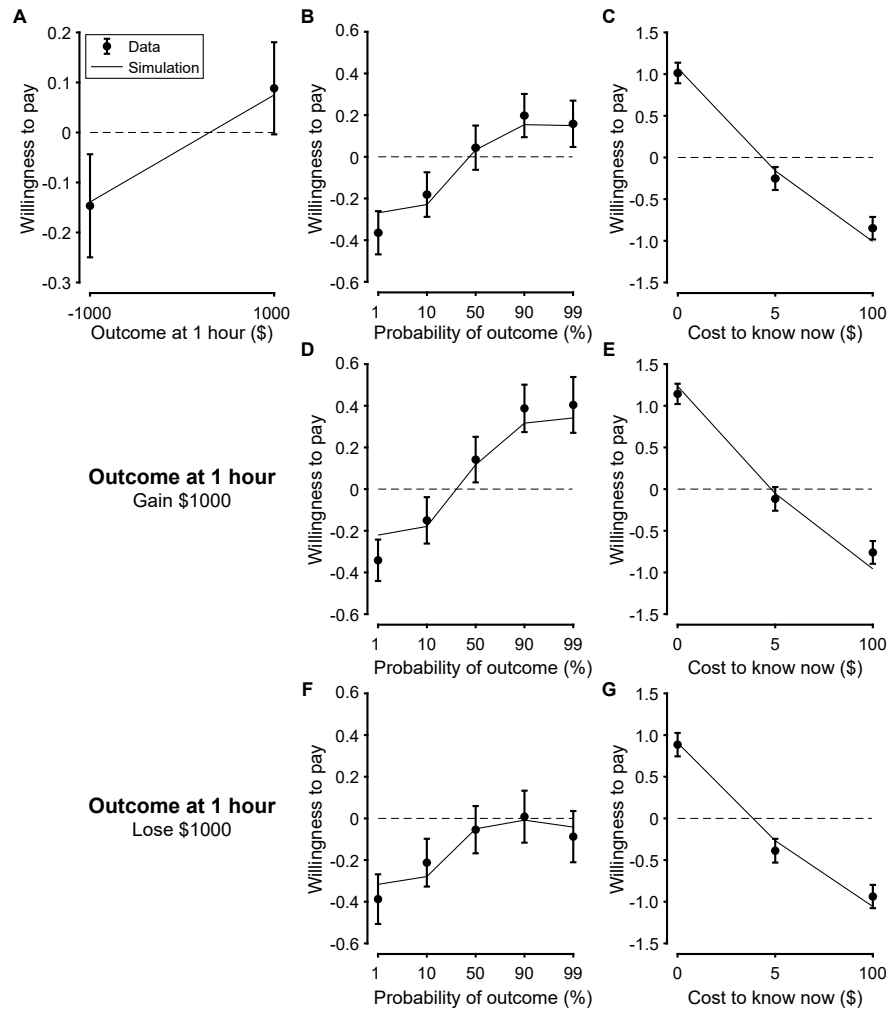
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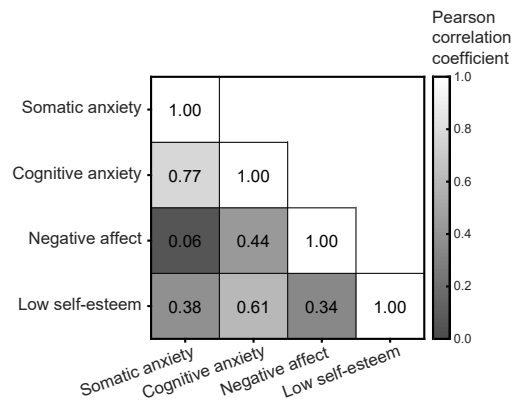
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**Figure S1: Willingness to pay, separately for gains and losses, with model simulations.** A,B,C) Willingness to pay as a function of outcome at 1 hour (A), probability (B), and cost to know now (C), overlaid with model simulations (solid lines). The behavioral data are the same as in Figure 1C-E.

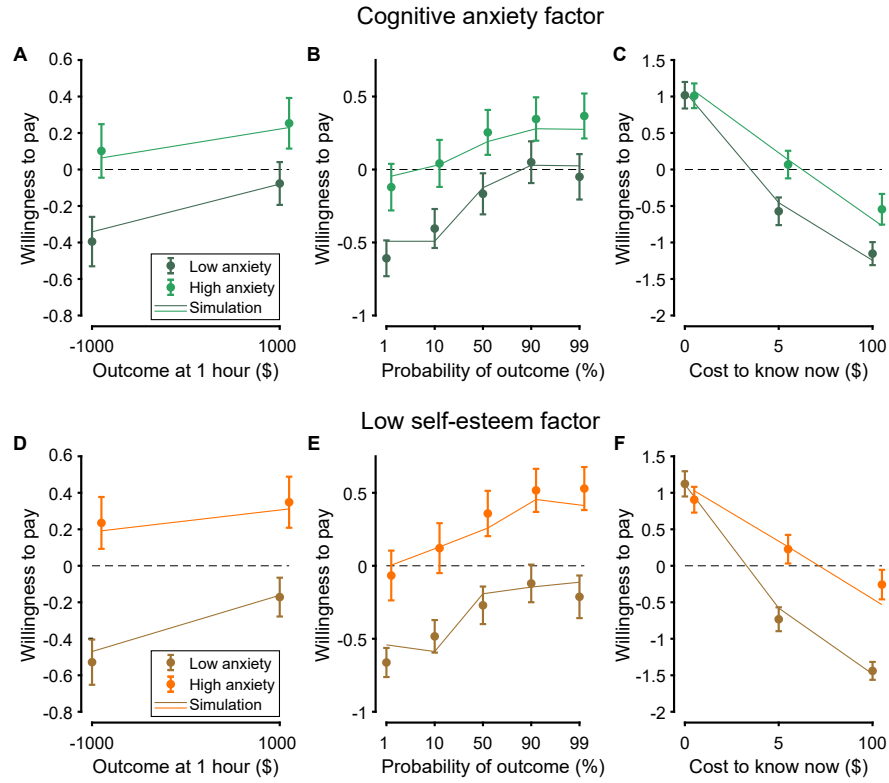
D,E) Willingness to pay for scenarios where the outcome was positive.

F,G) Willingness to pay for scenarios where the outcome was negative.



**Figure S2: Anxiety factor scores correlation matrix.**





**Figure S3: Willingness to pay as a function of cognitive anxiety and low self-esteem.** A,B,C) For cognitive anxiety, willingness to pay as a function of outcome at 1 hour (A), probability of outcome (B), and cost to know now (C). D,E,F) For low self-esteem, willingness to pay as a function of outcome at 1 hour (D), probability of outcome (E), and cost to know now (F). The apparent differences in willingness to pay as a function of cognitive anxiety and low self-esteem are due to correlations between anxiety factors (Figure S2) and disappear when all factors are considered simultaneously (Figure 4)

STAIT Item	Anxiety factor loadings			
	Somatic anxiety	Cognitive anxiety	Negative affect	Low self-esteem
1* I feel pleasant	-0.019	0.115	<b>0.811</b>	-0.064
2. I feel nervous and restless	<b>0.301</b>	<b>0.356</b>	0.217	0.089
3* I feel satisfied with myself	-0.128	0.099	<b>0.720</b>	0.171
4. I wish I could be as happy as others seem to be	0.058	0.182	0.106	<b>0.322</b>
5. I feel like a failure	0.100	0.292	0.179	<b>0.441</b>
6* I feel rested	-0.007	-0.030	<b>0.722</b>	-0.087
7* I am ‘cool, calm, and collected’	-0.002	0.077	<b>0.797</b>	-0.062
8. I feel that the difficulties are piling up so that I cannot overcome them	0.297	0.229	0.176	<b>0.335</b>
9. I worry too much over something that doesn’t really matter	0.031	<b>0.558</b>	0.087	0.169
10* I am happy	-0.017	-0.000	<b>0.823</b>	0.059
11. I have disturbing thoughts	0.248	<b>0.393</b>	-0.006	0.269
12. I lack self-confidence	0.149	0.129	0.143	<b>0.521</b>
13* I feel secure	0.053	-0.058	<b>0.825</b>	0.072
14* I make decisions easily	-0.123	0.213	<b>0.673</b>	-0.090
15. I feel inadequate	0.101	0.264	0.186	<b>0.497</b>
16* I am content	0.075	-0.157	<b>0.846</b>	0.054
17. Some unimportant thoughts run through my mind and bother me	-0.102	<b>0.785</b>	-0.075	0.169
18. I take disappointments so keenly that I can’t put them out of my mind	-0.081	<b>0.655</b>	-0.025	0.228
19* I am a steady person	-0.004	-0.072	<b>0.773</b>	0.030
20. I get in a state of tension or turmoil as I think over recent concerns and interests	0.080	<b>0.513</b>	0.019	0.265

**Table S1: Factor loadings on the STAIT.**

The anxiety-absent items marked by \* were reverse-scored prior to computing factor weights.

STICSAT Item	Anxiety factor loadings			
	Somatic anxiety	Cognitive anxiety	Negative affect	Low self-esteem
1. My heart beats fast	<b>0.741</b>	-0.019	0.077	0.008
2. My muscles are tense	<b>0.718</b>	0.094	0.135	-0.062
3. I feel agonized over my problems	0.120	<b>0.676</b>	0.110	0.063
4. I think that others won't approve of me	0.165	<b>0.524</b>	0.068	0.180
5. I feel like I'm missing out on things because I can't make up my mind soon enough	0.124	<b>0.672</b>	-0.004	0.046
6. I feel dizzy	<b>0.807</b>	0.001	-0.007	-0.025
7. My muscles feel weak	<b>0.757</b>	0.087	0.074	-0.053
8. I feel trembly and shaky	<b>0.775</b>	0.100	0.030	-0.039
9. I picture some future misfortune	0.194	<b>0.582</b>	0.104	0.075
10. I can't get some thought out of my mind	-0.060	<b>0.918</b>	0.040	-0.072
11. I have trouble remembering things	<b>0.383</b>	<b>0.425</b>	0.075	-0.061
12. My face feels hot	<b>0.861</b>	-0.056	-0.143	0.078
13. I think that the worst will happen	0.229	<b>0.546</b>	0.182	0.062
14. My arms and legs feel stiff	<b>0.831</b>	-0.010	0.043	0.011
15. My throat feels dry	<b>0.724</b>	0.062	0.017	0.061
16. I keep busy to avoid uncomfortable thoughts	0.048	<b>0.755</b>	-0.054	-0.036
17. I cannot concentrate without irrelevant thoughts intruding	0.096	<b>0.824</b>	0.014	-0.069
18. My breathing is fast and shallow	<b>0.861</b>	-0.032	-0.042	0.043
19. I worry that I cannot control my thoughts as well as I would like to	0.141	<b>0.747</b>	0.043	-0.032
20. I have butterflies in the stomach	<b>0.737</b>	0.059	-0.066	0.021
21. My palms feel clammy	<b>0.722</b>	0.038	-0.131	0.037

**Table S2: Factor loadings on the STICSAT.**

Model	Expected log predictive density difference $\pm$ SE
Full model	Reference
No outcome scaling ( $s_{\text{gain}} = s_{\text{loss}} = 1$ )	$-122.6 \pm 23.4$
Shared $C_{\text{info}}$ across all subjects	$-741.2 \pm 33.7$

**Table S3: Model comparison using Pareto-smoothed importance sampling leave-one out cross validation.** A difference in the expected log predictive density of 4 points provides evidence in favor of a model. The ‘Full model’ is strongly favored over the others. The ‘No outcome scaling’ model weights gains and losses equally ( $s_{\text{gain}} = s_{\text{loss}} = 1$ ). The ‘Shared  $C_{\text{info}}$ ’ model has a single  $C_{\text{info}}$  shared across all subjects.

Parameter	Pearson correlation between ground-truth and recovered parameter (95% CI)
$U_{\text{outcome}}$	0.818 (0.710 - 0.884)
$C_{\text{plan}}$	0.728 (0.460 - 0.872)
$C_{\text{info}}$	0.984 (0.969 - 0.991)
$U_{\text{leisure}}$	0.959 (0.932 - 0.976)
$s_{\text{gain}}$	0.716 (0.538 - 0.817)
$s_{\text{loss}}$	0.824 (0.721 - 0.891)

**Table S4: Parameter recovery.** The ‘Full model’ was fit to all subjects to generate a ground-truth set of parameter estimates. Mean parameter estimates for each subject were used to generate a synthetic dataset using the exact same task that the subjects completed. The ‘Full model’ was fit to this synthetic dataset to generate a recovered set of parameters. We estimated the mean parameter estimates for each subject and computed the Pearson correlation between the ground-truth parameter estimates and the recovered parameter estimates. We computed 95% confidence intervals by bootstrap sampling.